Cognitive Fit and Visual Pattern Recognition in Financial Information System: An Experimental Study

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Abstract. This experimental study uses traders to understand the effect of cognitive fit on the performance of decision makers for pattern recognition tasks using financial information systems. Building upon signal detection theory, we find that performance is affected by both attention level and working memory capacity while the level of knowledge in finance and experience in finance have no significant impact. Our results also suggest that overconfidence has a detrimental effect on performance.

Keywords: Decision Making · Behavioral Finance · Cognitive Fit · Pattern Recognition

1 Introduction

Despite the rise of machine learning and artificial intelligence, there are still numerous IT jobs that rely on visual pattern recognition in monitoring tasks. This is the case of traders using financial information system (FIS) who must be able to recognize recurrent patterns in visual task monitoring. By recognizing those patterns, technical traders are making investment decisions based on their anticipation of market reaction. The objective of this paper is to study the effect of cognitive fit [1] on the performance of decision makers for pattern detection in a FIS. Specifically, we conducted a laboratory experiment to examine the effect of attention and working memory on the performance of traders in a recall financial task.

2 Literature Review

Attention refers to the selectivity mechanisms that allow us to process the information we classify as important [2]. Selective visual attention allows us to ignore irrelevant information and direct our processing capacities to the stimuli that are aligned with our goals processing only relevant information. In connection with decision making, visual attention narrows attention to fixate on stimuli required for decision making. Fixating a stimulus improves perceptual representation by strengthening its visual attributes and location, thus reinforcing the influence of fixated stimuli as compared to the non-fixated stimuli [3]. Attention also plays an important role for pattern recognition [4].

Working memory refers to the cognitive system responsible for manipulating information temporarily available for processing in short term memory [5]. It has been shown that working memory capacity predicts performance on a wide range of cognitive tasks such as reasoning, reading, and more [6,7,8]. However, this system can only store a limited amount of information, and for a short period of time [9,10]. Different types of errors can occur when trying to recall information that were previously stored in working memory. Such errors are accounted for in the signal detection theory, which sorts pattern recognition trials into one of four categories (Hit: pattern present and respond present, Miss: pattern present and respond absent, Correct rejection: pattern absent and respond absent, False alarm: pattern absent and respond present) [11].

Further, a strong relationship between attention and working memory has been demonstrated by the eye-mind assumption [12]. This theory holds that working memory's limited capacity leads individuals to rely on fixations to reduce working memory's cognitive load during challenging tasks [13,14,15]. Eye-tracking studies testing the eye-mind assumption have demonstrated a significant positive relationship between working memory load and both the number of fixations [16] and fixation durations [17].

3 Hypotheses Development

Before developing our hypotheses, we will make two assumptions. Since attention and working memory are useful mechanisms in problem representation as well as in pattern recognition, we expect that they will be positively correlated to the performance of decision makers.

H1 - The performance of decision makers is positively correlated to their working memory capacity.

H2 - The performance of decision makers is positively correlated to their attention level.

We also expect that decision makers will perform differently depending on their signal classification trials by the signal detection theory [6,7,8]. More precisely, we expect that decision makers with higher propensity to think they face a seen pattern will perform better in general but will have a lower performance for false alarms trials. Indeed, these participants will rely on what they feel was previously manipulated in their working memory to solve the task while no actual interaction with the pattern in working memory will have been conducted before. Thus, decision makers with biased working memory will think they saw previous patterns more often than unbiased decision makers. This situation could represent overconfidence resulting in poor decision-making [18,19].

H3 - The performance of decision makers is impacted negatively when facing a new task which they think they have previously faced (false alarms trials).

Finally, it is expected that decision makers will show different attention levels based on their trial classification by the signal detection theory [3,4]. More specifically, we expect that they will show a lower attention level for hit trials, as they will accurately recognize a pattern they have previously been exposed to. This implies that a lower attention level is required to make an appropriate decision.

H4 - The performance of decision makers is less impacted by their attention level for a task they know they previously faced (hit trials).

4 Methodology

To answer the research question, we conducted a within subject experiment. Thirty individuals (22 males) aged between 18 and 42 years (average 24.63, std. dev 5.90) were recruited from our institution's research panel. Ethics approval was obtained by our institution's Research Ethics Board. Since our study focuses on novice investors, participants needed to have completed a maximum of three finance courses to be eligible. In exchange for their participation, individuals received a 20$ gift card that could be exchanged at the university's bookstore. Their performance was incentivized by a chance to win an additional 200$ gift card to the bookstore.

The experiment consisted of four separate blocks that were conducted in a financial information system (FIS) context. First, participants answered a questionnaire gathering demographic information, such as gender, age, self-reported knowledge in finance, working experience in finance, and their experience investing in capital markets.

Two five-minute trading simulation tasks were then presented to the participants so that they could become familiar with the trading platform and the behavior of the fictive market index we used in this experiment. During these simulations, participants were given the objective to generate the highest profit possible.

In the third block, participants were exposed to 16 scenarios which were part of what we call the "Investment Survey". Each scenario featured a chart showing the evolution of the price of the same fictive market index as in the second task. Half of the scenarios were taken from the second task and the other half were unseen scenarios. The charts displayed a price path length equivalent to one fifth of simulation. For each scenario, participants had to make an investment decision and to determine the number of contracts they wanted to trade. They also had to determine if they recall seeing the price path shown by the chart during the second task. The scenarios were presented in two random groups containing eight different scenarios. For each scenario, we calculated the participant performance based on a predetermined ending price. The ending price for scenarios taken from the second task were simply the price value 15 seconds after the end of each chart shown in the scenarios, while the ending price for the unseen scenarios were designed like scenarios that could be expected in the trading simulations and were all the same for each participant.

Finally, for the fourth task, participants underwent a n-back 1 test to assess their working memory capacity [20]. During this test, small white squares appear on the screen at one of the 15 possible locations and participants had to determine if the square they saw was at the same place as a previous square. This test gave a n-back 1 score which represents working memory capacity and a n-back 1 bias which measures the propensity to answer positively (that the square is in the same place as the previous one) [21]. Thus, the n-back 1 bias indicates the participant's propensity to report a scenario as seen.

We used eye tracking to record the participant's eye movement during the experiment [22]. The eye movements were tracked using an infrared pupil reflection system (SMI RED250) with a sampling rate of 60 Hz. We constructed one area of interest (AOI) which captured the whole chart for every scenario of the Investment Survey allowing us to generate eye fixation related data for the chart area. The number of fixations and the fixation durations in the AOI are both variables measuring visual attention [22].

5 Results

To test our first two hypotheses, we performed two independent linear mixed model regressions shown in Table 1. For each of these regressions, we included five control variables (gender, age, level of knowledge, job in finance and investment experience of participants) and they were not significant for all regressions. The first regression tested the impact of the n-back 1 score on the total profit in the Investment Survey with the control variables. We found that the n-back 1 score positively predicts the performance. The second regression tested the impact of the number of fixations in the chart on the total profit in the Investment Survey with control variables. We found that the number of fixations in the chart also affects positively the total profit.

Table 1. Summary of linear mixed model regressions of working memory and attention on total profit (with control variables)

Effect on total profit	B	SE B	DF	t	p
(H1) N-back 1 score	22.938	12.921	450	1.43	0.038*
(H2) Number of fixations in the chart	1.041	0.614	449	1.34	0.045*

**p<.05 (one-tailed)*

Table 2. Summary of linear mixed model regressions of the interaction between working memory or attention and the type of scenario on total profit (with control variables)

Effect	B	SE B	DF	t	p
(H3) N-back 1 bias	64.501	25.548	448	2.52	0.012*
(H3) N-back 1 bias with false alarm trials	-82.598	26.478	448	-3.12	0.002*
(H4) Number of fixations in the chart	1.625	0.647	447	2.51	0.012*
(H4) Number of fixations in the chart with hit trials	-1.702	0.628	447	-2.71	0.007*
(H4) Fixations duration in the chart	0.004	0.002	448	2.17	0.031*
(H4) Fixations duration in the chart with hit trials	-0.006	0.002	448	-2.81	0.005*

$*p<.05$ (two-tailed)

We next performed linear mixed model regressions to see the interaction between the n-back 1 bias and the type of scenario based on whether participant saw it previously or not, and whether he reported it as seen or unseen. We also used the same control variables as in the previous regressions (see Table 2). We found a positive relationship between the n-back 1 bias and total profit, but this effect is less important for false alarms trials (unseen scenarios that were reported as seen). We also did the same type of regression on total profit with the number of fixations in the chart as well as with the fixations duration in the chart. Both regression showed the same results; a positive impact on total profit with a less important effect for hit trials (seen scenarios that were reported as seen).

6 Discussion and Conclusion

These first results show that both attention and working memory capacity are positively correlated to performance of decision makers, which supports H1 and H2. They also support previous findings for both working memory-performance relationship [6,8], and attention-performance relationship [23]. Having a higher working memory capacity and looking longer at the chart result in a superior performance. Additionally, the smaller effect of the n-back 1 bias on total profit for false alarm trials (unseen scenarios reported as seen) supports H3 and could indicate that participants were affected by overconfidence. It has already been demonstrated that investors affected by overconfidence make poor investment decisions which results in lower investment returns [18,19]. We also found that the longer and the more frequently participants look at the charts, the higher the profit they generate, but this effect is less important for hit trials supporting (seen scenarios reported as seen) H4. This finding could indicate that participants rely more on what was previously manipulated in their working memory when making investment decisions in presence of scenarios they know they already saw rather than putting too much weight on their external memory. Sadly, this situation is not representative of real investment decisions when capital markets are efficient. The situation does correspond, however, to markets where technical analysis is extensively used.

In conclusion, the objective of this study was to study the effect of cognitive fit on the performance of decision makers for pattern detection in a FIS. We found that both attention and working memory capacity are positively correlated to performance which confirms the importance of using the right type of external representation as stated by the cognitive fit theory [1]. It would be interesting to incorporate a function reporting the resemblance degree of visual patterns when creating new FIS to simplify decision making process. We also found that decision makers are subject to overconfidence. However, these results are limited to novice investors and therefore should not be considered as representative of all decision makers. Future research should focus on expert decision makers to see if we will find the same results. It would also be interesting to test the impact of decision makers emotional reaction at the time of fixation during the problem-solving performance [24]. Finally, it would be interesting to evaluate the impact of overconfidence on decision makers' problem-solving performance.

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How Attention Networks Can Inform Research in Information Systems

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Abstract. Attention is a construct that has been pursued throughout the information systems literature. It is also a topic that has been extensively studied in the cognitive neuroscience literature. To our knowledge there has not been any comprehensive work to bridge these two bodies of work. This idea paper introduces the Attention Networks model, which is one of the prominent models of attention in cognitive neuroscience. We also introduce the Attention Network Test, one of the prominant measures of attention networks. We explore two ways that the model can inform information systems research and conclude that there are many other potential ways that the study of attention networks can advance research in information systems.

Keywords: Attention · Attention Networks Test · NeuroIS research methods

1 Introduction

Information Systems researchers have identified a number of contexts where the study of attention is relevant. For example, attentional capacity has been identified as relevant to optimal virtual workplaces [1] or the sorts of ideas that are generated when brainstorming [2]. In the context of NeuroIS research, attentional processes have recently been investigated for the role they play in e-commerce decision making [3] its relationship with affective states in the context of user assistance systems [4], and has been identified as an area of interest among the NeuroIS community [5]. It is likely that attention will continue to be a relevant topic of interest to information systems in the future. However, despite the interest in attention, to the best of our knowledge there has not been comprehensive work describing the role of attention in IS research. Though there is a significant literature in cognitive neuroscience, key findings from this field have not been influential on information systems research to date. In this paper we discuss the Attention Networks model developed by Michael Posner and colleagues [6], one of the dominant attention models in cognitive psychology and cognitive neuroscience. We then propose some ways that this model can inform and extend the understanding of attention in information systems research.

2 The Study of Attention in Cognitive Sciences

Attention is among the most enduring subjects of inquiry in psychology and neuroscience. William James, one of the pioneers of psychology, investigated the phenomenology attention and identified it as a process to focus on "one out of what seem several simultaneously possible objects or trains of thought." [7]. Rather than a single mechanism as identified by James however, modern cognitive science identifies attention as a number of cognitive processes that work together to yield the attention phenomenon, and could even reflect different mechanisms for different domains (eg. auditory, visual) [8]. Though there are different models of attention, we will focus on the well-established Posner attention networks model in the context of visual attention [9,10].

2.1 Attention Networks

Attention networks describe the networks of neurons that govern the functions of attention. The original Posner attention model was imagined based on cognitive functions observed by psychologists in the 1970s and 1980s. These accounts distinguish three fundamental functions that are essential to the experience of attention: alerting, orienting and executive control. *Alerting* describes the function of maintaining a high degree of sensitivity to stimuli and is often distinguished from general arousal. *Orienting* describes the process of aligning with the source of sensory signals. *Executive control* describes the resolution of conflict among stimuli, including selecting some stimuli for attentional focus while inhibiting responses to other stimuli. Though each of these functions were envisioned based on research in cognitive psychology, they form the foundation for many ongoing research programs in neuroimaging and are foundational to much of the applied work on attention in clinical applications.

In the original attention networks model, the alerting network was originally identified by observing sustained vigilance in behavioral studies and was later correlated with brainstem activity and networks in the right hemisphere [8]. Knowledge of the alerting functions have significantly expanded since the publication of the original model but have largely corroborated alerting as a distinct network [10]. For instance, the effects of neuromodulator norepinephrine have been studied in monkeys and were observed influencing orienting functions, but not alerting, which supports this distinction [11]. However, in most real-world scenarios, the alerting function is observed in conjunction with orienting, leading some to question the independence of the networks [12]. Nevertheless, alerting is still commonly studied as a distinct phenomenon.

Orienting was originally distinguished by Posner in his works on attentional shifts [8]. In its original conception as a network, orienting functions were observed in association with the pulvinar and superior colliculus. However, more recent work suggests that orienting is more complex and involves multiple brain areas including the dorsal system [10,13,14]. Orienting continues to be a subject of considerable interest among cognitive neuroscientists not least because it governs the fundamental mechanism of feature selection, the process of recognizing visual patterns or relevant visual stimuli. Orienting is often further divided into *overt* and *covert* orienting, which rely on different observations. Where overt orienting is typically associated with eye movements or other overt behaviour in the direction of the attended stimulus/location, covert orienting does not necessarily evoke eye movements or other motor activity towards the attended stimulus/location but nonetheless engages similar neural networks [15-17]. Recent work on orienting networks have continued to explore this overt/covert distinction and its implications for attention networks research [18,19].

Executive control is a function that was originally conceptualized to describe target detection and explain the limited capacity of attention. Models have found this function to be associated with connections between the medial frontal and anterior cingulate cortex. Recent understandings of executive control have expanded on this original conception. The original conception of executive control considered it to associate with focal attention. Recent theories suggest two separate executive control networks, as evidenced by neuroimaging studies which reveal distinct frontoparietal and cingulo-opercular networks [10,20]. Other conceptions of executive control identify it with the same network as working memory or as a component of working memory [21,22] or recognize it as many distinct networks for different domains (ie. visual, auditory) [23]. Though the extension of executive control networks continues to be a live topic of inquiry, the original conception of executive control continues to play a significant role in attention research today. Though the Posner three systems model has been arguably the most historically influential model, there is significant ongoing work in attention networks to move beyond this model, especially in the space of the executive brain. Contemporary models have introduced other networks that have been observed since and have incorporated them into an extended attention networks model [24].

2.2 Measuring Attention Networks Using the Attention Networks Test

Attention networks performance are often measured through neurocognitive tests that are designed to separably tap each of the three independent networks. The Attention Network Test (ANT) is the most prominent example of such a test [25,26]. The ANT measures the three attention networks through a combination of flanker tests, which are tasks designed to test response inhibition, and reaction time from cuing tasks, which were designed to measure attentional shifts [27]. In the ANT, the participants' task is to respond as quickly and accurately as possible indicating the direction of an arrow (left or right). The attention networks are differentially engaged by, on different trials, preceding the target with either spatially informative (orienting) or uninformative (alerting) cues, and by arrows flanking the target that are either congruent (same direction) or incongruent (opposite direction) stimuli flanking the target when it appears (executive control). Differences in reaction time can be used to measure the efficiency of alerting and orienting, while executive control is examined by measuring successful responses to the cues.

Though the ANT is the dominant test to advance the study of attention and population research, it has limitations. In response, researchers have investigated expanded measures to explain functioning of attention networks. Studies of the ANT have found weaker associations between alerting and orienting network scores and other attention measures such as those used in the Dalhousie Computerized Attention Battery (DalCAB) [24]. DalCAB is an example of a new attention battery, which uses eight reaction time tests to improve on the ANT by introducing additional measures such as vigilance [24]. As research in this field continues to advance, NeuroIS can benefit by observing the advances in neurocognitive tests and adapt them to IS contexts.

2.3 Measuring Attention Networks Using EEG and MEG

Much of attention networks theory has been validated using neuroimaging, notably electroencephalography (EEG), magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI). Many studies observe correlations between attention task performance, such as the ANT, and the neurophysiological indicators of attention [12,28]. While fMRI research and attention networks is an active area of inquiry and has been demonstrated in the context of attention networks and the ANT [12], there are also common EEG (and consequently MEG) correlates that are observed, particularly with event related potentials, which are short changes in electrical potential on the scalp triggered by neural activity. We introduce two EEG correlates because EEG has been identified as an accessible technology to IS researchers and is applicable to many IS contexts [29], while noting that considerable work has been done on identifying Attention Networks using fMRI and other neuroimaging tools.

The P1-N1-P2 complex is a mandatory response triggered by early attention control mechanisms in the occipital regions of the brain and is sensitive to both visual and auditory stimuli [30]. When a stimulus is detected by the auditory or visual system, this pattern of electrical potentials can be observed at 100-220 ms. Attended stimuli can be observed having higher electrical amplitudes from this response. Early negative electrical potential responses have been found to be associated with alerting and have be observed during the Attention Networks Test [10]. The P1-N1-P2 complex is thus a useful neurophysiological response that can be used to observe alerting and orienting networks in the context of human-computer interactions.

A second EEG component that is often studied in attention research is the P3 component. The P3 response occurs immediately following the P1-N1-P2 response, typically between 250-500 ms, but only in response to task-related, attended stimuli. The P3 is known to be driven by the activation of executive attention and contextual updating in working memory [28,31]. In the context of the ANT, the P3 is evoked during the cuing and can be observed having lower amplitudes depending on attention capacities [28]. Study of the P3 response can thus also be a useful neurophysiological indicator to observe executive functions or dysfunction in IS contexts.

3 Improving IS Measures with Attention Networks

Though there are many potential applications of this research [29], perhaps the most promising contribution of attention networks to the information systems field is in the improvement of IS measures. As mentioned, though alerting, orienting and executive control networks can be identified as separate phenomena, they are often examined in conjunction. A number of research topics in information systems such as awareness displays [1], visual search in web/e-commerce [32-34], electronic brainstorming [35], and online wait times [36,37] have examined topics where the alerting and orienting networks may play a role in the phenomena observed. The methods used in these works included construct questionnaire measures [32,37], comprehension measures [33] or task success measures [34-37]. These represent constructs that could be examined using neuroimaging to determine the impact of attention networks on the tasks, particularly by observing EEG event related potentials such as the P1-N1-P2 response or the P3. By doing so, we can improve the attention-related IS constructs perhaps most noticeably by adding *specificity* and *temporality* to the measures.

Though we are not aware of any extant work in the information systems literature that leverages the neuroscience of alerting or orienting, some work considers the role of arousal, which has long been noted for having common psychophysiological correlates [8]. Electrodermal activity and EEG oscillatory activity has been employed to observe changes in users' cognitive states and to observe flow, which may have some similarities [38]. Considering orienting networks, notable recent work has been conducted by Léger et al., which [39] established the P3 ERP and eye fixation-related potentials as significant measures in information systems research. These methods reflect the state of the art in overt orienting research [40] and open a new area of inquiry for the field with applications to is research with a visual component. Covert orienting, by contrast, remains a potential topic of interest for IS research involving this type of attention without a visual component. Such questions might benefit by leveraging covert orienting measures such as auditory event related potentials [41].

We anticipate that this line of reasoning presents a larger research project on the topic of attention which has the potential to advance IS and human-computer interaction research. In this paper, we discussed the neuroscience of attention networks, an important concept in the neuroscience of attention that, to our knowledge, has not been addressed in the information systems or NeuroIS literature. We also propose a potential application where attention networks can advance research in information systems. However, we conclude that there are also many other potential applications of the attention literature that remain to be seen. For instance, attention networks could inform the creation of new IT artifacts or could inform the creation of brain-computer interfaces [29]. We anticipate that deeper understandings of attention will not only help advance the field but offers the potential to raise entirely new domains of inquiry into the interaction between humans and information technology.

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A Domains Oriented Framework of Recent Machine Learning Applications in Mobile Mental Health

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Abstract. This research illustrates how the interdisciplinary integration of mobile health (mHealth) and Machine Learning (ML) can contribute to implementing mobile care for mental health. 94 articles were identified in a literature review to derive functional domains and composing information items improving the comprehension of ML benefits with mHealth integration. Identified items of each domain were pooled into clusters and information flow was quantified according to prevailing occurrence of included articles. We derive a comprehensive domains oriented framework (DF) and visualize an information flow graph.
The DF indicates that the utilization of ML is well established (e.g. stress detection, activity recognition). Because deployment and data acquisition currently relies heavily on mobile phones, only 65% of current applications make fully integrated use of data sources to assert patient's mental state. Big data integration and a lack of commercially available devices to measure physiological or psychological parameters represent current bottlenecks to leverage synergies.

Keywords: machine learning · application · mobile health · mental health · framework

1 Introduction

Rates of diagnoses for mental and behavioral disorders have increased substantially worldwide resulting in an expanding demand for treatments and interventions [1]. Traditionally, on-site monitoring devices, such as electroencephalogram (EEG) monitor, and medical appointments have been used to sense and store medical data relevant for mental health. Additionally, assessment by a medical professional or psychiatrist is intensive human labor.
The major strength of Machine Learning (ML) is to generalize beyond the examples given from an observation [2]. That seems to be a good fit for medical applications due to the fact that no matter how many medical resources there are, it is very unlikely that one will see those exact medical symptoms, with the same severity, under the same circumstances again at time of medical examination. New technologies such as wearable computing and the prominent development of sensing devices have facilitated the process of collecting attributes related to the individuals. At the same time, the amount

of healthcare data gets bigger and much more difficult to handle and to process, because the number of combinations of attribute values and activities can be very large. The raw data provided by sensors are often useless and therefore systems make use of ML tools, which enable to recognize activities and to build patterns to describe, analyze and predict data [3].
In the scope of this paper, we will have the high-level view of mental disorders as abstract descriptions, which makes ML the perfect diagnosis tool for the aspects of mental disorders and is shown by an increase in computational approaches [4]. In addition, with the pervasive use of connected technologies (above all the internet), wearable medical sensors (WMS) and wireless body networks (WBN) emerged in the last decade [5]. mHealth accordingly no longer only relates to telemedicine but manifests itself in WBN, WMS and mobile phones. Still, using data to predict mood or depression, is an active research field that at the moment largely relies on self-reported surveys (e.g. PHQ-9 responses) in order to obtain and assess the underlying mental state [6].
Hence, introducing ML algorithms provides immense potential to leverage synergies of those three fields and by that to increase a patient's autonomy and safety through mobile mental health applications while improving quality of diagnosis, treatment and enhanced clinical trials as well as reducing medical errors and costs. For this purpose, the following contribution derives a domains oriented framework (DF) in order to get a better understanding of information items and obstacles for interdisciplinary integration of mHealth and ML within the increasingly important field of mental health.

2 Methodology

Table 1. Keyword combinations

Mental health keyword			*and*	*mHealth application keyword*	*and*	*ML keyword*
General	*or*	*Specific*				
mental health, disorder, psychology		depression, anxiety, attention-deficit, hyperactivity, oppositional defiant, conduct, disruptive behavior, behavior		smart phone, cell phone, android, iPhone, app, sensor, wearable, mobile & [device, phone, technology, sensor]		machine learning, decision support, pattern recognition, supervised, classification, unsupervised

This paper follows the idea of the Theoretical Domains Framework [7], derives a framework for implementation research and provides a theoretical lens through which one can view the applications and their recent influence in mental health [8]. First off, keyword combinations (see Table 1) suitable to find recent application cases and derive a representative and recent (initially Jan 1st, 2012 or newer) overview were developed. We decided to search for recent cases that focused on the description of a conducted study or an application case while not being an overview of a set of applications, because we wanted to visualize a quantified information flow afterwards (cf. [9–11]). The underlying set to the DF after screening was supposed to consist of literature that met the following inclusion criteria: (1) The article implies that the case provides diagnosis, treatment or support for (2) mental health as its main goal. (3) The article implies that the application case uses ML for handling or providing information. (4) The data was acquired by a system developed for mobile native use and compatible with smartphones, wearables (e.g. smartwatches) or sensors somehow gathering or requesting subject's individual input data. A subject may not only be a patient but also includes users seeking for support in stress management or for the prevention of mental health issues. Application cases using ML for comorbidities (e.g., depressed people with heart diseases) were excluded because different care needs or outputs dilute the model to be built. An analogous situation was identified for Internet of Things devices, where i.e. webcams are not classified as mobile because they belong to a specific stationary environment even if that environment is deployed at home.

3 Results

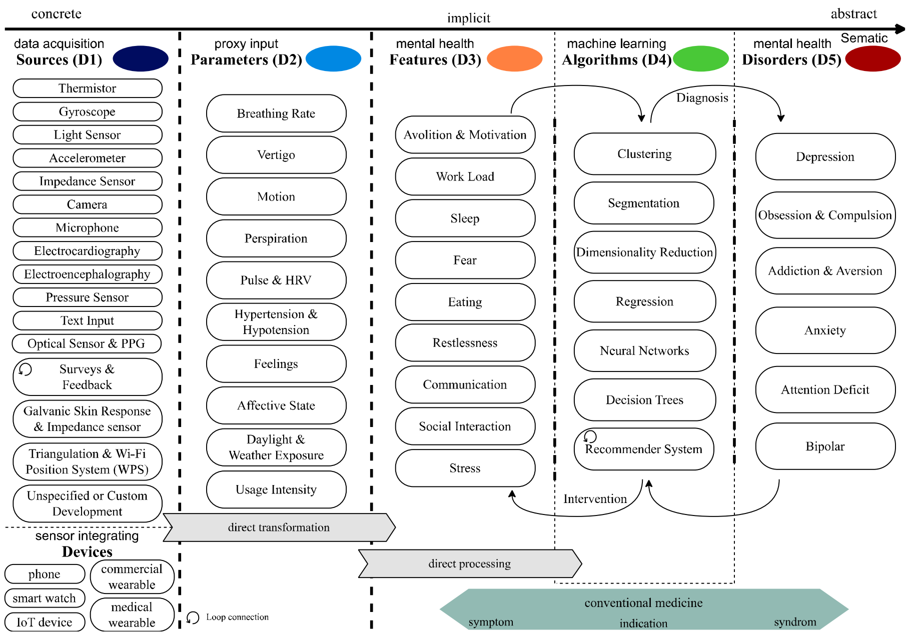

Fig. 1. Domains oriented framework showing functional layers and its characteristic items in a hierarchy from concrete to abstract mental disorder.

The identified applications and studies represent a functional layered hierarchical DF (Fig. 1), as this illustrates a number of processes, issues, and algorithms currently being treated from a research perspective. Due to the strong ability of ML to generalize [2], direct transformation of electric signals into mental health features are possible as well as taking input parameters directly to be processed by ML without knowing what mental feature they represent. The generalization aspect is visualized by the decreasing number of items in each domain when going from left to right. Going through the characteristics, we will describe the clusters of items that are necessary to look at the information flow in a quantitative way in Fig. 2. The domains are characterized as follows:

Sources D1. Data sources found in application cases vary the most and represent different format, mean of mobility, and granularity. While per search strategy all devices are wearables, they can be separated into commercially available *Wearables* and *Medical* grade devices. *Medical* grade devices in our definition are used under medical supervision and not accessible for patients outside a hospital environment (i.e. [12]). Driven by the trend of the quantified-self ubiquitous sensors are commercially available. The last cluster for the general *Input* consists of diary studies and surveys like the Perceived Stress Questionnaire [13] or the Depression Anxiety Stress Scale [14, 15].

Parameter D2. The biggest group describes the *Activity* of the patient most commonly also referring to vital parameters or its current motion (e.g. sitting or walking). The aspect of heart rate is very central here and might get directly processed by ML [16]. With the help of galvanic skin response, skin temperature or electrocardiography (EEG) feelings and states of affection are described [17] representing the cluster of *Emotion* of D2. The *Environment* itself on the other hand influences the mental health as a stressor [18, 19]. The *Interaction* cluster represents to what intensity a patient interacts with an object or situation. Main items are addiction and usage [20, 21].

Features D3. Mental health features compose disorders and might be seen as parts of the diagnosis for an actual medical mental disorder (symptom). I.e., motion from D2 is mainly followed by a general description of the physical *Constitution* of patient. The *Burden* of a patient aggregates features like restlessness, fear or bad sleep [22]. *Social* aspects are the characteristic feature for mental diseases, which we decided on since depression is associated with social isolation [23, 24].

Algorithms D4. As expected included articles display a variety of ML algorithms [2] (SVM, NB, GMM, J48 etc.). We decided to cluster them based on their approach and intention into *Regression* (i.e. predicting [25]), *Classification* [26] and *Network* approaches like Artificial Neural Networks or Decision Trees, that are widely used for descriptive reasons when input is of high-dimensionality [27, 28]. We found that the input for the ML algorithms is widely spread across D1 to D3, which is explained by the generalization ability of ML approaches.

Disorders D5. The disorders domain is dominated by the prevalent diseases of mental health [1]. Most frequently mentioned were *Depression*, *Anxiety* and *Bipolar* disorder (e.g. [29–31]). However, we found that in most cases there is no output of an actual mental health disorder (53 cases) rather than diagnosis of *Stress*, *Mood*, or *Emotion* as a kind of sickness [16, 26, 32].

Information flow. For a substantial discussion and overview of research activities as well as gaps regarding the derived framework, we created a flow graph (Fig. 2). For descriptive reasons, not every item from every domain of the DF (Fig. 1) was included, but items were pooled in clusters. Size depicts simple observation count of an article classified in the according cluster by its item. As one can see, a lot of cases were categorized, except for the edges leading to the *NoInformation*-Vertex. Those edges are also representing the *direct transformation* or direct processing aspect from the DF (Fig. 1), which make up for 12 cases only.

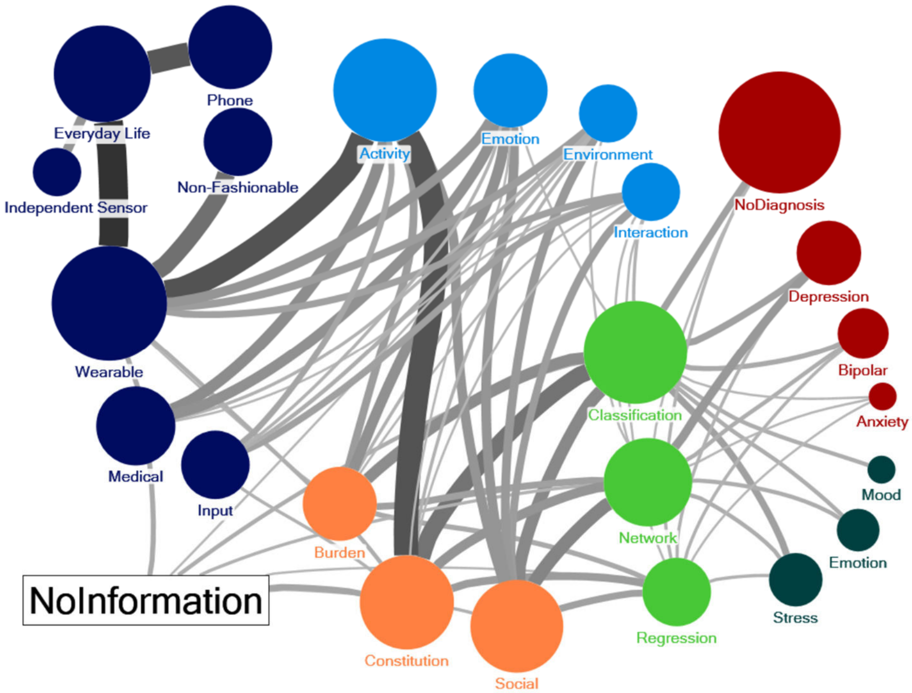

Fig. 2. Application cases flow graph. Clusters were pooled from the DF items. Linearity applies to vertices as well as edges (i.e. double the sizes follows double the observations).

To identify the most common application one may follow the biggest vertices and strongest edges from domain D1 to domain D5. The most frequent application is a commercial *Wearable* (51 cases) used to model *Activity* (41 cases; 25 from *Wearable*), from which the *Constitution* (34 cases; 25 from *Activity*) of the individual is deduced. The *Classification* (23 cases; 17 cases from *Constitution*) approach is implemented resulting in the most found diagnosis of *Depression* (16 cases; 6 from *Classification*) or Stress (11 cases; 6 from *Classification*). In addition, selecting the right currently commercially available hardware for mental health seems problematic: In 18 cases of 51, the chosen *Wearable* is a bulky or at least *Non-Fashionable* device, whereas fashionable wearables would have been beneficial (see [24]). This is leading to the conclusion that the desired data of handy or fashionable sensors is either not measured, not detailed enough or not directly (only via cloud) accessible. The most important example on this issue are ECG and EEG measurements, which are very important for diagnosis of mental disorders. Sensors are available only in a *Non-Fashionable* mean and commercially available devices are not really at a consumer level of usability. Mentionable *Non-Fashionable* devices from the included literature are the Shimmer 3, ActiGraph GT3X+, Zephyr BioPatch™, Empatica E3 wristband, Q-Sensor Affectiva and EMOTIVE EPOC+ Headset. The remaining 36 devices suitable for *Everyday Life* consist of 27 cases where solely *Phones* were used and 9 *Independent Sensors*.

Success rate of domain transition. For further verification and reasons of logical conclusion we bring together the content of Fig. 1 plus Fig. 2 to follow a potential application success rate in Fig. 3. Therefore, we calculated the share of applications that were successfully grouped into that category for every domain:

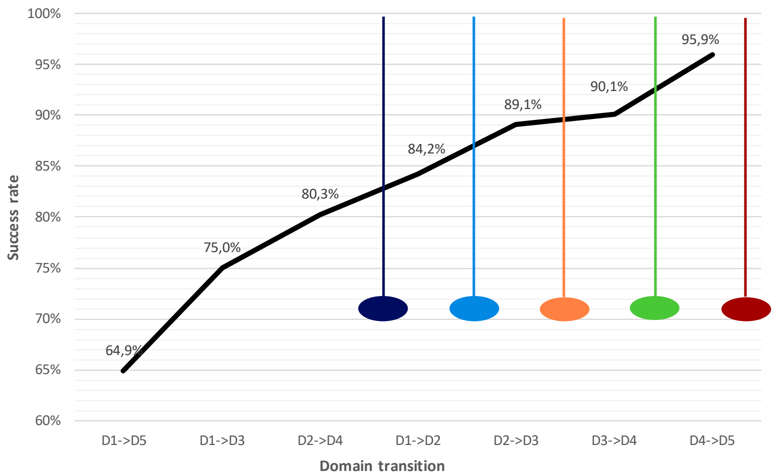

Fig. 3. Success rate of domain transition

$$P_{D\mathrm{n}-1 \to D\mathrm{n}} = \frac{\text{successfully categorized in } Dn-1}{\text{successfully categorized in } Dn} \qquad \forall n \in \{2,3,4,5\} \tag{1}$$

For D1 an extra condition applies, that the data source is not part of a mobile phone, since this paper originally was intended to include true wearable sensors. Direct transformation and direct processing have been calculated analogous. The interpretation of Fig. 3 is, that the more abstract the starting domain for an application is, the higher is the probability that the next domain can be clearly assigned. For example, if one wants to develop an application and starts with the raw skin conductance data there is an 84% chance ($P_{D1 \to D2}$) he is able to relate this data to an affective state successfully. If this developer would start with information about a parameter like the affective state, the chance to relate this information to stress would increase to 89% ($P_{D2 \to D3}$). Implementing the *direct transformation* from skin conductance to stress has a success rate of only 75% ($P_{D1 \to D3}$), as our data indicates. This finding is congruent to the assumption that more concrete values (i.e. from D1) are harder to relate to mental health disorders, since there are more steps in between, that one has to derive (i.e. stress from D3). If someone is able to directly access feature from D3 relating those to mental health disorders is significantly easier ($P_{D3 \to D5} = 86\%$). To get an overall probability to successfully explain a mental health related state of a patient one may simply multiply the probabilities of all domains:

$$P_{D1 \to D5} = P_{D1 \to D2} \times P_{D2 \to D3} \times P_{D3 \to D4} \times P_{D4 \to D5} \tag{2}$$

According to the DF we built and the categorization process, this means: If one wants to develop a new application for mental health using a wearable sensor this has a 65% ($P_{D1 \rightarrow D5}$) chance to result in a meaningful assertion about patient's mental state.

4 Discussion

While analyzing the included literature, we found reoccurring arguments that help explaining obstacles of the DF and its representation in the information flow graph:

1. Big data or multimodal sensor integration (like weather data [33] or pollution [34]) as an input for ML falls short in mobile mental health (see *Environment*, *Interaction*). On the other hand, when making use of big data, most cases focus on describing syndromes (i.e. *Classification*) rather than recommending interventions, which is represented by the smallest cluster of *Regression* in Fig. 2.
2. We see from the proportion of the disorders group in the flow graph of Fig. 2 that in most cases ML algorithms do not diagnose classical disorders rather than conditions. Of those being *Stress* the most occurring. Additionally it seems complex to develop a comprehensive application that uses physical sensors and derives an assertion of the mental health, which is supported by $P_{D1 \rightarrow D5} = 65\%$.
3. There are not enough commercially available (labeled *Everyday Life*) wearable devices, whereas mobile *Phones* are not a sufficient replacement. They are not able to measure physiological parameters, because they do not have continuous body contact.

The issues identified in this article are in consensus with recent research and challenges faced by mobile wearable systems [35]. ML employment was not yet able to overcome all technical and integrative challenges. Only 65% of current applications make fully integrated use of data sources and we found that the more semantically abstract information is, the easier it is to derive an assertion of a patient's mental health.

Limitations. This framework derivation has some limitations. We systematically scanned for ML approaches, whereas there is the possibility that an unneglectable set of application cases uses ML without mentioning it. The more modern eHealth makes use of ML, the more it becomes a background technology by default. In addition, the used keyword combinations may not cover the huge interdisciplinary area that was to investigate. Secondly, this review focuses only on published literature cases in ML in context and therefore does not consider the wide field of applications such as app stores. There are still means to be found to academically assess prototypes and software.

Implications. The derived DF for mobile application scenarios based ML shows the potential to remove barriers to care, adjust to users individually, and alleviate suffering for a large number of people with mental disorders at a modest cost and with minimal daily life intrusion. In summary, research efforts towards improving measurements quality (especially EEG and ECG), mobile and environmental data integration, process partitioning, deployment to smart watches or commercial wearables and extending the ML into the field of intervention recommendation are necessary. To relate information to a mental health assertion successfully, it is recommended to start with the least concrete described (raw) data set or information. Information science should address the topic of workload distribution to maximize utilization.

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Microsaccades as a predictor of a user's level of concentration

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Abstract. In comparison to voluntary eye movements (saccades), microsaccades are very small, jerk-like and involuntary. While microsaccades and cognition has become one of the most rapidly growing areas of study in visual neuroscience [Trends Neurosci 32: 463-475], microsaccades are still neglected in NeuroIS. Using experimental data by Walcher et al. [Conscious Cogn 53:165-175; Data Brief 15:18-24] we demonstrate the potential of microsaccades to evaluate the level of concentration a user perceives during task fulfillment. As a result we found a substantial negative relationship between the magnitudes of the microsaccades and the level of concentration ($p < 0.01$).

Keywords: NeuroIS, eye-tracking, microsaccades, concentration

1 Introduction

Microsaccades are the very small and fast movements of a human's eyes including tremor, drift and correcting saccades when fixing on a visual target [1-3]. Microsaccades can be defined as "small, fast, jerk-like eye movements that occur during voluntary fixation" [3]. In medicine and psychology microsaccades play an important role in helping us understand visual attention, mental concentration and information processing [4-17]. From a physiological point of view microsaccades correct and stabilize visual attention [1] and optimize the sampling for visual scenes [4]. From an information processing perspective it has been found that microsaccades are linked to mental concentration related concepts such as attention [13], concentration [14] and memory load [15], workload [16], task difficulty [10, 11, 15, 17], and mental fatigue [12].

Despite the important role of microsaccades in mental concentration processes, NeuroIS related eye-tracking research only uses (regular) eye saccades [18], gaze fixations [19], and several pupil derivatives [20-25], while microsaccades are neglected [26].

That is why – using existing data for secondary analysis [27, 28] – this paper evaluates the potential of microsaccades to determine the level of concentration a user perceives during task fulfillment.

2 Methodology

2.1 Data

The data used for this analysis were hosted by S. Walcher et al. [27, 28] at the Open Science Framework (OSF) (https://osf.io/fh66g/).

2.2 Participants

Forty-eight healthy participants (19 to 27 years old; 32 females, 15 males, 1 NA; normal or corrected-to-normal vision), mostly university students, participated in the experiment conducted by Walcher et al. [27, 28].

2.3 Instruments and devices

Binocular eye data was recorded using 500 Hz EyeLink 1000 Plus Tower Mount eye-tracker (SR Research) [27, 28]. Stimuli were presented on a 19-in LG flatroon L1920P monitor run a 60 Hz and a 1240×1024 pixels resolution [27, 28]. EyeLink Experiment Builder software (SR Research) was used for stimulus presentation and response recording [27, 28].

The level of concentration a user perceived during task fulfillment was measured using the six-point Likert scale by Walcher et al. [27, 28].

2.4 Stimuli and procedure

Data comprises eye-tracking information from eight idea generation tasks (alternate uses task by Guilford [29]) and eight letter-by-letter reading tasks (by Walcher et al. [27]) under two background brightness conditions (RGB color codes: 204, 204, 204 and 102, 102, 102) [28]. All stimuli were presented as counterbalanced.

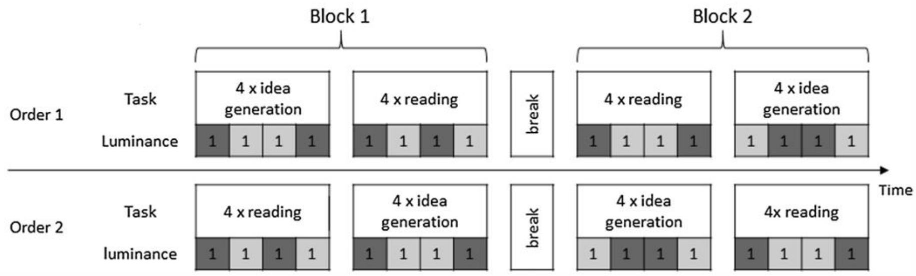

Fig. 1. Test procedure; from [28, p.168].

3 Results

In both types of task (idea generation, and reading) we found a substantial negative relationship between the magnitudes of the microsaccades and the level of concentration (Table 1).

Table 1: Relationship between the magnitudes of the microsaccades and the level of concentration (Spearman test)

Type of task	**Level of correlation**	**Level of significance**
Idea generation task by Guilford [29]	-0.32	$p < 0.01$
Letter-by-letter reading tasks by Walcher et al. [27]	-0.27	$p < 0.01$

4 Discussion, limitations and future research

Our results are in line with the results by Steinman et al. [14] who found lower microsaccadic magnitudes when the participants have to concentrate themselves (holding their eyes still).

The results demonstrate the potential of microsaccades for evaluating the level of a user's concentration. Using the microsaccades bio-data NeuroIS scholars can better understand a user's concentration as an Information Systems construct (cf. NeuroIS guideline 4 [30], [31] in general).

4.1 Limitations and future work

Since the concept of concentration is not clearly defined and it is not distinguished from to other concepts such as attention, flow [32] or boredom [33], a validity-related measurement weakness exists in our analysis. Future work could use scales measuring concentration related concepts. Another measurement related weakness is concerned with the sole use of a one-item scale to indicate the level of concentration [27, 28].

Future work should address these weaknesses using multi-item instruments measuring the level of concentration and concentration-related concepts.

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Tracking and Comparing Eye Movements Patterns while Watching Interactive and Non-Interactive Videos

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Abstract. In this paper, we demonstrate how our eye moments differ when we are watching non-interactive videos (sports clips) vs. interactive videos (video games clips). We obtained the eye tracking data from Collaborative Research in Computational Neuroscience's (CRCNS) data sharing set; we analyzed the subsets of eye movement data which were tracked while the test subjects were watching sports clips (videos whose contents are non-interactive) and video game clips (videos whose contents are interactive). We then compare the variations of both x- and y-coordinate eye movements between watching real videos and watching animated videos to identify the difference in eye movement patterns between the cases. Moreover, we also conducted tests on to see if there exists any difference in the distribution of the eye status of fixation or saccade between the cases. Our results provide insights into the cognitive processes when people are watching videos. We also discuss the implications of our results to the various applications in IS field.

Keywords: video watching, fixation, saccade, eye tracking, eye movements

1 Introduction

In recent years, two research streams have obtained increasing interests from researchers who want to gain insights into people's cognitive processes. One is the eye movement data acquisition and analysis, and the other is video game playing/video viewing analysis. Eye tracking has become a conventional technique for studying cognition processing for visualization (e.g. [1], [8], [12]). This technique is applied in some research studies which involves reading sentences [4], comparing reading speed between low-frequency words and high-frequency words and missing letters [9], some real-time situations like how a batsman hit the ball [6], and social desirability bias [5]. The insights obtained from the eye tracking data analytics facilitate our understanding of human cognitive architecture, and eye tracking information can serve "as a window onto cognitive processes in dynamic visualization environments" [1]. On the video game playing/viewing stream, one crucial insight is from [13], which identifies the sense and practice of control during video game playing vs. regular video viewing as an essential factor that impacts people's cognitive processes during the respective experiences. However, there are not sufficient literature that systematically integrates these two promising research streams. And there are much exciting research questions remained to be addressed. There were some studies which compared animation / dynamic pictures with static pictures (e.g. [2] and [3]). The purpose of these surveys is straightforward; the authors want to investigate if there is any difference in learning between animation/dynamic picture presentation and static picture presentation. In neither of these experiments did they use any eye tracking data.

In this paper, we attempt to integrate the research in eye movement and video game playing/video viewing and address the question whether the eye movements differ during video game playing and regular video viewing. We compare the patterns of human's eye movement while watching video clips of sports events and video clips of video games. We hypothesize about the possible relationships between the type of the videos people are watching and their eye movement patterns and collect data to test the relationships. Our results provide insights into how people's eye movements differ when watching sports videos vs. video game clips. Consequently, our results have significant implications to various IS applications, such as the design of IT artifacts, the design of learning technologies, and the design of online advertisement.

The rest of the paper proceeds as follows: in section 2, we review relevant literature and formulate our hypotheses. In section 3 we describe our data, followed by the data analyses and results in Section 4. And finally, we discuss the implications of our work and conclude in section 5.

2 Literature and Hypothesis

2.1 Literature Survey about Eye Movement

There has been increasing interests among researchers in neuroscience and psychology to understand how human's eye movements can tell us about how our brain works [14], [15]. Besides experiments from a strict laboratory environment, researchers have also conducted experiments with natural stimuli. In [4] we can see how mind wandering effects one's eye movements. They found that brain wandering effects the speed of reading and also the ability to understand a sentence. Also, for persons who were into the task took less time to go through less frequent words somewhat compared to mind wandering persons. The same was also stated in [10] where the researchers had found less time for frequently used words when compared to rarely used words. They also observed fewer fixations before mind wandering. In [11] they found a contradicting result saying that mind wandering persons have taken less time for going through to difficult words than of the persons who are in focus. They argue that the persons who are not concentrating do not care to understand or give some extra time for understanding where the persons who are focused on task will try to spend more time on understanding. In [7] researchers found a difference in understanding a concept with both text and pictures among different age groups. More specifically, they have discovered that fourth-grade students faced more significant difficulty in interpreting the pictorial representation (in this case flower and its description). In addition, they found that they spent much less time on pictorial representation when compared to text, whereas the adults have spent a considerably equal amount of time looking at both text and pictures.

There is also some research to analyze eye tracking and differentiate between good batsmen in cricket compared to regular batsmen [6]. Concentrating on a right place with efficient timing is very important for any ball sports such as cricket or tennis. "Keep your eye on the ball" is the first advice given by the coaches when you are playing cricket or tennis. In cricket, batsmen can somehow anticipate the ball by some predictions based on the finger moment of bowler or pitch behavior. However, they found that a short latency in the first saccade in the batsmen eye movement differentiates good batsmen from standard batsmen. The critical factor is how fast you understand the line and length of the ball.

2.2 Literature Survey about Video Game Playing / Regular Video Viewing

Video gaming as a mechanism to understand the human cognitive processes has garnered significant interests from the researchers ([16], [17]). In addition, eye movement data collection and analyses during video games have been implemented to obtain further insights on the player's cognitive processes ([18], [19]). One common theme identified in these video games literature is the sense and practice of control for the players. In [13] the author pointed out that the interactive nature of video games usually results in the player's sense and practice of control over the contents and development of the game, and this is one major factor that differentiates peoples' cognitive processes while watching movies (i.e., non-interactive) vs. playing video games (i.e., interactive). [13] pointed out that compared to regular videos, video games are transformed "into an interactive form that enables the player actively to participate in shaping the games." This interactivity afforded by video games is the most significant factor that distinguishes video games clips and regular videos such as sports clips. Many other aspects of the two types of video clips remain quite similar. For example, while researchers have noticed that for many video games, users' eye movement focus more on the center areas of the screen (e.g., [21], [22]), researchers also notice that for regular video clips (e.g., [23]), including the sports clips (e.g., [24]), the viewers' eye movement also have a high degree of fixation with the center of the screen, presumably due to video making conventions placing the most relevant information in the center of the screen. Thus the sense and practice of control derived from the interactivity nature of video games should be the main factor that could potentially impact the eye movement patterns.

It is reasonable to believe that in the scenario of watching a video game clip, a person would also display the sense and practice of control, even though the person is not interactively playing the video games. We believe that this element of control due to the interactivity nature of the video game would play a role in the viewer's eye movement. In the existing literature, we are not aware of any research that specifically studies this possible variation between the eye movements when watching video clips of various levels of interactivity. We fill this void in this paper.

2.3 Hypothesis

We study two possible aspects the levels of video interactivity can impact the eye movement. The first aspect is the variation of the eye movement, represented by the x- and y- coordinates of the eye movement data. When watching video game clips, people will have a higher level of sense of control due to the interactivity nature, and as a result, their visual attention would be more focused, compared to when they watch non-interactive sports clips. Thus, their eye movement data should display various levels of variations between the two types of video watching. Therefore, we obtain the following Hypothesis:

H1: Variation of eye movement co-ordinates does not significantly differ between watching non-interactive videos (sports clips) and watching interactive videos (video games clips).

For this null hypothesis, we formulate our alternative hypothesis as: variation of eye movement co-ordinates is higher in the case of watching non-interactive videos (sports clips) than watching interactive videos (video games clips).

The second aspect is the distribution of eye status. Eye tracking data usually include the statuses of the eye. Those statuses can be categorized into 6 groups, which will be explained in the next section. We believe that when watching non-interactive videos (sports clips) vs. watching interactive videos (video games clips), there should be a difference in the distribution of the eye status. Therefore, we obtain the following Hypothesis:

H2: The distribution of statuses of the eye is not significantly different between watching non-interactive videos (sports clips) and watching interactive videos (video games clips).

For this null hypothesis, our alternative hypothesis is that the distribution of eye statuses is affected by whether people are watching non-interactive or interactive videos.

3 Data Description

The data used herein is obtained from Collaborative Research in Computational Neuroscience's (CRCNS) data sharing set [20]. The data consists of not only eye tracking movements but also provide us with pictures and videos of how the eye coordinates move while someone is watching a video. For our research, we took sports and video games videos eye movement data files which include eye movement trace for each video clip of five sports videos and nine video games videos which were taken at a frequency of 240Hz(i.e., 240 samples/s). They include the following information that we analyze in this paper about the eye movement:

- (x, y): instantaneous eye position coordinates while watching the screen.
- Pdiam: pupil diameter; it has defaulted to 0.
- Status:
  0 = fixation, excluding eye blinking.
  1 = in saccade, excluding eye blinking
  2 = fixation, during an eye blink
  3 = saccade, during an eye blink
  4 = smooth pursuit, excluding eye blinking.
  5 = unknown (e.g., loss of tracking)

More detailed descriptions of the data can be found in [20].

4 Data Analyses and Results

4.1 For Hypothesis1

To test H1, we perform a one-tailed F-test between the x- (and y-) coordinates of eye movement data when watching sports clips and those when watching video game clips. Table 1 shows the result.

Table 1. The F-test result for comparing x- and y- coordinates of watching VG and SP videos.

Pair	num df	den df	F	p-value	C.I	ratio of var.
VG x - SP x	128730	40197	0.51	< 2.2e-16	0.00 - 0.52	0.51
VG y - SP y	128730	40197	0.98	0.0213	0.00 – 0.99	0.98

VG: video game data; SP: sports data

From the result, it is noticed that for both coordinates, the results are significant, and the null hypothesis is rejected. That means when watching non-interactive video clips (sports), people's eyes do wander around more, both horizontally and vertically, compared to when watching more interactive video clips (video games). One possible explanation for this phenomenon is the sense and practice of control initiated by video game playing, which we believe carry over to just watching video game clips.

4.2 For Hypothesis2

To investigate whether the distribution of the eye statuses is independent of the types of the videos people are watching, we performed a Chi-square test for the independence. Table 2 shows the results.

Table 2. The Chi-square result for comparing eye status data of watching VG and SP videos.

Pair	X-squared	Df	signifcance
VG - SP	296.25	25	< 2.2e-16

VG: video game data; SP: sports data

From the result, it is noticed that the distribution of the eye statuses is not independent of the types of the videos people are watching. Whether people are watching interactive videos or non-interactive videos will affect the distribution of their eye statuses.

5 Managerial Implications and Future Directions

Eye movement information has been one focal point of interests from researchers who want to investigate people's cognitive processes. Through the data collection and analysis of eye movement data while people engage in various activities, researchers have attempted to shed new lights on various cognitive processes. On the other hand, researchers have studied video game playing/viewing and their impacts on cognitive processes, especially when compared with regular video viewing [13]. However, there is limited literature that studies the eye movements during watching video game clips vs watching regular videos. In this paper, we attempt to fill this void. Based on [13]'s theory of sense and practice of control due to the interactivity nature of video game playing/viewing, we hypothesized about the relationships of watching different types of video clips (video game clips vs. regular sports clips) and their corresponding eye movement patterns. Based on the public eye tracking data available from Collaborative Research in Computational Neuroscience's (CRCNS) data sharing project, we show that when watching non-interactive video clips (regular sports), people's eye wander around more than when watching more interactive video clips (video games). We also show that the type of videos people are watching significantly affect the distribution of their eye status.

Our results have significant implications for a wide variety of IS practices and research directions. For example, in the learning technology design for children, researchers have realized that eye movement data capture and analyses is an ideal approach to infer the physiological behavior of children [25], as children may not be able to reliably express their conditions verbally. Our results may inform the learning technology designers to implement more interactive features on the components to which they want more focused visual attention from the children, in order to obtain betterment of learning process in children.

Another example is the design of IT artifact interface, such as website, which is an essential interface for HCI. By the eye tracking movements measure, we can observe the patterns of users surfing website with different levels of complexity [26]. Based on our results, we can improve the design of the website by enhancing interactive components in places where we prefer higher user visual attention and diminishing interactive features present in the places where we require less user's attention. This may lead to maximizing the likelihood of user satisfaction and return visits to the website.

Furthermore, in digital marketing, we can measure the effects of an advertisement stimulus on consumer attitudes [27]. Eye tracking can be used as one of the cognitive approaches, where we can track the eye movements and can relate the consumer psychology for better advertising methods. Based on our results, we can introduce higher interactive components in strategically located places in the advertisement in order to draw user's visual attention and develop an interest in the product.

In all of the above cases, designing experiments to verify the validity of those identified correlations would be of interest to many researchers. Once those correlations are validated, further research can be conducted to design the approached to actually implement the identified correlations.

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The Impact of Using a Gamified Interface on Engagement in a Warehousing Management Task: A NeuroIS Research Proposal

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Abstract. Engagement, or rather lack thereof has become a major issue because of its negative impact on productivity. Recently, gamification has successfully been implemented into corporate technological interfaces to increase engagement of employees. This paper proposes a theory-driven experiment that examines the impact a gamified interface has on engagement and performance of workers in a warehouse-management task. Specifically, the experiment proposed in this paper compares how the integration of two different types of goal-setting (self-set goals or assigned goals) into a warehouse-employee interface will affect engagement and performance.

Keywords: Engagement·Performance·Gamification·Information Systems·Electroencephalography

1 Introduction

Nearly two-thirds of warehouse employees are not engaged in their work [18]. This leads to a lack of employee productivity, a high turnover rate, more errors and less profitability; all factors greatly affect organisational efficiency [32]. In recent years, gamification of employee interfaces has been employed to combat this issue. Gamification is defined as the "use of game design elements in non-game contexts" [9]. In other words, gamification employs the engaging nature of elements used in video games to create engagement in another context. Some of the common elements used in gamified interfaces are points, levels, goal-setting, feedback, badges and leaderboards. Building upon Tondello et al.'s framework [38], the current study will focus on two of these: goal-setting and feedback. There have been very few attempts at integrating gamification into an employee user interface for technology used within a warehouse setting [22], [38]. As noted by Coffey [6], optimization within this setting has mostly focused on the task itself, rather than on the human performing it. Small [31] adeptly proposes that the lack of focus on the human provides a great opportunity to increase employee engagement through gamification.

The objective of this paper is to propose an experiment that can determine how the gamification of a warehouse employee interface affects employee engagement and performance. The experiment will also allow for the examination of the physiological mechanisms by which gamification affects performance. First, employee engagement and gamification literature will be reviewed. Hypotheses will then be presented, followed by the experimental methodology.

2 Literature Review

Literature on engagement shows that engagement is a multifaceted concept. It is comprised of behavioral, emotional and cognitive engagement. Behavioral engagement relates to participation and involvement. Emotional engagement comprises positive and negative reactions. Cognitive engagement relates to investment, thoughtfulness and willingness to put in effort towards the task [13]. Intuitively, it is easy to understand how an engaged workforce performs better. Empirically, Harter et al. [17] performed a meta-analysis using 339 research studies and found that employee engagement is related to nine performance outcomes: profitability, productivity, turnover, absenteeism, customer loyalty, safety incidents, shrinkage, patient safety incidents and quality (defects).
Self-determination theory (SDT), a psychological theory of human motivation, has emerged as the leading theory with regards to explaining human motivation. SDT distinguishes between two types of motivation: intrinsic, which refers to motivation that comes from within, and extrinsic, which refers to motivation that results from assigned outcomes or reward. Research shows that intrinsic motivation is the main type that is used to explain underlying motivational effects of game design elements [36]. SDT states that satisfying three basic psychological needs will lead to increased intrinsic motivation: (1) competence, described as an employee feeling they can efficiently and competently deal with a challenge; (2) autonomy, defined as the sense of freedom and will when performing a task; (3) relatedness, which is the feeling of connection to others [7].

So how exactly does intrinsic motivation from a gamified interface increase employee engagement? This can be explained through the lens of the Job Demands-Resource (JD-R) model. Basically, this model proposes that the intrinsic motivation generated through the satisfaction of SDT's three basic psychological needs by the implementation game design elements results in a greater availability of motivational resources. JD-R states that when employees have enough resources to deal with job demands, engagement is greatly increased [10]. For example, integrating a self-set goal mechanism into an employee interface can increase intrinsic motivation and available resources through the autonomy of the competence aspect of SDT. In other words, allowing employees to set their own goals may give them a certain sense of autonomy.

Complementary to SDT, goal-setting theory, another well-established theory of human-motivation, provides further insight into how game elements can increase engagement, specifically, the goal-setting game element. This theory states that people are generally motivated to achieve goals. This motivation is because of self-regulation, which is the modification of thought, affect, and behavior [19,20], [24]. In fact, decades of psychological research exist documenting how goal setting increases engagement and performance [23]. However, there is much debate on whether self-set goals or assigned goals produce greater engagement and performance. As is noted in a meta-analysis by Harkins and Lowe [16], most of the previous studies comparing self-set versus assigned goals did not take into account necessary factors for a valid comparison. Other research into this comparison has shown that goal commitment is higher when goals are self-set [29]. Because goal commitment is a strong moderator of the relationship between goals and performance [27], it can be argued that self-set goals may lead to better performance and possibly more engagement. Based on the reviewed literature, we have developed two hypotheses:
H1: The use of a gamified interface where goals are either self-set or assigned and feedback is received will lead to higher engagement and performance, when compared to no gamification.
H2: The use of a gamified interface where goal-setting is self-set will lead to higher engagement and performance, when compared to assigned goal.

3 Methods

3.1 Experimental design

This study uses a within-subject design. Twenty subjects aged between 18-25 will participate in this study. They will be taken from our institution's participant pool. The current experiment was approved by our institution's research ethics board.
Building upon recommendations by Liu et al. [26] our experiment was designed bearing two types of outcomes in mind: experiential and instrumental. The following experiment will examine the impact of using a gamified interface on an experiential outcome (engagement) and an instrumental outcome (task performance) during a warehousing management task. In this case, a warehouse management task refers to picking specific items from various shelves and placing them into a bin. The implemented elements are goal setting (self-set vs. assigned) and feedback. Goal-setting and feedback have been integrated together because research has consistently shown that the motivational effects of goal-setting are most effective when the participant knows how he/she is progressing towards that goal, via some sort of feedback [16].
Three experiment conditions were developed to answer the research questions. Condition 1: in this condition, participants will go through the picking task (see section 3.2 for details about the task) without any set goal, without any feedback. This serves as a control condition.

<u>Condition 2:</u> in this condition, participants will be able to set their own goals at the beginning of the condition (e.g. The average time to complete the following task is five minutes. Today, I want to beat the average by 45 seconds). When participants are done, they will receive on-screen feedback about their performance (e.g.. "Good job, you have reached your goal").
<u>Condition 3:</u> in this condition, participants will be assigned a goal (average completion time). All 20 participants will be assigned the same goal. They will also receive on-screen feedback about their performance.
We have chosen to always present condition 1 first based on what has been found in the literature. It is clear within the literature that having a task with a goal followed by a task without a goal will lead to lower engagement and performance in the latter task [30]. The order of the conditions 2 and 3 will be counterbalanced to reduce a possible ordering effect.

3.2 Experimental Setup and Stimuli

A simulated warehouse was set up at the institution's research facilities, the room is 11x17 feet and has five metal bookshelves lined up on a wall. Also, there are four cameras set up around the room, so the participant can be seen at all times. The bookshelves were divided into three columns and four rows. Each compartment having its own unique identifier (e.g. A01001). The picking device used is the Panasonic FZ-N1, a fully rugged device with the Android operating system (version 6.0.1) (see figure 1). This device is about the same size as an average smartphone. This device will be strapped to the participant's arm.

Fig. 1 Panasonic FZ-N1

3.3 Experimental Tasks

Participants will have to complete 12 picking tasks in each condition. A single picking task consists of taking a certain quantity of the same item from a compartment (e.g., pick five blue pens from A03002). Not all picks are equal in complexity (e.g. two erasers versus five small white paper clips in small box with about 100 paper clips in various colours). Pick complexity therefore had to be operationalized to assure equal complexity in all conditions. An order picking complexity matrix was created based on research by Frazelle [12] and Errasti [11]. Simply put, pick complexity was determined by the quantity of the picked item, and its number of characteristics that add complexity (e.g. size, colour, brand, type). Because each of the 12 picks had a score, we are able to make sure pick complexity is constant across all conditions.

3.4 Measurements

As mentioned above this study will look at engagement and performance as outcome variables. Physiological measures were used to be able to capture the task engagement without interfering in the task itself, therefore maximizing the ecological validity. All physiological data will be synchronized to allow for the best possible quantification of engagement elements, as is recommended by Leger et al. [25] and Charland et al. [5].

In this case, two of three facets of engagement can be measured physiologically. Emotional engagement can be inferred by measuring emotional valence (positive or negative), as well as emotional arousal (calm/aroused). Electrodermal activity, which is the variance in electrical conductivity in response to sweat secretions, has been shown to be a valid measure of arousal. Electrocardiography, which measures the heart electrical activity is another valid measure of arousal [3]. As for emotional valence, it can be with electroencephalography (EEG) [38]. Cognitive engagement is measured using electroencephalography (EEG), which is the measurement of neuron synchronization in the brain. To properly measure cognitive engagement, Pope et al. [34] created a validated engagement index which measures the power spectral density of three bands (beta/(alpha + theta)) [4], [14]. This index is more complex than the one suggested in the NeuroIS literature (e.g. [33]). For more information about the physiological tools in this study, refer to the book "Fundamentals of NeuroIS", written by Riedl and Léger (2016). Goal commitment and the emotional facet of engagement will be measured with questionnaires. They will be answered on a tablet at the end of each condition, therefore they will not interfere with the task. As mentioned above, the emotional facet of engagement can be inferred by measuring valence and arousal. The Affective Slider [1], which composed of a valence slider and an arousal slider, is one of the most reliable ways to measure self-report valence and arousal. The Affective Slider is composed of two sliders. To measure goal-commitment, a five-item questionnaire recommended by Klein et al. [21] was used. As for picking performance, it will be based on two factors: time taken to complete the task compared to the average (calculated during pretests) and task errors (wrong item or quantity).

3.5 Procedure

Firstly, the physiological measures will be installed on the participant. Participants then fill out a demographic questionnaire. Participants will then be explained the picking tasks and they will have the opportunity to practice with a training task. Participants then complete the conditions. After each of the 3 conditions, participants will answer the Affective Slider, as well as the goal-commitment questionnaire on a tablet.

4 Next Step and Conclusion

We believe that the proposed experiment addresses the need for theory-driven gamification research that allows practitioners to understand the underlying mechanisms behind the integration of game-design elements within a technological interface. Moreover, this study will contribute theoretically and practically to the current body of knowledge. Theoretically, this study will allow for the direct comparison of self-set versus assigned goals, a topic that is still under debate. Practically, this study tests game-elements that can be implemented into a variety of interfaces in diverse contexts, making it of interest to practitioners. Preliminary results will be presented at the conference.

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Effect of Emotion on Content Engagement in Social Media Communication: A Short Review of Current Methods and a Call for Neurophysiological Methods

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Abstract. Engagement with content is vital for companies to achieve overall marketing goals (e.g., sales). Emotional content has the potential to grab attention and evoke the desired engagement. Our goal is to review the research methods used in the extant literature on the emotional effect on content engagement in social media communication. The findings show an unbalanced use of methods. Content analysis and emotion coding procedures are the dominant methods, while other methods have hardly been used. Based on this finding, we argue that future research needs to deploy neurophysiological methods to capture the complex emotion construct. Because neurophysiological methods are often applied in experimental settings, an increasing use of these methods would also imply a more advanced discovery of causal effects, thereby better clarifying the role of emotion in the content engagement process.

Keywords: content engagement effect · emotion · social media communication

1 Introduction

The global dissemination of social media platforms makes them indispensable channels in marketing communication. Companies can contact social media users and communicate with them. However, intense usage produces a vast amount of data from users and companies. Companies need to create content in order to gain users' attention and evoke engagement on a regularly basis [1]. Emotional content could grab attention in order to evoke engagement, but companies struggle in the challenging process of content creation [2, 3].

Due to the nature of social media, engagement indicates the efficiency in marketing communication. Engagement appears in an interaction experience and can be expressed in three dimensions: behavior, cognition, and emotion. The emotional component of the definition indicates an emotional effect to the social media content, thereby affecting users' engagement with the content (e.g., a like for a posting). Emotion is well known for its influence on communication processes in marketing and information systems research [e.g., 4, 5]. Importantly, studies demonstrate an effect of emotion on content engagement in social media communication [6]. Although social media have significant relevance in the daily routine of millions of users, it has been researched with low intensity [e.g., 3].

Our goal is to review and assess prior research from a methodological perspective about the effect of emotion on content engagement in social media. Specifically, we address the following research question: *Which methods have been used and which methods could be used to study the emotional impact on content engagement in social media marketing communication?* The following section contains a theoretical background of the relations between engagement, emotion, and content. The next sections delineate the literature analysis method and findings. A discussion, conclusions and future research are described in the last section.

2 Engagement in Social Media Marketing

Engagement has frequently been stated as a common goal in social media marketing communication [7]. Customer engagement is defined as "[…] a *psychological state* that occurs by virtue of *interactive, cocreative customer experiences* with a *focal agent/object* (e.g., a brand) in focal service relationships. It occurs under a specific set of context-dependent conditions generating differing CE levels; and exists as a *dynamic, iterative process* within service relationships that *cocreate value*. […] It is a *multidimensional concept* subject to a context- and/or stakeholder-specific expression of relevant cognitive, emotional and/or behavioral dimensions." [8, p.260, italics in original]. Engagement with content comprises the user's interaction experience with a company's content on social media platforms, where the response can be expressed on cognitive, emotional, and/or behavioral levels. This expression (e.g., share of a post) is dependent on the context and can occur within a dynamic, iterative process (e.g., brand excitement). Previous studies provide evidence of content engagement's positive effect on sales performance [9] and branding goals [10]. Therefore, content engagement affects the success of social media marketing.

The stated customer engagement definition already reveals the effect of emotion on content engagement. The term *emotion* involves various definitions and interpretations. Schmidt-Atzert et al. (2012) define emotion as „ […] a qualitative, descriptive state, which occurs with changes on one or more levels: feeling, physical state and expression" [11, p.25, translated by the authors]. Scherer (2005) extends the term as "episode of interrelated, synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism" [12, p.697]; thus, triggers of emotion can be internal or external stimuli such as marketer-generated content. Importantly, this definition highlights the importance of neurophysiology, because changes in an organism as a response to stimuli are inherently biological. It follows that studying the influence of emotion on content engagement implies a multimethod approach. Specifically, a research approach that does not consider neurophysiology is incomplete. From a measurement perspective, the emotion construct can be captured via the dimensions valence and arousal [e.g., 13], or categorically (e.g., happiness or anger) [e.g., 14].

Emotions have been proven to have essential effects in marketing communication [e.g., 5]. Previous studies have already shown that emotions may influence the advertising effectiveness (e.g., attitude) of content [5]. Marketers need to create branded content with affective messages in order to elicit emotions [15] and subsequently to provoke engagement in social media. Therefore, emotions (indirectly via content engagement) will have an effect on the success in social media marketing [6, 16].

3 Literature Review Method

To answer the research question, we conducted a structured literature review [17]. First, we carried out a literature search with keywords and used various sources, such as leading journals and conference proceedings. Additionally, we conducted forward and backward research. Based on the results of a first search on Google Scholar, we generated a keyword list[1]. The keywords were paired to produce search terms for a systematic search. We conducted a literature research and applied our keyword list within information systems research[2] based on the basket of 8[3] and marketing publications[4] based on the German Academic Association for Business Research[5]. We removed publications where we had no match of topic and content or due to a non-empirical research approach. Finally, we were left with 50 papers[6] focusing on content engagement in social media. We investigated the constructs of the research models and the applied research method characteristics.

4 Results

Our results show that the interest in the topic started in 2011 (see Figure 1). Most of the studies (33) apply a mixed methods approach (qualitative and quantitative methods). Further nine publications use a pure qualitative and eight publications a pure quantitative research approach. A total of 42 studies investigated the engagement construct in the context of Facebook, whereas a limited number considered Twitter

1 Keyword list: social media engagement, popularity brand post, popularity brand content, interaction brand post, interaction brand content, engagement brand post, engagement brand post, social media content, facebook like, customer brand engagement + social media, content engagement, online engagement, user engagement, content strategy, viral online content, social media content emotion, emotional content, emotional text, emotional communication, emotional video, emotional picture, emotional image content, affective content, emotional virality, emotional engagement, emotional participation, emotional interaction, emotional popularity, emotional reaction, emotional endorsement, emotional rebroadcasting, affective engagement, affective virality

2 Information systems journals*: INFORM SYST RES, MIS QUART, J MANAGE INFORM SYST, J ASSOC INF SYST, J INF TECHNOL, INFORM SYST J, J STRATEGIC INF SYST, EUR J INFORM SYST

3 http://aisnet.org/?SeniorScholarBasket

4 Marketing journals*: J MARKETING RES, J MARKETING, J CONSUM RES, MARKET SCI, INT J RES MARK, J ACAD MARKET SCI, J RETAILING, J SERV RES-US, J INTERACT MARK

* Abbreviations are based on Web of Science (https://images.webofknowledge.com/WOK46P9/help/WOS/A_abrvjt.html)

5 http://vhbonline.org/vhb4you/jourqual/vhb-jourqual-3/teilrating-mark

6 The complete list of papers is available upon request.

(3), YouTube (3), Instagram (2), or other platforms (5; Kaixin, MySpace, Weibo, Groupon, Renren).

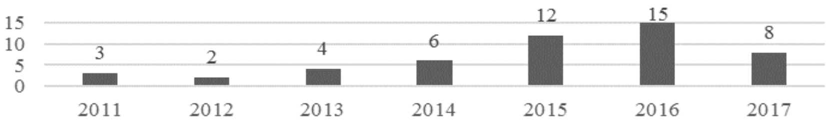

Figure 1. Publications by year (absolute numbers)

Next, we analyzed the research models. Overall, 32 publications focus on the content-engagement (C-EG) relation. This type of research model is investigated intensely and dominates the research domain. Further 15 publications focus on the content-emotion-engagement (C-EM-EG) research model. Another three publications investigate the content-emotion (C-EM) relation, and no publication focuses on the emotion-engagement (EM-EG) relation. These findings reveal a lack of investigations in the emotional effect on content engagement. Specifically, publications which conceptualize emotion as mediator between content and engagement are rare (i.e., low number of C-EM-EG).

So far, most researchers performed content analyses (40), which frequently were implemented in a case study design; we identified this method combination 20 times. Additionally, the case study method is used 22 times overall. The survey method is mainly applied within field experiments; both research methods are used with moderate frequency. Previous studies were hardly conducted in the form of laboratory experiments (we identified only one study). Other research methods such as development of algorithms (e.g., for prediction models) are identified in four papers. As preliminary studies have almost totally neglected experimental research, our findings do not show a high degree of methodological plurality (see Figure 2.).

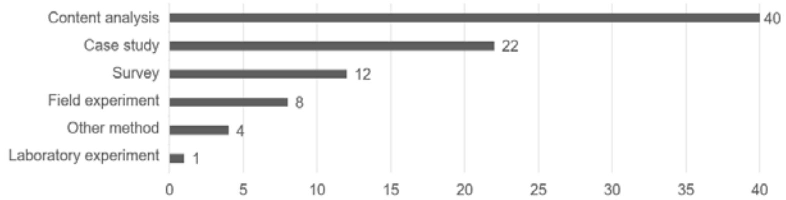

Figure 2. Research methods used in previous studies (absolute numbers)

A limited number of literature (15 papers) have investigated in the impact of emotion on content engagement. Considering the operationalization of the emotion construct, mainly three categories can be identified: (i) emotion dimensions, (ii) emotion categories, and (iii) general emotional message appeal. Result on (i): Eight studies operationalize the emotion construct dimensional whereby eight studies measure valence, one study measures arousal and no one considers dominance for emotion measurement. Result on (ii): Seven publications apply categories to capture emotion. The number of categories varies from 7 to 32, some of them did not mention the number. Result on (iii): Four studies exert a message appeal approach where they rate if emotions occur or not [e.g., 18]. Overall, our results indicate that most of the studies operationalize the emotion construct by using highly simplified measurement approaches, such as a pure valence-based approach withouth measurement of arousal.

5 Discussion, Conclusion and Future Research

The first publications, which targeted the topic of this paper, have been published in 2011. Our findings show that the emotion construct is hardly considered in the content engagement process in marketing and information systems research. Methodologically, we found that the emotion construct is predominantly measured by coding procedures based on valence only. Although the literature provides different perspectives and definitions of the emotion construct, all agree on the complexity of emotions [e.g., 19, 20]. Therefore they recommend to capture emotional responses based on multiple methods [21]. The Use of neurophysiological measures could overcome the observed shortcoming and provide more holistical insights on emotional impact [22]. In essence, physiological methods and tools support a deeper understanding of why and how emotions influence content engagement in social media, as outlined for IS research in a book by Riedl & Léger [23]. We propose to extend the self-report measurement framework by neurophysiological methods and apply, for example, startle reflex and skin conductance to measure emotional valence and arousal in social media communication (see Table 1).

Table 1. Proposed emotion measurement in social media communication

Emotion	Measurement method		Reference (Example)
Category	Self-report	Semantic differential	[13]
Valence, arousal, and dominance	Self-report	Self-Assessment Manikin (SAM)	[24]
Valence	Neurophysiological method	Startle reflex	[25–27]
Arousal	Neurophysiological method	Skin conductance	[26–28]

The variety in research methods is currently low and unbalanced. For example, experiments, in particular those using neurophysiological measures, are hardly conducted. Because laboratory experiments are critical to establish causal relationships (here the nomological network is content → emotion → content engagement), future research should overcome the current methodological deficits in order to make possible a better understanding of the role of emotions in social media marketing. Neurophysiological methods will—most likely—reveal novel insights into this nomological network. Moreover, it is critical to mention that startle reflex and skin conductance are not the only neurophysiological methods which can be used in the present study context. In addition to these methods that relate to autonomic nervous system measurement, also methods related to central nervous system measurement could be applied, such as functional magnetic resonance imaging (fMRI) [e.g., 29] and electroencephalography (EEG) [e.g., 30]. Further methods are described in the NeuroIS literature [e.g., 23, 31, 32] and in other disciplines such as psychophysiology [e.g., 27].

A limitation of our work concerns the process of the literature review which involved not all possibly relevant keywords, and the keywords were not applied in all possibly relevant research fields. Further research, therefore, should extend the keyword list and consider research in other disciplines, such as psychology. Finally, it is also critical to mention that emotion in content engagement processes is related to other concepts. For example, one major concept in psychology is flow. The flow construct is considered as a cognitive state in an interaction process (e.g., during navigating a website) [33–35]. It follows that future research should consider the existing insights on flow (and the knowledge on its neurophysiological foundations) [e.g., 36], as well as the knowledge on related constructs, in order to advance research on the effects of emotion on content engagement in social media communication.

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To Like or Not to Like in the World of Instagram: An Eye-tracking Investigation of Instagram Users' Evaluation Process for Liking an Image

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Abstract. For image-based social media (e.g., Instagram or Snapchat), understanding people's decision behind their liking of photos is critical to researchers and practitioners. The liking decision toward an image, however seemingly simple and effortless for browsers, involves an interplay among evaluation dimension (hedonic vs. utilitarian), social influence (pre-existing number of likes), user characteristics, and underlying cognitive activities (effort and attention). The preliminary results from our eye-tracking studies show that the utilitarian evaluation of an image is negatively associated with its liking probability, effort (pupil dilation), and attention (fixation time). Social influence is shown to affect long-term social media users by increasing their hedonic rating and liking intention. The results suggest that using eye movements to predict the liking intention in social media requires the understanding of products' prominent evaluation dimension and users' characteristics. Discussions and future work are also presented.

Keywords: Social Media, Social Recommendation, Eye-tracking, Image Evaluation

1 Introduction

Recently, picture-based social media such as Instagram have been widely used not only by individual users but by sellers as a channel to broadcast their products. Gaining likes for picture are important for both categories of posters because likes seem to generate more likes, and in turn, due to the algorithms applied by social media, increase exposure of both pictures and their posters [1]. However, while pressing a "like" button seems easy to browsers, making this decision actually involves complex interaction between preference and social influence that are built toward a picture. In addition, the preference constructed toward a picture might involve multiple evaluative dimensions, especially the hedonic (enjoyment) utilitarian (usefulness) ones. Specifically, consumers can be motivated to focus either on the hedonic or the utilitarian dimension, and this focus biases subsequent buying and evaluation behavior [2]. Consumers motivated by a utilitarian goal pay more attention to utilitarian aspects of a product, and attend more to the hedonic aspects when a hedonic goal is activated [3]. While the two evaluative dimensions have long been identified and studied, how social influence can interact with the two dimensions remains largely unknown. Besides, the dichotomous outcome of a liking decision (to-like vs. not-to-like) is a surrogate result of the interplay between preference (can have more than one evaluative dimension) and social influence, masking the specific contributing effect of each individual factor.

Given all these complexities it has been difficult for practitioners and researchers, who usually merely examine behavioral outcomes, to disentangle the contributing factors. A good way to unpack these complexities is to examine the attentional process that underlies the interaction between preference and social influence. Attention, captured by eye trackers, is strongly related to people's cognitive activities, including even those complex ones such as decision making and problem solving, and can be used to infer peoples' emotional states and cognitive load [4]. Those data are useful to compensate behavioral outcomes by providing additional information and even opportunity to test competing theories [5]. With the eye-tracking technology, we further explore the mechanisms that contribute to a liking decision. Here we raise the following research questions: can we predict liking decision from eye movements? How may social influence affect this prediction?

Attention is strongly coupled with preference. Specifically, decision making studies that involve comparison among pictures have shown that attention, measured by eye fixations, is biased toward those chosen pictures. That is, the probability that people fixate at the eventually chosen picture increases over time. This phenomenon is called "gaze cascade" effect [6], which might be explained with mere exposure and preferential looking. However, this line of study examines mostly the preference construction process and has not considered social influence. Because of its usefulness in predicting purchase and subsequent user ratings, the importance of social influence in modern shopping scenarios cannot be overestimated [7]. Besides, gaze cascade studies involve a comparison among pictures, while in picture-based social network pictures are usually displayed in a single evaluation situation. To examine this problem, a study has applied the drift-diffusion model, which asserts that a choice is made when attention process has accumulated enough evidence toward it, has shown that pictures of products are more likely to be chosen when positive reviews are fixated and negative reviews are not fixated and vice versa [8].

Nevertheless, previous studies have not considered the fact that a product can be evaluated with the two critical dimensions: hedonic and utilitarian. These two dimensions have different effects on satisfaction [9], emotion [10], decision making [11], and intention to use [12]; besides, compared with utilitarian evaluation, hedonic evaluation might be performed with less effort [13, 14]. In a similar vein, eye tracking studies of online shopping have shown that people using emotional decision process, compared with those using calculative decision process, tend to pay less attention toward choices [15]. It is, therefore, likely that the two evaluative dimensions can result in distinct types of cognitive activities, which can be observed with attention (fixation time of image) and effort (pupil dilation). Furthermore, while eye-tracking studies have examined the effect of customer reviews on product evaluation, it remains uncertain how social influence can affect the two evaluative dimensions. One possibility is that hedonic evaluation is more susceptible to social influence because users spend less time for this dimension [14] and hence social influence might gain more weight on the final liking decision. In short, this study examines (1) how the two dimensions affect attention and liking intention, and (2) how social influence affect the evaluation of the two dimensions.

In our two studies, we have adopted cake images to answer the questions. Cake images are selected because they can be evaluated simultaneously from hedonic and utilitarian dimensions [16] and are common content that users share on picture-based social media. Average pupil dilations are collected as index for processing effort and fixation time of image for attention. Social influence is manipulated using different levels of pre-existing numbers of likes associated with the images. Behavioral results include liking intention and ratings of hedonic and utilitarian evaluation. We also include users' experience using Instagram to examine its effect on image evaluation.

2 Method

2.1 Study 1 (Behavior Study)

The purpose of study 1 is to establish an image pool, in which each image has its properties measured. We collected 164 cake images from Instagram. A total number of 124 participants were recruited in multiple sessions to rate these images on PCs in a computer room. Taste rating and convenience rating were used as the hedonic and utilitarian dimensions for the subsequent eye-tracking study. Forty cakes images were selected so that the scores of the two dimensions were uncorrelated.

2.2 Study 2 (Eye-tracking Study)

To examine the effect of evaluation dimensions (hedonic vs. utilitarian) and social influence (pre-existing number of likes), the stimulus of study 2 mimicked the look of Instagram but with only two pieces of information: an image centered on the screen and a number of pre-existing likes presented on the left bottom (Figure 1). Note that this manipulation allows us to exclude other contributing variables (e.g., posters' comments).

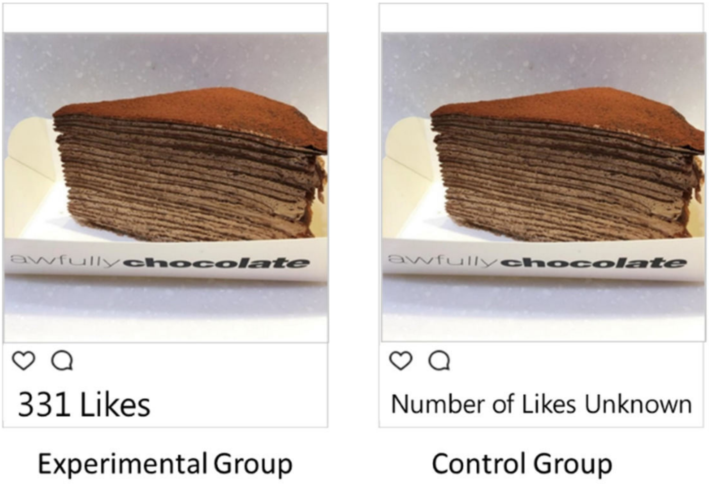

Fig. 1. Examples of stimuli

A group of 99 participants joined our eye-tracking study. They were instructed to imagine that they were viewing images on Instagram at their own pace. Participants were assigned to either experimental group (n=56) or control group (n=43). In the experimental group, participants were provided with 20 levels of pre-existing numbers of likes (ranging from 0 to 2,754,229). The presentation order of cake images and their combination with numbers of likes were randomized. In the control group the social influence was printed as "number of likes unknown." After viewing each image, they were asked to indicate whether to "like" the image and rate their taste and convenience scores on a 1 to 5 Likert scale (the higher the score, the tastier and more convenient the image is perceived). Specifically, for the taste score, participants were asked "I think that the cake is tasty" (not agree – agree). For the convenience score, participants were asked "I think the cake is available in nearby supermarket or convenience store." Then participants completed a demographic questionnaire to indicate their Instagram experience and were compensated and debriefed.

The fixation and pupil data were collected using the Eye Link 1000 system (SR Research Ltd., Canada) at 250 Hz sampling rate. Participants' heads were stabilized with a chin rest, and a nine-point calibration was executed before the experiment. During the experiment, a drift correction was performed between pictures to increase eye movement measurement accuracy. Pictures (visual angle was 13.87° width and 21.98° height) were centered on a 19" LCD and at a levelled distance of 60 cm to participants' eyes. Fixating time was quantified with the sum of fixation duration of all fixations that landed on pictures. Average pupil dilation, which is a relative measure, was retrieved from the Data Viewer software.

3 Results

3.1 Manipulation Check

The ratings of taste and convenience dimensions remained uncorrelated in study 2 ($r = .02$, $p = .88$). This suggested that in study 2 the utilitarian and the hedonic dimensions were independently rated.

3.2 Attention, Ratings and Liking Intention

To examine factors affecting liking decision toward an image, we conducted an image based analysis. Data were aggregated on the basis of individual image, resulting 40 analytical units. Then we conducted a path analysis (Figure 1). In this model eye movements (pupil dilation and fixation time of cake image) predict taste and convenience ratings, which in turn predict liking intention. The results showed that effort (pupil dilation) and attention (fixation time) were negatively correlated with the convenience score. Conversely, pupil dilation and attention were positively correlated with to taste rating but were not statistically significant. Furthermore, liking intention could be positively predicted by taste score and negatively predicted by convenience score.

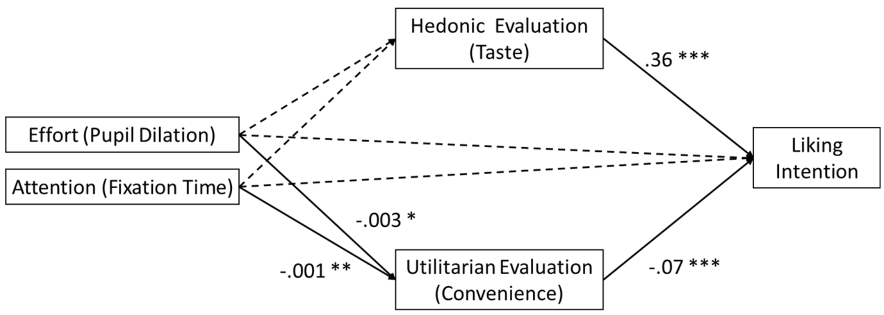

Fig. 2. Path analysis results of image evaluation (* $p < .05$, ** $p < .01$, *** $p < .001$)

3.3 Social Influence

To examine the effect of social influence (pre-existing numbers of likes) on evaluation and liking intention, we aggregated data on the basis of individual pre-existing number of likes, resulting in 20 analytical units. The control group was aggregated into one unit as a comparison to the experimental group. Furthermore, the analysis was conducted separately between the more experienced users, who had used Instagram for more than 3 years (the median score), and the less experienced users, who had used it for no more than 3 years. Participants who never used Instagram were excluded from analysis (n=12, 5 in the experimental group, 7 in the control group). Correlations were conducted between log-transformed pre-existing number of likes (0 was excluded) and convenience rating, taste rating, and liking intention.

For the less experienced user group, the social influence had negative but unreliable effect on convenience rating, taste rating, and liking intention (Figure 2, left column). For the experienced user group, the social influence had no significant effect on convenience ratings, but had positive effect on taste ratings and liking probability (Figure 2, right column). The average ratings of the control group (also separated by Instagram experience) were plotted with horizontal dotted lines. Finally, we did not find social influence's effect on pupil dilation or attention in either of the user groups.

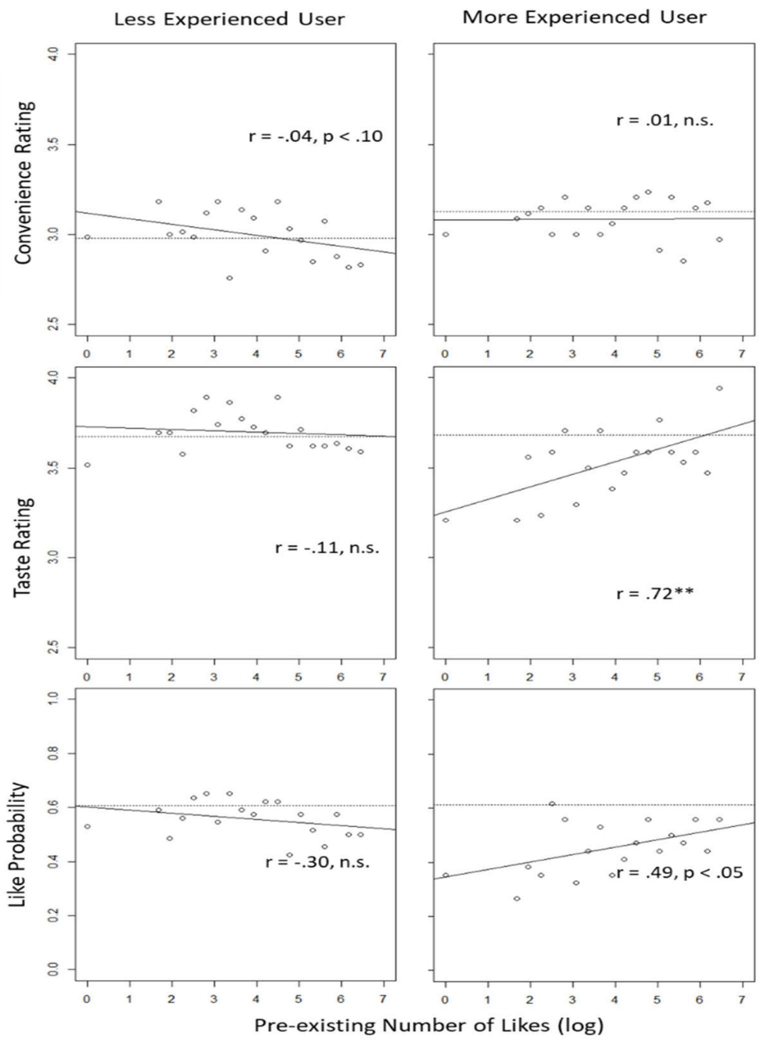

Fig. 3. Results of social influence (pre-existing numbers of likes), separately tested in more and less experienced Instagram user group

4 Discussion

Previous attentional studies on the interaction between preference and social influence have not considered that preference can be constructed with hedonic and/or utilitarian dimensions. Our preliminary results might inform this line of studies in three aspects.

First, our results show that utilitarian evaluation negatively predicts people's liking decision of pictures, while hedonic evaluation positively predicts this decision. This result supports the notion that a product image can be simultaneously evaluated in multiple evaluative dimensions [9, 11-14], and that the dimensions can independently contribute to the dichotomous and surrogate liking decision. This suggests that, for both practitioners and researchers, to understand preference to a product picture it is important to consider the prominent evaluation dimension of this product.

Second, our study also shows that social influence (pre-existing number of likes) can increase hedonic rating, but this effect is only evident in the long-term Instagram user group. While this finding remains preliminary, it nevertheless suggests that the perception of social influence is affected by evaluative dimensions and user characteristics.

Third, we showed that effort and attention are negatively correlated with the utilitarian rating (statistically significant) but are positively correlated with the hedonic rating (though not significant). The negative association between attention and utilitarian dimension suggest that utilitarian dimension of a picture acts as a piece of negative information [8]; paying attention to this dimension decreases the likelihood that a picture is liked. However, we find no evidence of a reliable relationship between eye movements (pupil dilation and fixation time) and the eventual liking intention or evidence showing that social influence can directly affect eye movements. Future work is needed to understand the robustness and generalizability of current eye movement results.

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Cognitive Work Protection - a new approach for occupational safety in human-machine interaction

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Abstract. Previous occupational safety concepts in human-machine interaction scenarios are based on the principle of spatial separation, reduction of collision force or distance monitoring between humans and robots. Collaborative robot systems and semi-automated machines are working closely with people in more and more areas, both spatially and functionally. Therefor a new approach for occupational safety in close human-machine collaboration scenarios is presented. It relies on a real-time EEG measurement of human workers with brain computer interfaces and a subsequent adjustment of the robot system based on the detected cognitive states.

Keywords: Occupational safety, human machine interaction, brain computer interfaces

1 Introduction

According to a study by the International Federation of Robotics, the number of industrial robots sold in 2016 was 16% higher than in the previous year. Annual sales growth of 10% on average is expected until 2020 [1]. In addition to the possible increases in efficiency and productivity made possible by the growing number of robots in working environments across countries, the protection and safety of the employees involved must always come first. Accidents at work not only have serious consequences for those affected but are also a cost factor that should not be neglected for the companies involved and the economy in general. The main causes of accidents at work are human behavior errors based on carelessness, stress or hecticness [2]. Especially in close cooperation with industrial robots, this is triggered by complex motion sequences, unpredictable changes in position and speed or unexpected starting of the robots [3]. Current safety strategies to avoid work accidents in human machine interactions are based on a strict spatial separation between the robot and the work area of the human operator. However, collaborative work scenarios that are characterized by a very close human-machine interaction are increasingly coming into focus. Collaborative robot systems and semi-automated machines will work closely with people in more and more areas, both spatially and functionally. Particularly in these situations, special attention must be paid to the protection and safety of people. Classical safety strategies can no longer be applied for these collaborative work scenarios. The close physical cooperation between man and machine requires adapted and reliable occupational safety concepts.

Another aspect is the problem of under- or overstraining at the workplace. According to stress reports of recent studies, already in 2012 about 18 percent of employees felt that they were either professionally or quantitatively underchallenged at their work. About 23 percent of those questioned suffered from work overload [4]. However, mental health problems can arise from permanent under- or overchallenging. In order to master the unavoidable change in work requirements in a socially acceptable manner, new methods are therefore necessary to optimally design the working conditions for the individual person.

In this paper we present a new approach to increase occupational safety in collaborative working scenarios, including the potential to optimize the individual working conditions in a rapidly changing environment. It is based on cognitive measurements of human workers which are analyzed and used to optimize the co-working situations with robots with the aim to avoid work accidents. Following a design science methodology [5], we first demonstrate the relevance of such an approach followed by a conceptual solution which acts as the artifact and a subsequent discussion and evaluation.

2 Related Work

Especially in the field of human-robot interaction, the aspect of occupational safety and security is of great importance. Current approaches for collaborative robot systems are mainly focused on aspects of force and power limitation as well as speed and distance monitoring [3], [6]. On the one hand, there are approaches to minimize the collision force in a potential human-robot contact. On the other hand, technologies were developed to detect persons entering the safety area of the robot to initiate appropriate safety measures of the robot [7,8]. The analysis and use of cognitive states to control and influence physical objects (such as robots) is an approach that has been less considered so far. Most of the current research relates to medical applications [9,10,11]. Especially in the industrial sector, i.e. in production or manufacturing, other requirements arise which have not yet been addressed to this extent. The electroencephalogram ("EEG") is a representation of electrical brain activity measured at the head surface and detected by means of metal electrodes and a conductive medium [12]. The EEG has so far mainly been used for the detection of neurological diseases in medicine, for the investigation of brain functions in research as well as in the context of therapy and rehabilitation. Further applications can be found in the field of brain-computer interfaces, i.e., the use of EEG signals to decipher mental states (fatigue, stress, etc.) and the improvement of human-machine interaction based on them [13,14,15]. The mental states can be analyzed in the EEG using the P300 or changes in the frequency bands. At a high workload, changes in the alpha and theta frequency bands are observed, e.g. increases in theta activity in the frontal brain area and reduction of alpha activity in the parietal area [16,17,18,19,20,21,22]. However, individual studies report increases in alpha activity [23, 24], which can be attributed to a general large variance of individual differences [25]. With onset of fatigue, however, activity in both frequency bands is increased [26,27,28,29,30,31]. In the case of the P300, a reduction in amplitude can be observed both with a high workload and with onset of fatigue [32], [14]. Errors in robot behavior or faulty human-robot interaction can be measured in the EEG as error-related potentials and detected in real time using machine learning methods [33,34,35]. The error-related potential can also be used as implicit feedback from humans (e.g. encouraging learning) in robot learning approaches [36].

Based on recent research a next step in the direction of implementing functional solutions within realistic industrial applications is needed to prove that cognitive work protection using physiological data is applicable and a strong contribution to worker's safety.

3 Technical Developments and Feasibility of the Approach

Our approach for occupational safety in close human-machine collaboration scenarios is feasible due to technical developments of the used core components that have come up over the last few years. This applies in particular to the fields of **EEG data analysis methods**, **digital platform technologies and robotic control**, as well as **smart devices** (e. g. in terms of wearables).

By means of the introduction of machine learning methods [37] and advanced signal processing techniques (e. g. [38]) **EEG analysis** is now possible in almost real time and more importantly cognitive states and intentions of humans can be detected or inferred in single trial [39]. This development is the basis for applying brain computer interfaces (BCIs) in real world settings, such as done by embedded Brain Reading (eBR) [39]. Further, the improvements in EEG recording and analysis techniques that allow EEG analysis and analysis of other physiological data recorded under non-static conditions such as walking and running [40] or cycling [41, 42] did also enabled the integration of psychophysiological data into the control of robots such as exoskeletons [15]. Thus, due to the combination of both developments it is no longer required that persons wearing EEG recording equipment are not allowed to move at all while recording the data in often shielded lab environments [43]. Instead, free movements in cooperation with robotic systems in real world settings is now possible [36].

On the other hand, the development of embedded processing hardware and advanced embedded software solutions [44] does even enable the implementation of small recording as well as analysis techniques that already incorporate advanced real-time EEG processing [45] and even classifier training or adaptation on embedded devices [55].

Despite improvements in hardware and data analysis techniques the integration of physiological data into the control of robots or its usage for the improvement of human-machine interfaces required new concepts for deep integration and failure free usage of highly uncertain data such as EEG data. New concepts were developed that allow to infer on the context of interaction to make use of low level information from EEG data to infer on high level intentions of a user or to automatically detect markers in the EEG based on the current activity of the supported person that can be used to infer on the cognitive or mental state of the user [46]. The latter one is even possible without using a secondary task to measure workload [14].

Finally, advances in **EEG sensor systems** regarding usability and costs lead to a widespread use of EEG data in gaming and entertainment (e. g. [56,57,58]). Similar to the development of mobile cell phones this development is a major driver for solutions in the field of low cost and easy to use EEG sensor systems that are of need for our proposed application.

Digital platforms are new marketplaces by which the exchange of goods, services and other added value can be organized and realized using digital technologies. They enable interactions and transactions between interested participants and objects (e.g. machines, networks, institutions, etc.) [47], [48]. In this context "digital technologies" such as standardized interfaces, user and role administration, service catalogs, database technologies, intelligence and analytics software components serve as enabler and technological framework for the running of this connecting technology. These technological developments lead to a widespread use of digital platforms in the production as well as in the service sector [47]. Within the Industrial IOT scenario, platforms have the potential to realize the holistic framework of a "smart factory", in which **centralized robotic control scenarios** can be established as well [49]. In the field of data intelligence and analytics, big-data scenarios in particular can be implemented e.g. as predictive analyses and real-time data processing [50].

The use of **smart devices** such as **wearables** reflects the current development of the "quantify yourself" trend, which mainly focused on tracking and analyzing data from everyday activities such as sports, weight control, sleeping activities and other habits [51]. Technologically, applications can be deployed on the wearable that establish an interface to other decentralized services thus analyzing data in real-time. Besides sports and clinical approaches [52], new approaches arise in field of occupational safety e.g. for personalized construction safety environment using techniques like physiological monitoring; environmental sensing; proximity detection; and location tracking [53].

Regarding those technical developments, the combination of the components leads to the conception of the following holistic approach.

4 Cognitive Work Protection

The first goal of our approach (Fig. 1 shows the holistic design) is to measure the cognitive condition, for example the stress level or the workers' ability to concentrate, and thus to optimize interaction with robots and machines in real time with a view to increased safety. The second objective is to reduce accidents at work that occur in cooperation between humans and robots and to promote the physical and mental health of employees.

Starting point of our approach are EEG measurements of employees during the operation of machines or in cooperation with robots. The electrical activity of the brain is determined by electrodes that measure the voltage fluctuations at the head surface. The focus is on the electrode design and the ergonomic design of the sensor system. The system is optimized for a minimum number of sensors that are able to detect the desired cognitive states. For this purpose, the brain and thus head regions are identified which have the highest information content when determining the various cognitive states.

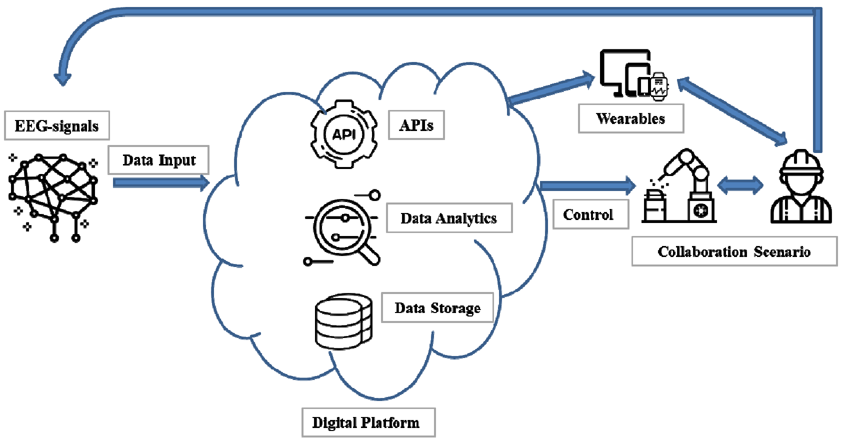

Fig. 1. Design representation of the holistic framework

The electrodes based on flexible polymer substrates are installed at the identified head- and electrode positions in safety goggles and thus integrated into the safety equipment that is required in any case. Based on the identified electrode positions, optimal electrode flexibility and shape is identified by various prototypes and tests on person. These optimal electrode shapes should ensure reliable hair penetration and head contact as well as high long-term wearing comfort.

The measured brain waves are recorded in real time and transmitted via a wireless interface to a central digital platform. The data is processed there by means of automated analysis methods. Based on data preparation, characteristics are generated and patterns are classified using methods of machine learning and artificial intelligence. Thus, online measured EEG patterns can be assigned to certain cognitive states. EEG analyses can be performed in regards to time and frequency. Regarding the timing sequence, changes in natural potentials generated by the brain can be detected. An example of this is the potential P300 attributed to the attention of a test person; with an increasing workload, the amplitude of the signal decreases. A higher latency of the potential can also occur. To do this, the data is first filtered in time and then a spatial filter (e.g. xDAWN) [38] is trained, which reduces the amount of data and extracts important characteristics. Then the extracted characteristics are classified with a classifier like a support vector machine [54]. If the target signal changes, the processing chain can no longer correctly classify this signal, which can then be an indication of an overload or distraction of the subject. Furthermore, there are different frequency bands in the EEG. The activity in the respective frequency bands allows conclusions to be drawn about the mental state of the subject. To use this online, the energy of the respective band is measured under normal stress or no stress on the subject. This can be done by spectral analysis, for example. The determined rest values are then continuously compared with the current values in the application in order to be able to evaluate any differences directly. Error related potentials [33,34,35,36] are generated in the brain when a subject perceives something unexpected, such as a robot behaving incorrectly. These potentials can be classified with a comparable processing chain to that of the P300.

The information about the employee's cognitive states is then used for two different functions: to optimize interaction with robots and machines and to provide feedback for the employee himself. Based on the determined cognitive state of the employee, a rule-based control of the robot is realized. For example, the higher the measured stress level of the employee, the lower the speed of the robot. The robot is also controlled in real time and is connected via wireless communication to the digital platform [47,49].

Within the feedback system, the real-time results of the EEG analysis, i.e. the information about the cognitive state, are visualized and made available to the employee via mobile devices. This ensures that the employee is permanently informed about his own data. This is realized via various visualization components (pie charts, alerts etc.) and haptic signals (e.g. vibration alarm). On the other hand, algorithms are included to identify patterns in continuous EEG measurements and to generate recommendations for optimizing working conditions. For example, with the help of a time series or classification analysis, which are usually found in Business Intelligence and Analytics components, mental state developments such as fatigue in time can be anticipated and thus recommendations can be displayed early via text windows and alarms (e.g. via wearables [51,52,53].

In order to ensure adequate data protection, the design of the system has to ensure that only the employee himself receives information about his EEG measurements. The resulting recommendations for improving working conditions are also only made available to the employee in a first step.

5 Discussion and Future Research

The Cognitive Work Protection approach has the potential to change the way occupational safety is realized in human-machine interaction scenarios. Compared to classical approaches it allows a close collaboration and real collaborative work between humans and robots. It is the first approach to directly detect the main reasons for work accidents - namely stress, fatigue, inattention - and to trigger countermeasures in a proactive way.

Besides occupational safety, the presented approach offers the possibility to improve the general working conditions in particular with respect to work overload and boredom. As discussed, this can be realized by providing recommendations for improving the working conditions to the employees themselves. In a next step however, the method can also be used for a company-wide management of human resources. Employees could be assigned varying tasks depending on their skills and level of satisfaction. For example, employees that typically feel unchallenged performing the same tasks every day could be dynamically assigned to frequently changing tasks, while the workload of employees feeling overstrained could be reduced. In this scenario, the presented approach therefore not only reduces work accidents and improves the working conditions of employees, but also has the potential to increase a company's productivity through managing human resources in an optimal way.

Despite the great potential of the approach, there are also challenges that need to be overcome for practical applications. From a technical point-of-view the main challenge is to construct a reliable and comfortable EEG measurements sensor system that does not interfere employees in their work. Current advances in EEG sensor systems show promising results in this regard and hint to a realistic possibility for a practical realization. The second and most important challenge comes with the fact that EEG sensors determine highly sensitive data in the human working environment within which the employee is in a relationship of dependence. In this regard, urgent questions arise which are of an ethical, social and legal nature and which must be sufficiently addressed before a practical realization.

In our future research, we plan to address these challenges and drive the development of a Cognitive Work Protection system, that is accepted by employees and employers alike. Therefor we will develop a prototype that can be tested and evaluated regarding usability, security and privacy issues.

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Analysis of Heart Rate Variability (HRV) Feature Robustness for Measuring Technostress

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Abstract. Technostress has become an important topic in the scientific literature, particularly in Information Systems (IS) research. Heart rate variability (HRV) has been proposed as a measure of (techno)stress and is widely used in scientific investigations. The objective of the pilot study reported in this paper is to showcase how the preprocessing/cleaning of captured data can influence the results and their interpretation, when compared to self-report data. The evidence reported in this paper supports the notion that NeuroIS scholars have to deliberately make methodological decisions such as those related to preprocessing of physiological data. It is therefore crucial that methodological details are presented in NeuroIS papers in order to create a better understanding of the study results and their implications.

Keywords: Data preprocessing · Heart rate variability (HRV) · NeuroIS research methodology · Technostress · Signal feature · Stress.

1 Introduction/Motivation/Related Work

In recent years, technostress has become an important concept in NeuroIS research (e.g., [1, 2]). It has been argued and demonstrated that mixed methods research, particularly involving physiological measures, is crucial for this research domain [2–6]. Amongst other methods, the collection of heart rate data and the calculation of heart rate variability (HRV) as a measure of stress have been proposed as viable additions, particularly to field studies investigating technostress [7, 8].

As part of a larger project, we are currently investigating the potential of several data collection methods for technostress research in a longitudinal field study. This includes heart rate data, which we collect using consumer level devices. In this paper, we report on a pilot study in which we tested the feasibility of letting individuals track their own heart rate during their working hours using a chest belt with a heart rate sensor. The objective of this pilot study is to assess the quality of the data generated in this manner. We showcase how the preprocessing/cleaning of captured data can influence the results and their interpretation when compared to self-report data, which we obtained by having study participants fill out a technostress questionnaire. By showing how data collected using consumer-grade devices can be useful to assess individual stress levels, we also specifically seek to support the call for further technostress research in field settings [2, 9].

In particular, we are interested in how data cleaning influences the correlation coefficient between HRV data and self-report data. While the HRV analysis methods investigated here are in no way particular to technostress research, they are nevertheless a necessary first step in every data processing endeavor.

In section 2, we present an overview of the data collection procedures that were applied, the heart rate features that were extracted and the how the features were preprocessed. Then, in section 3, we present our results regarding the influence of preprocessing methods on the results and their interpretation. Finally, in section 4, we discuss our findings and present some recommendations for future research utilizing heart rate data in technostress research.

2 Material and Methods

2.1 Data Collection

We collected our data in the week of 11/27/2017-12/01/2017 using a Polar H7 chest belt in combination with a smartphone app[1] that collected the captured data. Fifteen employees (12 female, 3 male) of a publishing company with its headquarters close to Salzburg, Austria, participated in the study. They were instructed to put on the chest belt after they had arrived at work and to start the data collection on the smartphone app. They stopped the data collection upon leaving the workplace. After removing unusable data, we retained 44 samples from 11 study participants from one week of data collection. At the end of the workweek, which for most of the participants was Friday, the participants were also invited to take part in an online survey, which included questions on their technostress level using a German version [10] of the “Technostress Creators” questionnaire by Ragu-Nathan et al. [11]. The questionnaire was deliberately handed out after the workweek as we wanted to avoid any changes in perception (e.g., situations that are pointed out as stressful in the questionnaire are then seen as more stressful due to heightened awareness) that could bias our results.

[1] https://itunes.apple.com/at/app/heart-rate-variability-logger/id683984776?mt=8 [03/05/2017]

2.2 Heart Rate Features

The literature reports on a variety of indicators extracted from electrocardiography (ECG) recordings that can help in assessing HRV [12, 13]. In general, most of these indicators are calculated either in the time-domain or the frequency-domain of the signal. When analyzing the signal in the time-domain, the most relevant aspect is the time interval between subsequent peaks in the QRS complex, i.e., the time duration of one heartbeat (for details, see for example [12]). This interval is known as the RR interval; RR intervals of normal signals are known as NN intervals. In this work, we focus on the following five indicators, which we will call *features* of the signal. The first three are from the time domain, measured in milliseconds, the last two from the frequency domain, measured in squared milliseconds [13]:

SDNN: The standard deviation of NN intervals in the signal.
SDANN: The standard deviation of the averages (taken over five minute segments) of the NN intervals in the signal.
RMSSD: This feature depends on the differences of subsequent NN intervals. Square these differences, then take the square root of the arithmetic mean of these squares.
LF: The power of the signal in the low-frequency spectrum (0.04 to 0.15 Hz).
HF: The power of the signal in the high-frequency spectrum (0.15 to 0.5 Hz).

2.3 Data Preprocessing/Cleaning

Preprocessing and cleaning of data is a necessary initial step in most data analysis tasks, particularly in analyses of physiological data. We chose the Kubios HRV software, a state of the art tool for studying the variability of heart-rate intervals, mainly for its data-cleaning functionality, ease of use, and the wide range of HRV features it calculates. Kubios thus fits our requirements, and can also be considered the standard software in this application domain (e.g., [14, 15]). It provides tools for artifact removal (missed or spurious beats), analysis methods in the time and frequency domains, as well as the ability to calculate a number of less frequently used features (such as entropy measures, or measures calculated from a recurrence plot).

Obtaining artifact-free raw data samples from a consumer-grade device is almost impossible in a real-world setting. In this study, the quality of the data obtained from the Polar H7 chest belt depends mostly on its correct placement. Most HRV features and metrics are highly influenced by noisy data [16]; the degree of preprocessing and noise removal thus has a direct influence on the features reported by HRV software tools.

It has to be noted, though, that using consumer-grade devices in this context is already a very important deliberate choice, with several associated benefits and challenges (e.g., low intrusiveness, but particular need for data cleaning). Nonetheless, despite the particular obstacles, Schellhammer and colleagues [7] have demonstrated that consumer-grade devices are a valuable addition to technostress research in the field, particularly if one is interested in heart rate measures. Yet, just as technostress studies in the field are still scarce [2], so are technostress studies that have applied heart rate measures and reported their data cleaning procedures, aside from simply referencing the tool they used (e.g., AcqKnowledge in [17]). We therefore focus on this particular step in the research process, but want to highlight that there are several other challenges generated by the selection of a specific research design and measurement method in NeuroIS [1].

Kubios HRV allows threshold-based artifact correction, with automatic correction available in some versions [18]. In this preprocessing step, every RR interval value is compared to a simple moving median over a time window. An RR interval value is considered an artifact if it differs more than a specified threshold from this local median. Five equidistant threshold values are available in Kubios HRV, corresponding to increasingly lenient requirements for values to be considered artifacts: On the lowest level, only those values further than 0.45 s from the median are removed; on the highest level, all values further than 0.05 s from the median are removed (these values, given here for 60 bpm, are adjusted for heart rate). The correction uses cubic spline interpolation, which can lead to unusual beats if too many beats are corrected.

3 Results

Below, we present two sets of numerical results: one for the effects of data preprocessing on the HRV features, and one for the effects of data preprocessing on the correlation of HRV feature values with self-reported technostress levels.

The effect of five artifact correction thresholds on the features described in section 2.2 is measured by average percentage change over all data sets. For each feature, its baseline value was calculated on the raw unchanged data samples. Compared to this baseline, the percentage change turned out to be quite high for most features. The results of applying five different artifact correction levels to five features is shown in figure 1. In this figure, we can observe that the correction at the threshold level "very low" already resulted in a percentage difference ranging from 2.6 to 20.9% on the different features. At this level, the average percentage of corrected RR intervals is only 0.46%. It is surprising that there is such a noticeable difference, given this small amount of correction. The percentages of corrected RR intervals were, in increasing order of artifact correction levels, 0.79%, 1.26%, 3.08% and 25.03%, respectively. The LF, HF, RMSSD and SDNN features especially show large percentage changes, and thus appear to be highly influenced by the degree of artifact correction.

It can be observed that the SDANN feature is much more robust than the other features. This can be attributed to the fact that the SDANN feature is defined as the standard deviation of the average RR interval calculated over 5 minute periods [13]; this additional averaging smooths out the effect of the artifact corrections.

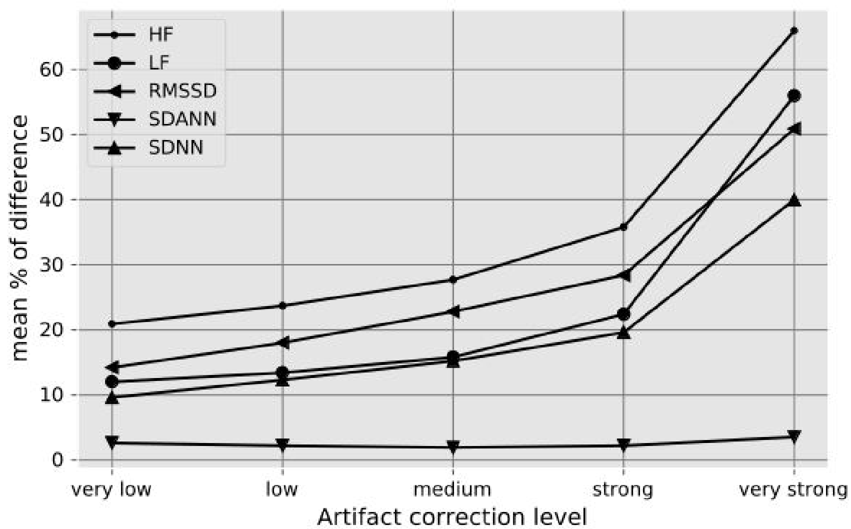

Fig. 1. Average percentage difference between baseline (raw feature values) and feature values obtained at different artifact correction levels.

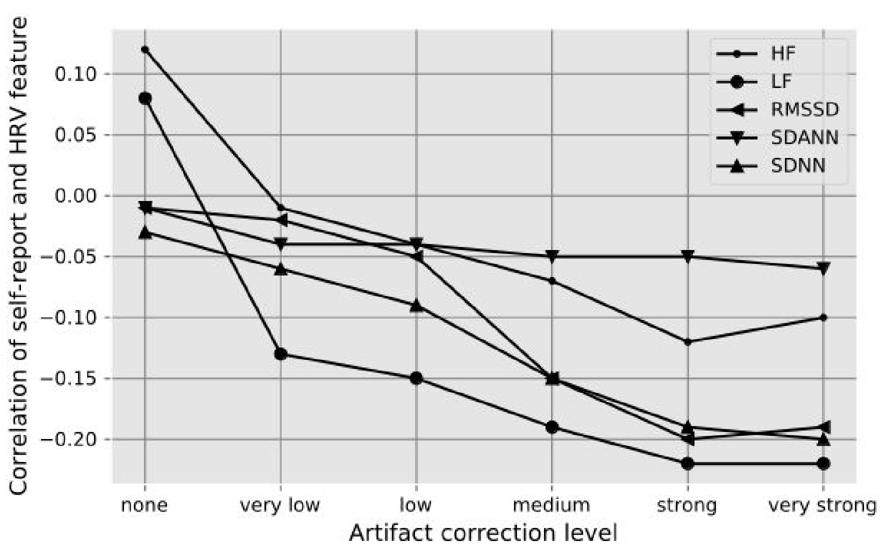

Fig. 2. Correlation of the questionnaire technostress level results and feature values obtained at different artifact correction levels.

Figure 2 illustrates the influence of the artifact correction level on the correlation coefficient between feature values and the self-reported technostress levels. We can observe that changing the correction level results, for two features, in a change of sign of the correlation coefficient between raw and corrected data. As in figure 1, the SDANN feature is the most robust feature, with the other features showing small negative correlations with self-reported technostress levels. This concurs with the literature, where high self-reported stress levels are reported to be correlated with low HRV standard deviations and low LF/HF ratios [8]).

4 Discussion

Our calculations suggest that analyzing an entire data sample may detect too many artifacts, and thus result in a biased overcorrection. According to the state of the art in HRV artifact removal tools [18, 19], there is currently no possibility to fully automate the detection, correction and analysis process. Therefore, a human investigator is necessary to select threshold levels appropriate for the particular data analysis task. Hence, in the context of the research reported here, determining how well self-report data correlates with HRV data requires human intervention in the data-preprocessing stage.

Previous reviews of the literature have shown that there is still a need for field studies applying neurophysiological measures in technostress research [2, 9]. Yet, current developments in the area of consumer-grade devices may allow for investigations using this approach to be conducted more frequently in the future [7]. In order to support individual researchers interested in such settings, who then have to preprocess the generated data we present in this paper a concrete example based on real world data. We show that in NeuroIS research, scholars have to make multiple decisions with respect to data preprocessing and analysis and present some potential effects of these decisions (e.g., on the correlation between measures).

As indicated by Riedl and colleagues in a paper on a NeuroIS research methodology ([1], see Section 5.5.), such decisions "may affect the corroboration and/or rejection of the research hypothesis [and therefore] it is important that authors report details related to study design, data collection, preprocessing, and analysis in their papers" (p. 26). Transparency in this regard may also help to foster the creation of more robust results which can then, for example, be building blocks for automated approaches to the analysis and use of data (e.g., when creating stress-sensitive adaptive enterprise systems [20]).

Based on the evidence reported in this paper, we make a renewed call for deliberately making methodological decisions (such as those related to preprocessing of physiological data) and presenting methodological details in NeuroIS papers.

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Wearable Devices: A Physiological and Self-Regulatory Intervention for Increasing Attention in the Workplace

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Abstract. Despite stress associated with work overload, employees are still expected to maintain attentional focus and generate new knowledge. However, attention in the work environment is a scarce resource making completing tasks under stress increasingly difficult. There are few technological interventions used in the IS literature targeted at both decreasing stress and increasing attention. Wearable device technologies may facilitate such processes due to their ability to collect real-time physiological measures and cue individuals at moments when they should take action. Self-regulation theories consider attentional resources and cognitive processes used to consciously control performance, thoughts, and the recognition of emotions. However, stressors reduce the availability of attentional resources, where maximum attention only occurs during moderate levels of physiological arousal. We examine both cognitive and physiological paths affecting attentional processes and propose a technology-mediated intervention to study these effects.

Key words: wearable devices • stress • haptic vibrations • self-regulation • attention • work overload

1 Introduction and Background

Maintaining attention is a key resource for knowledge workers. However stress may be impeding attentional focus. Work overload is a significant workplace stressor and results in employee turnover intentions and work exhaustion [1], [2]. Work overload is the perception that assigned work exceeds an individual's capability or skill level [3], [4]. Increases in stress in a work environment can negatively affect employee performance [5]–[10]. Despite perceptions of work overload, employees are still expected to generate useful information and knowledge. In order to do so, they are required to maintain their attentional focus. However, reduced barriers to interruptions and increased expectations of availability seem to be creating an environment where demands exceed individuals' abilities [11]–[13]. Despite what is known about the negative effects of stress on performance and the struggle to maintain attention in the work environment, there are few interventions targeted at both decreasing stress and increasing attention.

Well-designed technology could help knowledge workers cope with stress, maintain attention, and keep up their performance. Technology may provide an effective means to promote individual self-awareness of stress [14], [15]. More specifically, wearable device technologies may facilitate such processes due to their ability to collect real-time physiological measures as an indicator of stress and cue individuals at moments when they should take action [16]. By using elementary features of wearable devices (i.e. heart rate sensors, notifications, and haptic vibrations) in combination with cognitive and physiological processes, we aim to reduce stress and increase attention.

Although IS research has focused on taking breaks to reduce strain from overload [17], [18], less research has examined the subsequent cognitive effects, despite calls to study these effects [14]. Taking a break may be important for maintaining attention, especially when performing resource intensive tasks [19]. However, simply giving employees the opportunity to take breaks may not always be effective. Motivated individuals may set high norms, making other workers feel pressured to continue working [11]. This pressure may be relieved through a short and discreet intervention facilitated by a wearable device. A short physiological and cognitive intervention may provide the stress-relieving benefits to sustain attention.

Resource allocation theories consider attentional resources in terms of *cognitive processes* and how they are allocated to direct and maintain attentional focus [20]. Such cognitive processes include self-regulation, which enables the ability to monitor performance and maintain attentional control [19], [21]. Self-regulation theories describe a cognitive process for the ability to consciously control task performance, thoughts, and the recognition of emotions [22]. For example, individuals who are more aware of their current mental activity, including those who have been trained in mindfulness techniques, are better able to regulate their attention [23]. Furthermore, stressors reduce the availability of attentional resources, where maximum attention only occurs during moderate levels of physiological arousal [24]–[26]. This illustrates a *physiological process* for decrements in attention. For example, stressed individuals tend to lose attentional focus and have more off-task thoughts [19], [24], [25]. Off-task thoughts are thoughts unrelated to the task at hand and detracts from performance on attentional tasks. Thus, we examine cognitive and physiological paths affecting attentional processes and propose a technology-mediated intervention. Against this backdrop, we aim to answer the following research questions:

(1) How can self-regulatory theories be used to explain the effects of stress on attention?
(2) Can cues on a wearable device facilitate relaxation techniques and decrease stress through physiological processes?
(3) Can relaxation cues on a wearable device increase attention through self-regulatory cognitive processes?

2 Hypotheses Development

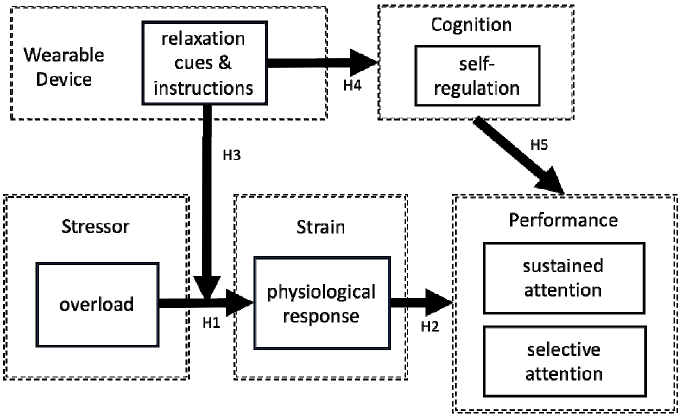

Fig. 1 Research Model

Lazarus & Folkman [27] describe stress as "a particular relationship between the person and the environment that is appraised by the person as taxing or exceeding his or her resources" (p.19). By this description, overload – the perception that assigned work exceeds an individual's capability or skill level [3], [4]– would also induce stress. Overload is experienced when the requirements of the task are too high and there are too many demands for the individual to fill [28]. Strain is the resulting psychological and physiological response to these environmental demands [29]. An increase in heart rate has been shown to accompany perceptions of a high load and compares favorably with identifiable stress during the work day [30], [31]. Thus, we propose that when facing overload, individuals will have a physiological response that can be detected by heart rate sensors on a wearable device. *H1: Overload will positively affect the physiological response to stress.*

Stressors reduce the availability of attentional resources, where maximum attention only occurs during moderate levels of physiological arousal [24]–[26]. Participants facing overload may have more work to complete, thus, providing more opportunities to seem productive. However, an increased physiological response due to overload results in more errors [32]. We propose that more errors are the result of attentional lapses due to strain. When experiencing stress, individuals tend to have more off-task thoughts and decrements in attention [18], [20], [24], [33], [34]. Thus, we expect that when individuals face overload and are strained, they will also have a reduced availability of attentional resources. Therefore, we propose: *H2: The physiological response to overload has a negative effect on sustained attention and selective attention.*

We propose that the features implemented in the wearable device will facilitate deep breathing (see section 3.1 for features). Deep breathing contributes to a physiological response characterized by decreased heart rate and increased parasympathetic activity [35]. Additionally, deep breathing can aid in decreasing perceived stress [36]–[39]. We propose that the features implemented in the wearable device will facilitate these processes. *H3: Relaxation cues and instructions will* *negatively moderate the relationship between overload and the physiological response to overload.*

Breathing techniques are an essential part of mindfulness [40], which promotes a balance between a relaxed and attentive state of mind [41]. Self-regulation is an essential component of mindful exercises where one must bring awareness and attention to the current moment and focus on the breath [40]. We propose that the features implemented in the wearable device will allow the facilitation of these self-regulatory processes. *H4: Relaxation cues and instructions will positively affect self-regulation.*

The ability to self-regulate has been found to be a key component in enhancing cognition and attentional processes [42]. Additionally, self-regulatory processes include self-monitoring and self-evaluation. They are responsible for directing and maintaining attentional control [20]. Theories of self-regulation illustrate that people can make themselves more aware of their current mental state and can regulate their attention to suppress and prevent the onset of unwanted thoughts [21], [23]. Thus, we propose that self-regulation can be used as a way to refocus and maintain attentional control. *H5: Self-regulation positively affects sustained attention and selective attention.*

3 Methods

3.1 Features of Wearable Device

Feature	Purpose	Function
Push notification	notifies participant of increased heart rate	awareness of physiological response
Screen	displays instructions telling individuals to inhale deeply while the device vibrates and exhale when it stops vibrating	informational instructions to facilitate deep breathing
Haptic Vibrations	rhythmic and kinesthetic vibrations creating the sense of touch - vibrates slowly 6 times per minute	sensory instructions to facilitate deep breathing

3.2 Experimental Design

To empirically validate our research model, we plan to perform a controlled experiment that allows us to measure physiological, behavioral, and self-reported data. We will use heart rate as a physiological measure to capture real-time responses to stress. Behavioral measures will be used to measure objective performance on an attention task. Self-report measures will be used to capture self-regulatory processes and perceptions of work overload stress. We use a multi-method approach because it can achieve better explanatory power and helps to avoid method-bias [10], [43]. Additionally, physiological measures of stress have been shown to explain and predict variance in performance over and above the prediction afforded by a self-reported stress measure [9]. We propose an independent group design with repeated measures. Participants will be randomized to one of two groups (wearable device vs control). The Apple Watch Breathe Feature has capabilities to detect heart rate and the accuracy has been tested [44]. Additionally, the application is used in combination with haptic vibrations and its goal is to relieve stress [45]. We will use this software and the Apple Watch to test our hypotheses.

Baseline Attention Task: The d2 Test of Attention will be used to measure baseline attention and changes in attention [46], [47]. The d2 Test of Attention is a paper-and pencil cancelation task measuring *sustained and selective attention*. The test was chosen because these abilities have been predicted to be positively affected by mindfulness training and brief mindfulness interventions such as deep breathing [36], [40], [48]. Such attentional processes are also important for knowledge workers [11].The psychometric properties of the test have been well supported [49]. The d2 sheet contains 14 lines of letters, and the task is to cross out "*d*s" with two dashes, which are interspaced with distractors. The time limit for each line is 20 s.

Pre-Test for Overload: To account for individual differences in perceptions of overload, participants will complete a baseline *overload* task [32], [50]. The test involves completing anagrams, or rearranging letters to form a word. Because one participant might perceive ten anagrams in five minutes overload, while another participant may perceive the same set of anagrams as a moderate workload, we concluded that it is necessary to get baseline measures. Participants will be given a test trial where they will be asked to fill out as many anagrams as they can while working at a normal pace. They will not explicitly be given a time limit, so they experience time pressure in the experimental trial, however, they will have five minutes to complete as many anagrams as possible. At the end of the test trial, the experimenter will collect the anagrams from participants and use the results to calculate the number of anagrams that each participant should receive in the experimental trial.

Heart Rate Baseline: Next, participants will be instructed to rest for 10 minutes while sitting still to measure baseline levels of physiological activity. 10 minutes is the resting period used in other standardized stress tasks [51]. During this time average *resting heart rate* will be measured. Heart rate is used as a measure of the sympathetic division of the autonomic nervous system and has been used in IS literature to measure physiological stress [8]. Heart rate will be continuously measured for the rest of the experiment.

Stress Overload Task: All participants will perform an experimental overload task [32], [50]. Participants will be told, "You will be given anagrams to decode and you should decode as many as possible in 5 minutes. The amount of anagrams you will be given is a standard rate, designed to be appropriate for college-ability students. After 5 minutes, the anagrams will be removed and you will be given more." Unbeknownst to participants, they will begin with 200% more anagrams compared to the pre-test trial and a timer will be displayed. Anagrams will be taken away after 5-minutes and participants will receive new ones. The task will go on for 15 minutes maximum or until the wearable device detects a heart rate above 20% of their resting heart rate. That is the average increase in heart rate after five minutes in a standardized laboratory stress task [51].

Intervention: *Wearable Device group*: When the wearable device group's heart rate exceeds 20% of their resting heart rate, the anagrams will be taken away and they will receive a push notification on the wearable device saying, "Your heart rate appears higher than normal. Take two minutes to relax and follow the instructions." Two minutes is chosen so that the intervention can be short and discreet, but still enough time to physiologically recover from stress [52]. The participant will have to click ‘continue’ at which point instructions will be shown, i.e. “Inhale deeply while the watch vibrates and exhale when it stops.” The vibrations will be formed by haptic vibrations. Haptic vibrations are kinesthetic vibrations that create the sense of touch. These vibrations will rhythmically vibrate slowly six times per minute for two minutes. Breathing at a rate of around six breaths per minute results in increases in heart rate variability [53] reflecting a reduction of stress levels. And heart rate is strongly correlated with heart rate variability measures [54]. *Control Group*: When the control group’s heart rate exceeds 20% of their resting heart rate, the anagrams will be taken away and they will wait 2 minutes before the next task. They will not be instructed to alter their breathing in any way and although they will be wearing a wearable device, it will not be activated.

Attention Task: All participants will perform the d2 Test of Attention for the second time in order to measure changes from baseline sustained and selective attention. We choose three outcomes hypothesized to be the most sensitive based on the literature mentioned above (1) the total error rate (E; commissions and omissions); (2) the error percentage (E%, calculated as E/TN x 100, where TN represents the total number of processed items); and, following the d2 manual, (3) the error distribution (ED), defined as the error sums for three test sections (lines 1–5, lines 5–10, and lines 11–14).

Self-Report measures: Before and after the experiment participants will complete the following questionnaires: perceived stress scale [55] on-task/off-task scales [20], [56] and self-regulatory processes scales [20].

4 Expected Contributions

This study would yield several practical contributions. It will illustrate how the physiological response associated with work overload can be used as real-time information to provide appropriate timing of cues for relaxation. The integration of bio signals into IS is an advantageous design aspect [14] and incorporate this aspect into the wearable device. Additionally, this research will contribute insights into how elementary features of a wearable device, such as cues and haptic vibrations, can be used to facilitate relaxation techniques. Such a device could be used in a work environment where employees need a high level of attention and have a high workload, for example financial traders or investors [5]. Additionally, the implications of such a device for agile software development teams may be promising, where individuals may work better as a team when under less stress.

This study will also provide theoretical insights for IS research by illustrating cognitive and physiological mechanisms for how a wearable device can influence both strain and performance. We explain these processes through resource allocation and self-regulatory theories. Self-regulation and physiological arousal appear to be important factors influencing the maintenance of attention [20], [22], [26]. We propose a technology-mediated intervention using these mechanisms to positively affect attention. Our comprehensive model illustrating the proposed effects will bring together research on resource allocation theories, self-regulation theories, and how information technology can facilitate these processes.

The results from this study will provide opportunities for future research. For example, these ideas may be extended to examine automatic use processes and how they can be facilitated through wearable devices. The effects on attention may be amplified through extended learning with the wearable device. After learning has occurred, a task becomes more automatic. Thus, secondary tasks can be completed with little cognitive effort [19], [57]. Therefore, individuals may be able to complete relaxation tasks while performing other primary tasks and maintaining attention. Using the elementary features described above may potentially facilitate these processes with little cognitive effort. Future research should consider how learning affects these processes.

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Exploring Flow Psychophysiology in Knowledge Work

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Abstract. We report on a first exploration of a new paradigm to study flow physiology in knowledge work that we call controlled experience sampling (cESM) in order to build a bridge for flow physiology research to more unstructured tasks. Results show that the approach elicits a consistent flow experience with intensities as least as high as in an established difficulty-manipulated math task. Yet, significantly lower stress perceptions and heart rate variability (HRV) responses are found in the cESM approach which highlights gaps and consequences for the diagnostic potential of HRV features for the understanding of flow physiology and automated flow observation in bio-adaptive systems.

Keywords: Flow • Psychophysiology • Knowledge work • Adaptive systems

1 Introduction

Flow, the experience of complete involvement in a challenging task where action occurs fluidly [1], describes a desirable state in the work environment as it is supposed to improve worker performance and well-being [2, 3]. Due to the complexity of knowledge work, flow has also been proposed as a metric to evaluate knowledge work outcomes and work environments [4]. While flow facilitation is still a major challenge [3, 5], due to the complex requirements (e.g. absence of distractions, structure of the task, challenge of the task, physiological and psychological state of the individual, etc.) [3, 5], especially the advancements on flow physiology [6, 7] propose interesting avenues for supportive bio-adaptive systems [8–10]. However, at present most of the physiological research is conducted in highly controlled game tasks, leaving gaps to understand flow physiology in more unstructured tasks that are typical in knowledge work [4, 11]. Especially as knowledge work demand is estimated to increase strongly due to artificial intelligence advancements [12], we aim to build a bridge towards increased external validity by adapting an original flow research method, the experience sampling method (ESM) [13], to a laboratory setting. This presents a controlled approach (cESM) in which individuals work on a knowledge work task whilst being observed using neurophysiological sensors and being interrupted multiple times to "catch flow in the act". By analyzing experience across interruptions, and by comparing them to a standard flow induction approach, we aim to answer the main research question of how well the cESM approach can elicit flow. Knowledge workers are a promising target population for flow physiology research as they are highly trained individuals that face challenging tasks requiring creative solutions. With this property, they fall perfectly in the theoretically described situation for flow experience [24]. Also, knowledge workers are often times working in sedentary positions in computer-mediated environments, which makes their natural work environment already similar to laboratory settings and ideal for physiological assessment. In sum, our work contributes significantly to the present literature by (1) advancing the understanding of flow elicitation in laboratory settings, by (2) extending flow physiology research to the knowledge work context, and by (3) delivering insights into flow physiology across tasks.

2 Background

Flow Theory. Flow is characterized by nine distinct dimensions in Csikszentmihalyi's theory: (1) challenge-skill balance, (2) clear goals, (3) unambiguous feedback, (4) autotelic experience, (5) action-awareness merging, (6) sense of control, (7) loss of self-consciousness, (8) transformation of time, and (9) concentration on the task at hand [14]. Dimensions 1-3 are deemed antecedents, 5-9 characteristics of the experience itself, and dimension 4 a consequence of flow experiences [15]. Flow has been studied in a wide range of different activities from sports [16] to artistic and musical performance [17, 18], computer gaming [11, 19], literary writing [1, 20] or reading [21], and been found to appear remarkably similar across tasks.

Research Paradigms. The flow characterizations have in the past primarily been developed from self-reports (first interviews, then surveys, especially by use of the ESM) [13, 22]. The ESM was developed early in flow research to overcome interview limitations and catch flow while it is occurring through repeated interruption over the course of a day [13]. Only more recently experimental flow induction has been developed with the primary paradigm of difficulty manipulation (DM) [22]. By providing a task in a low, balanced, or high difficulty condition, experiences of boredom, flow, and overload are to be elicited respectively. While the approach has been deemed useful to elicit contrasts, it has also been criticized as to whether real flow experiences are elicited (given the low involvement often present in experiment tasks) [11].

Physiology. Flow physiology research has extensively made use of the DM paradigm. Having surveyed 20 studies on the peripheral nervous system (PNS) [6] and two studies published since then [23, 24], we find that 12 of 22 studies used this paradigm. Furthermore, 16 of 22 studies used game tasks. This shows a focus with limitations to external validity, that has spawned calls for creative laboratory research [7]. In this research, we provide an approach adaption by transferring the ESM method to a controlled setting (cESM), with similarities to previous work with musicians [25, 26]. In doing so, we build on established psychometric instruments, like the Flow Short Scale (FKS) [27] to assess flow experience, together with biometric measures. Central hypothesis on PNS flow physiology are moderate [28–30] or high sympathetic activation in flow [25, 31, 32] (compared to boredom or overload experiences).

Also, the parasympathetic modulation of sympathetic nervous system activity (maybe even non-reciprocal co-activation) [19, 23, 28] has been discussed. Therefore, especially HRV metrics have so far played a central role in understanding PNS activation levels during flow [6].

3 Method

Materials & Procedure. Our study was conducted in a laboratory setting with air-conditioned cabins, one participant at a time. Each participant worked on (1) writing a research project report, and on (2) solving math equations manipulated in difficulty both within the same session. Scientific writing represents a challenging and frequent task for scholars and students (typical knowledge workers). Furthermore, writing has in the past been related to flow and engaging experiences [1, 20, 33]. Participants brought their own thesis, were given time to review the state of their work and to define a challenging, yet achievable goal for a writing session of 20-25 minutes using the SMART mnemonic [34, 35]. The math task was chosen as reference to an established, DM flow induction paradigm [32, 36, 37]. This task, in which participants sum two or more numbers, was replicated from [36] with two adjustments as task difficulty was found to be too high in initial pre-tests. The adjustments are: In the boredom condition, subjects had to always solve randomly generated equations in one of three forms (101 + 1, + 2, or + 3). In the flow condition, difficulty was increased/decreased when three responses in a row were correct/incorrect. The order of math and writing task was randomized and so were the orders of the three math task conditions, resulting in a total number of 12 procedures (2 tasks * 3! math condition combinations) that were all executed once. The complete procedure is outlined in figure 1.

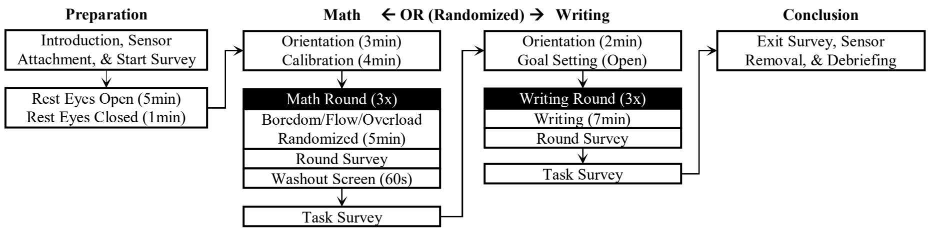

Figure 1. The Experiment Procedure Visualized

Measures. Round surveys included instruments on flow & task demand (the ten item Flow Short Scale by [27] and one additional task demand item also by [27]), stress (a five item construct by [38]), and affect (the single item SAM scales for arousal and valence by [39]), amongst others. Task surveys included instruments on task importance [27]. All reported survey instruments used 7-point Likert scales (with the exception of the SAM affect scales which used 9-point Likert scales). ECG data was collected using gelled chest electrodes in Lead II configuration. EDA data was collected from the left foot using gold cup electrodes. Both ECG and EDA were collected through a BiosignalsPlux hub at a sampling frequency of 1000Hz. Additionally, participants wore a 14-channel Emotiv Epoc+ EEG headset. In this report, we focus on the analyses of ECG data only.

Participants. 12 students (3 female) ages 21 to 30 participated voluntarily. In the recruitment survey participants reported average thesis challenge levels of 4.3 (SD: 0.98) and Wilcoxon comparisons showed no difference in preference for math or writing tasks as measured by three items from [36].

4 Results

Data Processing. In the scope of this article we report on four psychometric (flow, demand, stress, arousal) and two physiological (RMSSD, HF-HRV as two HRV features derived in processing ECG data) variables compared across six sampling points (three math conditions, three writing interruptions). For all variables, outliers were removed (>2 SD from the construct mean). Normal distribution (Shapiro-Wilk test) and variance homogeneity (Fligner-Killen test) were violated for many samples, prompting the use of non-parametric tests. One item was removed from the stress construct, improving Cronbach's Alpha in the math boredom condition. Given the high internal consistency across samples (see table 1), and corroborating results from the self-assessment manikin arousal item [39], the stress construct was kept in the analysis. Friedman tests indicated the presence of main effects at significant levels ($p < 0.01$ for psychometric data, $p < 0.05$ for physiological data). Variable means and standard deviations are shown in table 2. Post-hoc pairwise Wilcoxon comparisons of group means are shown in table 3.

Table 1. Cronbach's Alpha Levels Across Sampling Points (M-F/B/O/All = Math Boredom/Flow/Overload/All Math Samples, W1-3/All = Writing Sample 1-3/All Writing Samples)

Variable	MB	MF	MO	M-All	W1	W2	W3	W-All
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

Table 2. Variable Means & Standard Deviations (in Parentheses) Across Sampling Points

Variable	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)
ΔRMSSD	-5.55 (9.44)	-1.42 (9.12)	-4.54 (8.05)	-10.49 (7.36)	-8.91 (6.01)	-8.59 (10.21)
ΔHF-HRV	-151.30 (319.30)	-197.48 (189.06)	-232.65 (199.07)	-434.16 (286.05)	-453.47 (305.14)	-374.23 (376.30)

Demand. For a difficulty manipulation check, the demand variable was inspected (cf. [28, 31]). Significant differences were found between all math conditions, showing increasing demand from boredom to overload conditions, confirming manipulation success. The demand levels in the writing samples lay consistently between the math boredom and overload condition, and possibly even below the math flow condition, indicated at trend level ($p<.09$). Aside from one trend level difference between writing sample 1 and 3, no differences were found within the writing task. In all other variables, no differences were found across the writing samples and comparison data was therefore excluded from the report.

Flow. Comparisons of the FKS reports indicate significant differences between the math flow and overload condition, and repeated, significant differences between the math boredom and overload conditions with the writing samples. Also, there is a trend level indication of higher flow in the first writing sample than in the math flow condition. Within the writing task, there were no significant differences. Therefore, flow was reported at least as high in writing consistently across all writing task interruptions. We also find support for this observation of consistency in the range of flow reports per participant (mean range = 1.13, SD = 0.62).

Stress & Arousal. Comparison of stress reports revealed significant differences between all three math task conditions, with increasing levels from boredom to overload. Within the writing task, the stress levels did not differ significantly. Stress levels were consistently lower in writing than in the math flow and overload conditions. Arousal report comparisons show almost the same pattern, with increasing arousal from math boredom to overload, although with only a significant difference between boredom condition and the other two. Arousal levels were consistently lower in writing than in math flow and overload conditions.

Table 3. Psychometric Data Wilcoxon Mean Comparison p-Values

	Demand			**Flow**			**Stress**			**Arousal**		
	MB	**MF**	**MO**	**MB**	**MF**	**MO**	**MB**	**MF**	**MO**	**MB**	**MF**	**MO**
MF	**<.01**			>.1			**<.05**			**<.01**		
MO	**<.01**	**<.05**		>.1	**<.05**		**<.01**	**<.05**		**<.01**	>.1	
W1	**<.01**	**<.09**	**<.01**	**<.01**	**<.09**	**<.01**	>.1	**<.05**	**<.01**	>.1	**<.01**	**<.01**
W2	**<.01**	**<.09**	**<.01**	>.1	>.1	**<.05**	>.1	**<.01**	**<.01**	>.1	**<.01**	**<.01**
W3	**<.01**	**<.05**	**<.01**	**<.05**	>.1	**<.09**	>.1	**<.01**	**<.01**	**<.09**	**<.01**	**<.01**

Table 4. Physiological Data Wilcoxon Mean Comparison p-Values

	ΔRMSSD			**ΔHF-HRV**		
	MB	**MB**	**MB**	**MB**	**MF**	**MO**
MF	>.1			>.1		
MO	>.1	**<.05**		>.1	>.1	
W1	>.1	**<.01**	**<.05**	**<.05**	**<.09**	**<.09**
W2	>.1	**<.05**	**<.05**	**<.05**	**<.05**	**<.05**
W3	>.1	**<.05**	>.1	**<.05**	**<.05**	**<.09**

HRV. We furthermore analyzed HRV metrics that have been central to previous flow physiology research [6]. In order to conduct this analysis, ECG data was processed using the Python toolbox NeuroKit [40] to derive time-series data of adjacent heartbeat intervals (RR-intervals). Afterwards, based on the RR-interval data, HRV features were computed in the same toolbox and cross-validated using the R toolbox

RHRV [41]. Similar to this research (cf. [19, 28, 31]) change scores were used in the analysis ($\Delta HRV = HRV_{task} - HRV_{baseline}$) of five-minute window time-domain (SDNN, RMSSD) and frequency-domain (LF-HRV, HF-HRV) features preceding each survey. Friedman tests of main effects across the sampling points were only significant for RMSSD and HF-HRV, which is why only these two measures were investigated further. Both are similar in post-hoc test results. Wilcoxon tests of mean differences revealed for the RMSSD feature a significantly higher level in the math flow condition than in the math overload condition. This was not corroborated by the HF-HRV feature, which indicated similar HRV levels across math task conditions, albeit with a decrease trend from boredom to overload condition, with the flow condition falling in-between. Similarity across sampling points was also found for all the writing task samples, in both features. However, most importantly, comparisons revealed significantly lower HRV levels in both RMSSD and HF-HRV in comparison to both math flow and math overload tasks. HF-HRV was also significantly lower in all writing task conditions compared to the math boredom condition, indicating consistently stronger parasympathetic withdrawal during the writing task.

Task Importance. After math and writing task, participants rated the importance of the task [27], with no significant differences (math mean = 3.82, writing mean = 4).

5 Discussion & Conclusion

Discussion. Within the math task, our results suggest a successful manipulation with comparable results to previous research, showing that flow experience (as indicated by self-reports) is experienced most strongly when task demands are optimally balanced with a participants skill levels [28, 29, 31]. Within the writing task, we find that all presented variables indicate a consistent experience, despite repeated interruption. This finding is important as interruptions are often considered a prime cause of lack of flow experiences [42]. Therefore, we initially anticipated more experiential variance due to repeated task interruption. It is possible that other factors in the writing task design (like the facilitation of goal setting early on) helped to mediate this interruption impact. Goal setting has been found to be an important step in the writing process that facilitates high quality work [34] and is theorized a prime conductor for flow experiences in the original theory [14]. We take the results here as first support that the cESM approach with a writing task can be used to elicit flow, at least at similar intensities that are elicited with a standard DM paradigm (the math task). However, even though tasks are reported as similarly important, writing is experienced as less stressful and demanding, and shows a stronger HRV reduction. A key reason for the stress difference could be the design-related, contrasted presence of multiple stress factors (demand overload, social-evaluative threat, lack of control) [43]. These factors have in the past purposefully been introduced to flow experiment designs in order to elicit motivated task performances [28, 36, 43] and have resulted in repeated sightings of psychometric reports that paint a picture of increased stress/arousal in balance and overload conditions compared to boredom conditions, even in contexts (e.g. gaming tasks) where threat experiences could be less likely than in for example math or public speaking tasks [19, 28, 29, 43]. Our results indicate, that a task that is naturally important to the individual [25], yet lacks these stressors, results in similar reported flow intensities without perceptions of strain. The critique on the aptitude of the difficulty manipulation paradigm to elicit real flow experience could therefore receive some support [11]. However, it should also be pointed out, that these results might indicate a central limitation to how flow is collected psychometrically (in this study, but also in general), as there could be experiential components to flow that are not captured by the FKS [27] that was employed here.

Within the math task, our HRV results are comparable with previous work showing increased PNS activation from flow to overload conditions (i.e. moderate activation in flow) [23, 24, 28, 29]. Within the writing task, the HRV similarity across the sampling points further supports the observation of a consistent experience. However, given this consistency it is hard to say if the reduced HRV (compared to the math task) is due to a qualitatively different flow experience, or due to other variables (e.g. task complexity, effort, etc.). Nevertheless, the finding that even though writing is perceived as less stressful, the corollary of lower HRV is interesting and could alternatively indicate that the proposition, that flow is actually a state of high physiological activation, is correct [25, 31, 32]. In any case, the comparison of the two tasks could explain these previously contrasting findings (i.e. why in some studies the physiological results point to moderate PNS activation and in some to high PNS activation) to be caused by experimental paradigms. Lastly, the results could also show a potential complication for future bio-adaptive systems work that uses physiological thresholds to infer experiential states.

Conclusion & Future Work. A central limitation of this study is the small sample size, which is why the results should be treated with care. Future work should increase variance in the writing task (e.g. by including a writing boredom phase, or temporally varied sampling), together with more psychometric scales (involvement, effort, effortlessness, etc.) to enable more nuanced insights on experiential and physiological processes. The indication of the aptitude of the writing task to elicit flow experiences in the lab is the first major contribution of this work. It highlights the potential of using the cESM approach as an alternative to study flow in laboratory settings. Secondly, the research contributes to the study of flow by extending it to the knowledge work domain. Thirdly, we contribute by studying the comparability and utility of physiological measures to observe flow. More work is needed to help us understand if our findings indicate increased or decreased diagnostic potential of PNS markers to observe flow experience in the context of knowledge work [9] and if CNS data, e.g. electroencephalographic (EEG) data, is additionally required for flow-supportive bio-adaptive systems. In this direction, most recent work highlights the potential of identifying EEG correlates of flow experiences in a DM paradigm (using the same math task that was used in this article) issuing calls for comparison with other tasks [44].

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Asking both the User's Heart and its Owner: Empirical Evidence for Substance Dualism

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Abstract. Mind-body physicalism is the metaphysical view that all mental phenomena are ultimately physical phenomena, or are necessitated by physical phenomena. Mind-body dualism is the view that at least some mental phenomena are non-physical. While mind-related concepts are usually measured using questionnaires, body-related concepts are measured using physiological instruments. We breakdown the narrowed measuring approaches within the simplified mind-body discussion to all four possible substance-measuring pairs and evaluate the mind-body substance dualism theory versus the physicalism theory applying perceived and physiological measured stress data using a wearable long-term electrocardiogram recorder. As a result we derive empirical evidence and strong arguments against physicalism, and assess the overall strength of the benefits of NeuroIS instruments as complementary measures.

Keywords: NeuroIS, mind-body problem, substance dualism, physicalism, stress, health data

1 Introduction

The mind-body problem is one of the most fundamental problems in NeuroIS research. This problem refers to open philosophical questions concerning the existence of a human mind and if so, the (causal) interaction of the mind with its physical body [1]. While the mind is concerned with mental processes, thoughts and consciousness, the body is concerned with the physical aspects of the brain and how the brain is structured [2]. One major theoretical approach refers to the idea that the mind does not exist distinct from the brain (physicalism); the opposite approach comprises the idea that mind and body are different substances (substance dualism). If physicalism is true, human perceptions – which Information Systems scholars investigate using self-rating instruments – simply reflect physical/brain activity, which could be directly analyzed using psychophysiological NeuroIS instruments. If substance dualism is true, it is interesting to see whether NeuroIS instruments can add complementary or contrary insights to subjective self-ratings.

While scholars have established arguments for both, physicalism and dualism (see [2] for an overview), we aim to derive more complete answers by systematically unpacking elements involved in the mind-body problem to all four possible substance-measuring pairs. More precisely, the stress concept can be measured using physiological instruments such as Heart Rate Variability [3-5] (body-related access) or using questionnaires such as the Perceived Stress Scale [6] (mind-related access). The discourse on the mind-body problem often narrows the discussion in the way that a concept is either measured physiologically (body-related concept physiologically measured) or mentally (perceived mind-related concept). This is not only true for the stress concept, but also for all other information systems concepts (e.g. mental workload [7-9]). To open the discussion to the two other possible measuring options (perceived body-related concept; mind-related concept physiologically measured), we propose the unfolded "mind-body matrix" as shown in Figure 1.

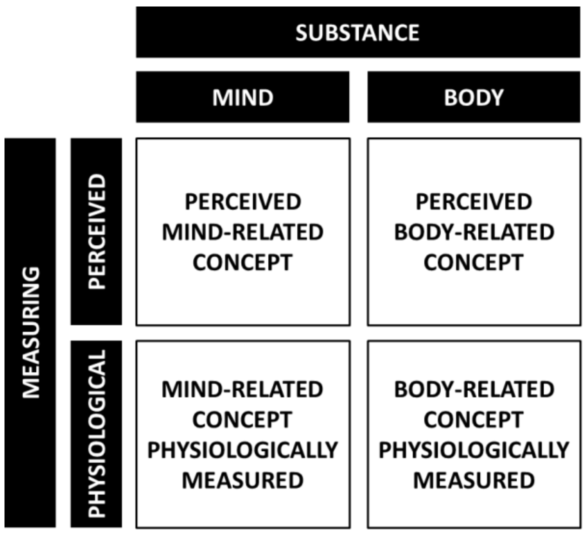

Fig. 1. The unfolded mind-body matrix.

To evaluate the possibility of gaining more insights into the mind-body problem using the unfolded mind-body matrix, this paper analyzes perceived stress data and body-related stress data, simultaneously captured from 851 participants.
While stress in general and technostress in particular are important concepts in the Information Systems (IS) and NeuroIS literatures [10-14], the stress context for the evaluation of the proposed mind-body matrix is an important one.

2 Methodology

2.1 Data and participants

Data used for this analysis were collected by corvolution GmbH, a spin-off company of the Karlsruhe Institute of Technology. 851 people (mean [±SD] age: 43.7±11.9 years; 361 females, 490 males) participated in the study.

2.2 Instruments and devices

Physically health data was recorded using the CM200 device, a wearable long-term electrocardiogram (ECG) recorder. The CM220 uses a patch-electrode-system with dry electrodes (Fig. 2). To improve ECG signal quality it is comprised of a 2-channel ECG redundancy and acquires additional context-data: barometer, thoracic-impedance, acceleration and temperature.

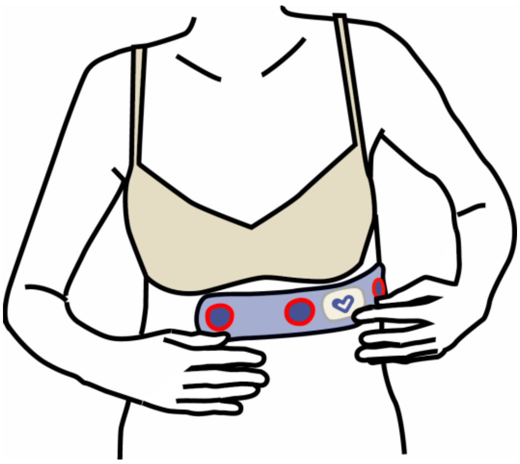

Fig. 2. The picture shows how the electrodes are attached to the body.

Based on this physiological health data, the Baevsky Stress Index [3] was calculated and used in our analysis. The Baevsky Stress Index is a heart-rate-variability derivative which is widely accepted in medicine to evaluate the state of the autonomic regulatory mechanisms of the cardiac rhythm under physical or psychological loads [4, 5]. Perceived stress as a mind-related concept was measured using the Perceived Stress Scale [6] with reliability according to Cronbach's α of 0.89. Perceived stress as a body-related concept was measured using the list of Thirty Stress Symptoms (e.g. 'I'm often tired over the day.', 'I often have tachycardia.', 'I often have digestive problems.') by Nathan and Rosch [15] with reliability measured by Cronbach's α of 0.94. Perceived stress as a mind-related concept directly measured by a physiological instrument is an open issue and an aim especially of NeuroIS scholars [16-19].

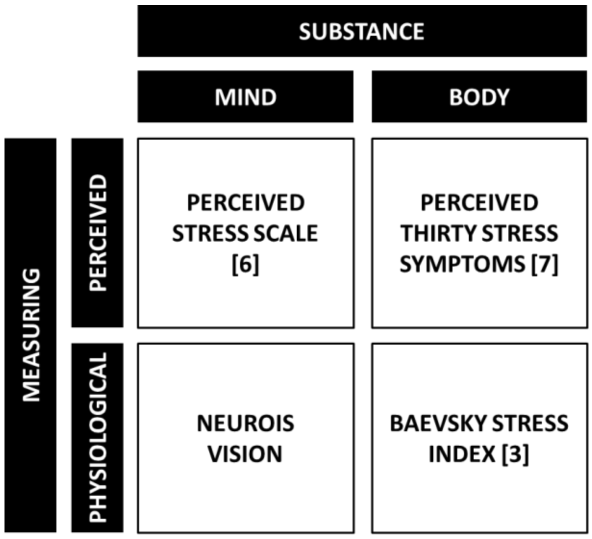

Fig. 3. The unfolded mind-body matrix with stress measures.

2.3 Procedure

Participants were asked to wear the CM200 electrocardiogram recorder over two days and to answer the questionnaires (Perceived Stress Scale and Perceived Thirty Stress Symptoms) after each day. All participants worked for at least one of the two days the measurement took place. They had no special task list to fulfil. The raw data from which the aggregated data were extracted comprise of 415 MB for each 48h measurement. The Baevsky Stress Index was calculated using all data points during recording. A mean of the answers was derived from the questionnaires over two days.

3 Results

The relationships within the unfolded mind-body matrix can be found in Table 1.

Table 1. Relationships within the unfolded mind-body matrix (Spearman correlation)

Relation	**Level of correlation**	**Level of significance**
Perceived Stress Scale [6] AND Perceived Thirty Stress Symptoms [7]	0.45	$p < 0.001$
Perceived Thirty Stress Symptoms [7] AND Baevsky Stress Index [3]	0.12	$p < 0.01$
Perceived Stress Scale [6] AND Baevsky Stress Index [3]	0.037	n.s.

4 Discussion

On the pure perception level, our results show a substantial correlation of 0.45 between stress as a mind-related concept and stress as a body-related concept ($p < 0.001$). Participants perceived a substantial level of congruency between stress as a whole and stress symptoms.

But, from a pure body perspective we only found a very low correlation between the physiologically measured stress data and the perception of stress symptoms ($r = 0.12$, $p < 0.01$). In addition, from the traditional mind-body perspective we found no relationship between the perception of stress as a whole and the physiologically measured stress data (n.s.).

To summarize, we found (a) a substantial congruency on the perception level between mind and body, but (b) no or even a negligible relationship between mind and body data from a measurement perspective (physiologically measured versus perceived data). Our study offers empirical evidence against physicalism since stress perceptions simply did not reflect physiological stress data; neither for perceived stress as a whole (mind-related) nor for perceived stress symptoms (body-related). Using the unfolded mind-body matrix our study strengthens the arguments against physicalism, which overall strengthens the arguments for using NeuroIS instruments as complementary measures [10-14, 16-19, 20].

5 Limitation and future work

The main limitation is related to the fact that the unfolded mind-body matrix is also based on the narrow conceptualizations of the concepts ‘mind’ and ‘body/brain’ as it is assumed in dualism and physicalism – assumptions that can also be challenged [2, 21].

In this work we report on body-related stress data physiologically measured only according to the Baevsky Stress Index. In the extended manuscript we will show the results for other ECG derivatives such as beat-to-beat measures, sinus arrhythmia, bradycardia or tachycardia [22].

In addition, future work could use other physiological stress measures such as skin conductance or stress hormones [12, 13, 20].

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Cardiovascular, Neurophysiological, and Biochemical Stress Indicators: A Short Review for Information Systems Researchers

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Abstract. We conducted a systematic review of the scientific literature on indicators for stress measurement. The full texts of 128 articles (published in the period 1970-2017) were analyzed and we identified a total of 21 different stress indicators, including cardiovascular, neurophysiological, and biochemical measures. Moreover, we analyzed the frequency of use of the indicators. Glucocorticoids including the hormone cortisol (52 out of 128 articles), heart rate (HR) and heart rate variability (HRV) (50/128), as well as diastolic blood pressure (DBP) and systolic blood pressure (SBP) (40/128), are the dominant stress indicators. Also, we found that half of the articles (64/128) report about at least two different stress indicators, thus a combination of biological measurement approaches is relatively common in stress research. This review holds value for researchers in the Information Systems (IS) discipline and related interdisciplinary research fields such as technostress.

Keywords: Blood Pressure · Heart Rate · Hormones · Measurement · Stress · Technostress

Introduction

Stress, in many respects, affects our social lives. By influencing our behavior individually, it has a distinct effect on communities, organizations, and society [1]. While in Eastern cultures stress is a sign of an unbalanced peace of mind, in Western countries it is viewed as “a loss of control” [2]. According to the American Psychological Association, in the US over two-thirds of the 2020 adults are supposed to be experiencing stress symptoms like fatigue. Already in 2005, every fifth person in the European Union was affected by work-related stress [3]. Expecting these numbers to rise, there is a great demand of research with the objective of developing stress-reducing methods. Moreover, a specific form of stress, referred to as technostress (i.e., stress caused by the use and ubiquity of information and communication technologies [4]), has become a major issue in organizations and in society in general.

In the last century, stress research has been typically divided into the areas of psychological, behavioral, or physiological studies [5]. Later, more specialized fields (i.e., psychoneuroimmunology) emerged [6]. Especially in scientific subfields like neuroscience, recently, there has been an increasing interest in human stress responses, including behavioral changes [1]. Stress is a "complex concept" often used in different ways with various meanings [7]. In general, a stress response should help people to manage challenging situations by keeping the organism in a state of homeostasis [1].

However, what does the term "stress" actually mean? Its physiological response was first shown empirically in 1936 by Hans Selye and at that time described as "a syndrome produced by diverse nocuous agents" [8]. In 1973, he stated: "Everybody knows what stress is and nobody knows what it is" [9]. Five years later, he defined stress as physiological non-specific reaction to exterior or interior demands [10]. The basic idea was that stress is a bodily response to environmental stimuli [5]. However, today we know that stress is not just a physiological reaction, but also related to psychological phenomena, such as a person's perception and cognitive reflection on a demanding situation, which, in turn, can result in physiological, neurophysiological, and behavioral responses [1, 2]. It generally describes a state that arouses the physiological or psychological homeostasis of our organism [11] and can even be activated by purely psychological states [6].

Importantly, stressor refers to the stimuli or challenging event, while stress response refers to the physical and emotional reaction or feedback caused by the stressor [12]. Whether and how humans respond to stress is determined by how we perceive a stimulus and how we react to it. Across paradigms, stress can be summarized as "a condition in which an individual is aroused by an aversive situation […]. The magnitude of the stress and its physiological consequences are influenced greatly by the individual's perception of its ability to control the presence or intensity of the stimulation" [13].

Apart from subjective assessments like self-reports and standardized questionnaires, most commonly, the measurement of stress is conducted by recording cardiovascular or biochemical processes and/or states [5]. More precisely, these processes and/or states typically represent a heightened excitability, vigilance, or arousal, which can be monitored and evaluated using, for example, electrocardiography, electroencephalography, neurochemical levels, or behavioral activity [13]. Therefore, a variety of signals produced by the body or chemical substances in saliva, blood or urine samples are examined. We describe major signals and substances in the following.

The cardiovascular system responds to stress with increased heart rate (HR) and blood pressure (BP) [3, 5, 14]. Blood pressure can be measured as systolic blood pressure (SBP) or diastolic blood pressure (DBP). Past research has shown that SBP may be more strongly related to interpersonal stressors than DBP [15].

The endocrine system reacts to demanding situations by changing neurochemistry [13]. To restore homeostasis disturbed by environmental demands, a physiological reaction starts, involving autonomic nervous, neuroendocrine, metabolic, and immune system components. The hypothalamus-pituitary-adrenal (HPA) axis, including the hormone cortisol, plays a key role in this response system (for a simple description of the HPA axis processes, see [16]). Additionally, catecholamines (i.e., adrenaline and noradrenaline) are released into the circulation by the adrenal medulla [1, 11, 17]. It follows that cortisol and/or catecholamines are a reliable and valid marker of stress-related neurophysiological changes in our body. These substances are usually determined in blood or saliva samples [13, 15, 18]. Another sensitive salivary biomarker used for measuring stress-related changes in the sympathetic nervous system is salivary alpha-amylase (sAA) [14, 19, 20].

So far, the influence of stress on various physiological processes is well documented in the academic literature. In this paper, we give an interdisciplinary overview about the procedures and indicators typically used for measuring stress symptoms with a focus on the frequency of use. Consequently, we identify the most common and prevalent methods. However, in this paper we do not evaluate the reliability, validity, or accuracy of different measurement approaches. From an Information Systems (IS) perspective this paper has the goal to comprehensively, yet parsimoniously, inform technostress researchers about cardiovascular, neurophysiological, and biochemical stress indicators. Technostress has become a major topic in the IS literature in the last decade, and the topic has been investigated increasingly often based on neurobiological approaches [4, 16, 21–26]. The technostress topic is also highly important from a practical perspective because increasingly more people worldwide are negatively affected by the use and ubiquity of information and communication technologies (e.g., unreliability of systems such as computer breakdowns or long and variable systems response times, or permanent use of smartphones). Thus, studying (techno)stress measurement approaches is critical for the progress of the field, thereby also contributing to the development of effective countermeasures in practice.

In the next section, we describe the search process and underlying concept of the literature research, followed by a review of articles that used, criticized, or reviewed indicators for the measurement of stress. After briefly discussing the results, we close this paper by providing insight on future research directions.

Method

We searched for studies in which any approach for measuring stress was used including review articles and critiques without restrictions on publication date and application domain. The research was conducted using the online search service EBSCOhost, a collection of full-text databases, e-books, subject indexes, point-of-care medical references, and historical digital archives.

During the search process *stress* was considered as a master keyword, and was therefore combined as *title* element by default. The keyword list has been extended continuously by backward research (reviewing older literature cited in articles of previous search results) and forward research (identifying articles citing key articles of previous search results) [27]. The complete keyword list for the search field *title* is presented in footnote 1 (*AND* combinations listed in brackets).[1] The search by *title* elements and their combinations was limited by the following *subject terms* categories: physiology, neurology, neuroscience, psychology, behavioral science, biology, medicine, radiology, business, and information science.

We included articles in our review which met the following criteria: (i) source type: academic journal or conference paper; (ii) availability: full text; (iii) language: English; (iv) research subjects: humans; and (v) research purpose: review of, or study using, stress measurement approaches.

Results

In total, the keyword search yielded a result list of 676 articles. The first step of screening involved evaluating full titles and subjects to determine whether articles met the purpose of this literature review and fulfilled all defined criteria (e.g., articles dealing with animal research were excluded). A total of 164 full text articles were downloaded and considered for an abstract analysis.[2] Overall, databases covered publication dates from 1970 onwards (to 2017), all as indexed by March 2018, the month in which the queries were executed.

Next, the abstract of each article was examined, and all articles that matched the five inclusion criteria were checked to match the complete article against these criteria. Studies with vague abstracts to allow for immediate elimination also received a full text review. During this step, 36 articles were identified as ineligible and not considered in further analyses. Finally, the full texts of 128 articles were analyzed to obtain detailed information about different stress indicators and measuring approaches. The focus of our analyses was on the methods section of the articles.

Table 1 shows the stress indicators used in the scientific literature (first column), the number of articles mentioning and/or using the indicator or method (second column), and the references (third column). Twelve papers (9.4%) were published prior to 1990,

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[1] Physiological, neurological, neurophysiological, electrophysiological, neural, nerve-related, biological (indicator, measure, response, parameter, feedback, reaction), measurement, measuring, reading, record, logging, notes, testing, scan, report, monitoring, evaluation (device, tool, equipment, appliance, instrument, application, gadget, hardware, software, machine, utensil, implement, technology); pupil dilation; dilation, pupillary, pupil, constriction (response); miosis; mydriasis; eye tracking; eye tracker; eye movement; electrodermal activity; EDA; skin conductance (level, response); galvanic skin, electrodermal, sympathetic skin (response); GSR; EDR; SCR; psychogalvanic reflex; PGR; SCL; E-meter; biofeedback; heart, heart rate, HR, pulse rate (variability); HRV; heart activity; blood pressure; BP; electrocardiograph; ECG; EKG; electrocardiogram; brain; electroencephalography; EEG; magnetic resonance imaging; MRI; computed tomography scan; CT scan; CT; hormones; strain; load; workload; pressure; liability; level measurement; distress; nervous.

[2] The sources of the articles and databases are (number of downloads in brackets): PsycINFO (60), MEDLINE (47), Psychology and Behavioral Sciences Collection (30), SocINDEX (9), Business Source Premier (8), ERIC (7), PSYNDEX (2), GreenFILE (1).

another twelve papers between 1990 and 1999, 43 (33.6%) papers were published between 2000 and 2009, and 61 papers (47.6%) in or after 2010.

Table 1. Stress measurement indicators and frequencies.

Indicator	*n*[3]	Reference
Heart/pulse rate or variability (HR, HRV)	50	[2, 3, 5, 12, 14, 28–72]
Systolic or diastolic blood pressure (SBP, DBP)	40	[2, 5, 12, 14, 28, 33–35, 42–45, 49, 52–54, 59, 61–65, 69–71, 73–87]
Respiration rate, respiratory frequency (RF)	8	[29, 30, 46, 47, 50, 53, 56, 72]
Electrodermal activity (EDA), skin conductance, galvanic skin response (GSR)	7	[30, 31, 46, 47, 70, 73, 88]
(Finger) temperature	4	[30, 46, 47, 53]
Event-related potential (ERP), electroencephalography (EEG)	4	[45, 53, 89, 90]
Respiratory sinus arrhythmia (RSA)	3	[3, 43, 48]
Pulse oximetry, oxygen saturation (SO2) at finger, photoplethysmogram (PPG)	3	[3, 37, 46]
Magnetic resonance imaging (MRI)	3	[2, 60, 91]
End tidal CO_2 ($ETCO_2$)	1	[46]
Phosphorylase activation ratio	1	[71]
Corticosteroids/glucocorticoids, steroid hormones (e.g., cortisol)	52	[1, 2, 5–7, 11, 12, 14, 17–19, 28, 36, 38, 39, 48, 51, 52, 54, 58–60, 62, 64, 68, 74, 77, 82–84, 92–113]
Catecholamines (e.g. (nor)adrenalin, (nor)epinephrin)	13	[5, 11, 54, 62, 63, 77, 84–86, 103, 107–109]
Adrenocorticotropic hormone (ACTH)	8	[2, 11, 54, 94, 96, 106, 108, 114]
Blood lipids, cholesterol	6	[5, 43, 77, 83, 108, 115]
Salivary alpha amylase (sAA)	5	[14, 19, 97, 100, 116]
Sex hormones (e.g., estrogen, testosterone)	5	[2, 34, 96, 105, 110]
Blood sugar, insulin	5	[5, 43, 77, 108, 115]
Uric acid	1	[5]
Secretory immunoglobin A (slgA)	1	[68]
Peptic ulcer	1	[5]

Across all articles, a total of 21 different stress indicators emerged. Similar measurement approaches (e.g., SBP and DBP) are considered as one indicator. In the upper half of table 1, which is more related to cardiovascular activity, the most frequently used indicators are HR/HRV (n=50, 39.1%) and blood pressure (n=40, 31.3%), followed by

[3] n = Number of articles mentioning, using, and/or reviewing the indicators or methods.

respiration rate (n=8, 6.3%) and electrodermal activity (EDA) (n=7, 5.5%). In the lower half of table 1, which represents neurophysiological and biochemical indicators, the category of glucocorticoids including the hormone cortisol (n=52, 40.6%) and the category of catecholamines including the hormone adrenalin (n=13, 10.2%) outline the most commonly used stress indicators. Moreover, half of the articles (n=64 or 50.0%) report about at least two different indicators, thus a combination of measurement approaches.

Apart from standard tools such as electrocardiography (ECG) and sphygmomanometers [29–31, 35, 43, 44, 55, 56, 75, 95, 117], also less frequently used tools were identified during full text analysis: Impedance cardiography (ICG) [55, 75], electrooculography (EOG) [117], electromyography (EMG) [30, 53, 62], high performance liquid chromatography (HPLC) [77] and microwave radar [56].

Furthermore, as a complement to cardiovascular, neurophysiological, and biochemical indicators, in almost half of all reviewed papers (n=63, 49.2%) self-report approaches (specific surveys and questionnaires) are used to measure stress perceptions.[4]

Discussion

For more than eighty years, stress and its conceptual antecedent attract the attention of scientific research [8]. With the development of disciplines such as neuroscience and discoveries in modern brain research, academia achieved a broader understanding of

[4] Standard questionnaire about participants subjective stress level (e.g., job tension, physical stress, psychological stress, strain) [44, 45, 59, 60, 63, 66, 74, 106, 118–126] or stress states and motivation (subjective work load, time urgency, state anxiety, involvement) [41, 44, 59, 89, 118, 120, 127], Trier Social Stress Test (TSST) [14, 36, 38, 39, 82, 92, 95, 103], Stress-Coping Scale (SCS), State-Trait Anxiety Inventory (STAI) or Iceberg Profile (IP) [38, 50, 64, 88, 117], Profile of Mood State (POMS) [64, 67, 88, 91, 128], Cleminshaw-Guidubaldi Parent Satisfaction Scale, Coping Resources Inventory of Stress (CRIS), Family Inventory of Life Events and Changes (FILE), Global Inventory of Stress (GIS), Parenting Stress Index (PSI), Parental Stress Scale or Perceived Stress Scale (PSS) [12, 40, 128–130], Health Opinion Survey, Population Health Perspective (PHP), General Health Questionnaire (GHQ) or Patient Health Questionnaire (PHQ) [12, 30, 131, 132], Hospital Anxiety and Depression Scale (HADS) [12, 30], Self-Assessment Manikin (SAM) [31, 48], Cox's Stress/Arousal Adjective Check List (SACL) [133, 134], NASA-Task Load Index (TLX) [135, 136], Social Stress Recall Task [130], Distress Tolerance Scale (DTS) [128], Montreal Imaging Stress Task (MIST) [91], Depression Anxiety Stress Scale (DASS) [3], State-Trait Anger Expression Inventory (STAXI) [88], Sports Anxiety Scale (SAS) [18], Pressure-Activation-Stress (PAS) scale [7], Parental Responsibility Scale (PRS) [12], Brief Symptom Inventory (BSI) [40], Perceived Stress Questionnaire (PSQ) [137], Affect-arousal Grid [42], Biographic Narrative Interpretative Method (BNIM) [138], Effort-Reward Imbalance Occupational Stress Scales [139], Anchoring-and-adjustment Questionnaire [75], Job Content Questionnaire (JCQ) [77], SWS-Survey [135], Survey of Health Care Professionals [140], Adjective Checklist on Emotions (EWL) [68], List of Cues for Determining Level of Stress [141], Pearlin and Schooler's List of Emotions [142], Taylor Manifest Anxiety Scale & Teaching Anxiety Scale [87], Role Strain Scale [143], and California Test of Personality (CTP) [132].

the complex biological mechanisms related to stress. However, despite the importance of biology in human stress, there has also been an increasing interest in the changes of human behavior in regard to stress responses [1, 6, 11, 93]. To contribute to this research domain, we focused on stress measurement. We provided a short review of the literature and identified the most commonly used stress indicators. The list of stress measurement indicators and frequencies (see Table 1) constitutes a valuable basis for IS researchers, in particular those working in the field of technostress.

The majority of articles analyzed in this review (81.2%) have been published in this century, and almost half of the total number of papers was published in the current decade. This finding indicates that our list includes the most recent research in the stress domain. Interestingly, half of the articles report more than one indicator and therefore use a combination of measurement approaches, presumably to increase validity and/or explanatory power. Across all articles, the category of glucocorticoids including the hormone cortisol (52 of 128 papers, > 40%), HR/HRV (50 papers, almost 40%), and blood pressure (40 papers, > 30%) were used, criticized, or reviewed with the highest frequency. We surmise that this result is not only a function of the indicators' reliability, validity, and accuracy, but also a function of their ease of use and application costs (if compared to tools such as EEG or fMRI). Overall, we found that these indicators are the three most commonly used stress measurement approaches of the past fifty years. However, there is also a growing body of research for other indicators like the salivary biomarker sAA, likely because these methods are "readily accessible and easily obtained" [20]. As a next step, the focus could be on the relevance of stress indicators for different technological stressors. It will be rewarding to see what kind of measurement approaches IS researchers will use in future studies.

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The neuroscience of smartphone/social media usage and the growing need to include methods from 'Psychoinformatics'

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Abstract. The present work gives a brief overview of the current state of affairs in the investigation of the neuroscientific underpinnings of social media use. Such an overview is of importance because individuals spend significant amounts of time on these 'social' online channels. Despite several positive aspects of social media use, such as the ability to easily communicate with others across long distances, it is clear that detrimental effects on our brains and minds are possible. Given that much of the neuroscientific and psychological research conducted up to now relies solely on self-report measures to assess social media usage, it is argued that neuroscientists/psychologists need to include more digital traces resulting from human-machine/computer interaction, and/or information shared by individuals on social media, in their scientific analyses. In this realm, digital phenotyping can be achieved via methods of 'Psychoinformatics', a merger of the disciplines psychology and computer science/informatics.

Keywords: Smartphone, social media, psychoinformatics, digital phenotyping, nucleus accumbens, anterior cingulate cortex

1 On smartphone and social media usage

Since the programming of the first HTML website by Tim Berners-Lee in the beginning of the 1990s, and particularly since the advent of Apple's IPhone in 2007, the digital revolution has dramatically changed the way we live in many areas of modern society. This groundbreaking movement towards a digital society is particularly evident in the ubiquity of the smartphone. This digital device strongly influences the way we communicate with others, entertain ourselves and travel around our environment. There are currently 2.5 billion smartphone users worldwide [1]. Much of our daily smartphone use is accounted for by the use of social media applications such as Facebook, WhatsApp and WeChat.

In line with the huge number of smartphone users worldwide, the number of users of these social media platforms is breathtaking. Facebook currently has almost two billion accounts [2], while the messenger application WhatsApp has an estimate of 1.5 billion users [3] and its Chinese cousin WeChat ('Wēixìn' literally, 'micro message') has about one billion users [4]. With its many features, the smartphone is not only omnipresent in terms of global user numbers, but also in terms of the length of daily usage. In work tracking more than 2,400 participants, it became apparent that the typical smartphone user spends about 2.5 hours each day on the phone [5]. Therefore, more than one work-day of a week is spent on the phone by many users. Self-report data indicates that most time spent on the phone is for leisure or private purposes, and not for business purposes [6].

Although the smartphone can help our productivity, our daily life can be negatively affected because of a constant influx of e-mails and messages via services such as WhatsApp, which can interrupt our work-processes [6,7] and can lead to stress and lower well-being [8]. Moreover, excessive usage of the smartphone has been associated with ADHD like symptoms [9,10]. This fits well with the observation that Internet addiction, with the specific form of Internet Gaming Disorder to be officially recognized in ICD-11 this year, has been repeatedly linked with tendencies towards ADHD [11,12]. This all suggests that smartphone usage might exert beneficial, as well as detrimental, effects on our lives. It is therefore of importance to understand under which conditions interacting with the digital world enhances our lives, and to what extent smartphone usage poses problems [13,14].

As mentioned above, the psychological literature has already shown that constant interruption and disruption of daily life activities might be the key to understanding when smartphone usage hinders our productivity and results in less happiness (namely, when the experience of flow at the work place is hindered by constant micro-breaks [15]). Taking a closer look at the usage of platforms such as Facebook or Instagram, it is clear that another source for negative emotionality can be found in the processes of social comparison and envy when consuming content from these social media platforms [16]. Social media is not always necessarily 'social', but may often be used to self-promote one's identity, personality and life events [17]. Typical images and messages posted often refer to the 'wonderful' and 'spectacular' life a person is living. Being confronted with these kinds of profiles could even result in depressive symptoms [18]. In light of this, it is not surprising that quitting Facebook for just one week can result in higher life satisfaction and well-being [19].

2 First insights into the neuroscientific underpinnings of social media usage

2.1 Neuroscientific studies of social media usage are still scarce

Although many psychological mechanisms have been proposed for explaining why we are so attached to our smartphones (for an overview on conditioning principles please see Duke & Montag [7]) and why many use social media such as Facebook so extensively (see motives for Facebook usage [20,21]), little is known about the neuroscientific underpinnings of social media usage (as is apparent in these reviews [22,23]). These well-conducted reviews show that much of what we know about the neural underpinnings of social media usage has been derived from bordering scientific areas, such as the investigation of social dynamics developing from in- and exclusion of individuals; e.g. see the cyberball-paradigm [24]. In this regard, Meshi et al. [22] correctly summarized that "Neuroscience research with social media is still in its infancy", but that „there is great potential for future scientific discovery" (p. 9).

2.2 Understanding the rewarding aspects of social media usage by means of functional magnetic resonance imaging (fMRI)

A well understood phenomenon with respect to the usage of social media platforms such as Facebook or Instagram is the rewarding aspect of getting so-called 'Likes'. This also explains why a 'Like economy' developed on social media platforms, such as giving 'Like' for 'Like' [25], leading the concept of receiving a 'Like' for a creative or popular post of a photo or text ad absurdum. Several recent fMRI studies [26,27,28,29] have observed that the nucleus accumbens plays a pivotal role in understanding why humans are 'hunting' online for 'Likes'. In recent studies [28,29] it was shown that processing pictures from one's own Instagram account with high versus low number of 'Likes' resulted in elevated activity in ventral striatal regions in the human brain (where the nucleus accumbens is located). In general, pictures with more 'Likes' (not necessarily one's own) elicited stronger activity in the accumbens region (see Figure 1 on the next page).

Based on much research, it is well known that this brain region plays an important part in SEEKING activity, a term coined for an emotional/motivational system in Panksepp's Affective Neuroscience Theory [30,31]. Activity in the SEEKING system describes a state of high energy accompanying motivated approach behavior in all mammals. Therefore, the expectation of getting 'Likes' might hijack the SEEKING system and urge Facebook users to return again and again to the social media platform. The SEEKING system has been proposed to be anchored in the medial forebrain bundle [30]. These results illustrate how bottom-up processes (i.e. activity from evolutionary old regions of the human brain [31]) may explain why many social media users spend more and more time on Facebook, WhatsApp and similar applications. Clearly, striatal activity alone cannot explain this phenomenon, because typically prefrontal regions of the human cortex exert a tight grip on these older brain regions. Of note here, younger people with a less developed prefrontal cortex are more likely to be affected by subcortical activity (for age effects see [29] and also the following overview [23]). Activity in the PFC can result in powerful regulation of inner emotional urges, such that a person might think 'No, I don't have time to go on Facebook now. First, I have to finish my school homework'. In a study using electroencephalography (EEG), smartphone addicts have been characterized by poor executive functions [32]. This means that they appear to have problems in exerting top-down control over the striatal regions, resulting in escalating social media usage, perhaps being characterized in extreme form as 'Internet Communication Disorder' (ICD) [33,34].

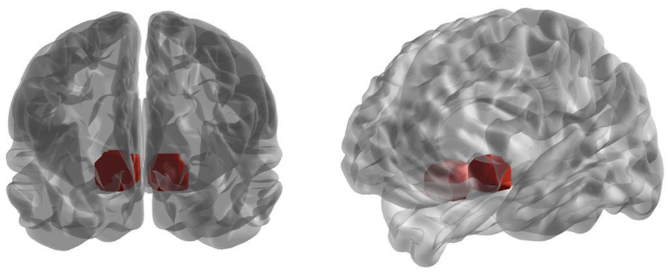

Figure 1 The nucleus accumbens is involved in reward processing and represents a critical area to also understand the rewarding aspects of 'Likes' in social media research. Clearly, it only represents one of many brain areas involved to understand the neural basis of social media usage. For an overview on many other relevant brain areas such as the inferior frontal gyrus, the anterior temporal lobe or the temporoparietal junction (also known as the mentalizing network) see [22]. Thanks to Sebastian Markett for providing CM with the figure.

2.3 Social media usage/addiction in relation to results from studies using structural brain imaging (sMRI)

Further insight into the neural underpinnings of social media usage stem from sMRI. In contrast to fMRI, structural imaging of the brain, amongst other features, allows researchers to get insights into individual differences in gray matter volume of the human brain. Such differences can be examined on a whole brain level, but also with respect to specific brain areas, such as the aforementioned nucleus accumbens. A recent study [35] observed that lower gray matter volume of the nucleus accumbens was associated with longer and more frequent usage of the Facebook application installed on smartphones. Of note, Facebook behavior was not assessed via self-report in this study, but directly tracked on the smartphones. This study therefore demonstrates the feasibility of combining real-world behavior with human neuroscience data. This will be discussed in more detail in the next section. Returning to the data linking lower gray matter volume of the nucleus accumbens to longer/higher frequent usage of Facebook on the smartphone, in the literature it has been observed that lower volume of the nucleus accumbens is associated with nicotine, alcohol and heroin addiction [36,37,38]. Of course, addictive behaviors in relation to these substances are not always directly comparable with ICD, but it could be suggested that some of the psychological mechanisms underlying excessive Facebook usage might partly resemble these other addictive behaviors. In line with this idea, a recently published study by Montag et al. [34] linked lower gray matter volume of the (subgenual) anterior cingulate cortex (ACC) to higher 'WeChat addiction' in a Chinese sample, a finding that fits with observations from both substance-dependency and Internet addiction (see discussion in [34]).

Although structural brain imaging gives no direct insights into the functionality of the human brain, the combination of results described in this section with those from the fMRI studies discussed further above reveal that subcortical areas react strongly in anticipation of social media usage (in particular in expectation of 'Likes'), and in 'social media addicts' dysfunction in top-down control mechanisms might lead to problems in the down-regulation of this increased activity from the ventral striatum [32]. Future studies will clearly need to paint a much more detailed picture on these many different activities and links with psychological processes such as mentalizing and self-referential cognition [23] while using Facebook and other social media applications. Much of what we currently know from a neuroscientific perspective on social media usage deals with the rewarding aspects of such platforms.

3 Adding methods from 'Psychoinformatics' to the Neuroscientist's toolbox

It has already been mentioned that a problem in much of the social media research conducted so far is the inclusion of self-report measures only. Without doubt, such measures will always be of importance because they give researchers valuable insights into subjectively perceived stress etc. due to social media usage, variables insufficiently operationalized by direct tracking of Internet or social media usage. Nevertheless, neglecting the possibilities of Psychoinformatics in the neuroscientific and psychological study of social media usage will ultimately lead to an incomplete understanding of why and how long people use these platforms [39]. Just consider the problems involved in estimating how long you spent on WhatsApp at a certain time last week? It has been reported in earlier work that people tend to have a distorted perception of time while using their phones, because they tend to get into 'the zone', and experience flow, on smartphones [40,41]. Ironically, this kind of psychological state is often necessary for productive work.

Psychoinformatics describes the use of methods from computer science, such as machine learning or pattern classification, to study digital traces from human-computer interaction [42,43] to do digital phenotyping [44]. Pioneering studies revealed the power of doing psychodiagnostics via analyzing the 'Like'-structure of a person's Facebook account (see meta-analysis [45]), and also via the study of Twitter accounts [46]. Amongst other things, it has been shown that it is possible to predict socio-demographic variables, political attitudes, sexual orientation and personality traits from Facebook 'Likes' [46]. As a consequence, this kind of data, and in future all data from the Internet of Things (IoT), could be used to enhance one's own study design, not only in psychology, but also the neurosciences (see further examples with research on social network size [47,48]). Nevertheless, many important obstacles have to be overcome in the near future. Among the most pressing might be addressing privacy issues, because digital phenotyping can clearly be misused for psychological targeting in sensitive areas [50,51].

4 Conclusion

In sum, the study of the neuroscientific/psychological underpinnings of social media use is still in its infancy and much additional work is needed to better understand the many psychological processes underlying the motivation to use platforms such as Facebook. With respect to the smartphone it becomes clear, that technology per se is neither good nor bad, but context matters. If used in the correct way, smartphones can makes us more productive, but there clearly exists a still to be defined point, where smartphones become detrimental for our mental health. Earlier it has been proposed that the link between productivity and smartphone usage can be described by an inverted U-function [15] with problems arising when a person is constantly interrupted by the smartphone and its social media channels. In addition and also in light of the recent Facebook-scandal [52], it will be necessary to re-think the design of the Facebook platform to make it indeed more social. Given the aforementioned possibilities to do psychodiagnostics via 'Likes', it will be also necessary to better protect the data of each user [53].

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