PHYSIO-ADAPTIVE SYSTEMS – A STATE-OF-THE-ART REVIEW AND FUTURE RESEARCH DIRECTIONS

Research paper

Loewe, Nico, Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany, nico.loewe@kit.edu

Nadj, Mario, Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany, mario.nadj@kit.edu

Abstract

Physio-adaptive systems define a class of information systems that refer to an innovative mode where system interaction is reached by monitoring, analyzing, and responding to hidden psychophysiological user activity in real-time. However, despite a strong interest of scholars and practitioners in physio-adaptive systems, there exists a lack of a structured and systematic form in which physio-adaptive systems research can be classified. Against this backdrop, this article showcases the current state-of-the-art of physio-adaptive systems research along three different stages, namely (1) collection of physiological data, (2) state determination, as well as (3) system adaptation. Analyzing 44 articles during the years 1994 – 2019, our main contribution resides in the synopsis of physio-adaptive systems literature along these stages. For instance, we illustrate that there exist three categories for adaptive responses: state display (20% of the analyzed studies), assistance offering (18%), and challenge adaptation (61%). On the grounds of our review, we propose seven promising avenues, which will support scholars in their endeavors on how to pursue with future research in the field of physio-adaptive systems.

Keywords: Physiology, Physio-adaptive Systems, Literature Review.

1 Introduction

In today's increasingly digital economy, the usage of IT presents an essential part of peoples' daily life (Agarwal and Karahanna, 2000). Hereby, an increasing number of activities are supported by IT already today and even more activities will be supported by IT in the future (Forrester Research Inc, 2017; van der Meulen and Bamiduro, 2018). While IT support is continuously increasing productivity and simplicity in many areas, the human-computer interaction (HCI) remained asymmetrical and dependent on mouse and keyboard or voice interfaces since many years (Hettinger et al., 2003; Fairclough and Gilleade, 2014). Against this backdrop, it has been argued that physiological data available about the cognitive and affective states of the user can create a symmetrical form of HCI and thereby increase the quality of the user experience (Hettinger et al., 2003). The recent rise of the NeuroIS field with the inclusion and development of physiological measures provides new opportunities in this direction by investigating these cognitive and affective user states (Riedl and Léger, 2016). Particularly towards responding to the user's needs in real-time, the benefit of increasingly reliable physiological measurement (Bastarache-Roberge et al., 2015; Labonté-LeMoyne et al., 2016; Shearer, 2016) but also the design and implementation of physio-adaptive systems have been emphasized in research (Adam et al., 2014).

Physio-adaptive systems define a class of information systems that refer to an innovative mode where system interaction is reached by the monitoring, analyzation and response to covered human psychophysiological activity in real-time (Fairclough, 2009). These systems may be designed to improve performance efficiency or the pleasure linked with HCI (Fairclough, 2009). Such systems incorporate a range of application areas, such as: (1) health (e.g., Bailey et al., 2006a), (2) gaming (e.g., Rani et al., 2005), (3) aviation (e.g., Wilson and Russell, 2007), (4) traffic (e.g., Cao et al., 2016), and (5) learning (e.g., Shen et al., 2009). For example, in the traffic environment, physio-adaptive systems rely on the driver's heart rate to control for certain vehicle actions. In the case of boredom, for example, a joke is told; in the case of panic the driver is advised to calm down (Nasoz et al., 2010). In the gaming context, on the other hand, physio-adaptive systems may manipulate the game difficulty based on the player's state. For instance, if the rule-based system is sensing overload relying on data from the electroencephalogram (EEG) the game difficulty is reduced, whereas states of boredom would trigger an increase in difficulty (Fairclough and Gilleade, 2012). Other studies controlled for the degree of automation by recording continuous signals from the EEG (Bailey et al., 2006b). Only if the EEG signals suggested that the user engaged with the task, automation was active; otherwise automation was deactivated to force the user to return to the task via manual control. Similarly, research efforts relied on EEG in combination with a number of autonomic variables (e.g., heart rate, respiration rate) to categorize different level of users' mental workload using an artificial neural net (Wilson and Russell, 2007). In case of users' "overload", some task elements are automatized. In sum, significant performance improvements could be shown when adaptation was controlled by psychophysiology.

However, in defiance of the relevance of physio-adaptive systems, a systematic approach to illustrate the current state-of-the-art in this domain is missing. Thus, reviewing this research area in a systematic way is needed due to several reasons: First, numerous articles have already been published which demand structuration. In addition, to the best of our knowledge, no systematic literature review (SLR) on physio-adaptive systems has been published to date. Second, although some researchers (e.g., Novak et al., 2012) formulated a rough process for the creation of physio-adaptive systems based on measures from the peripheral nervous system, an overall guidance for future research endeavors to be well-directed still need to materialize to date. Third, physio-adaptive systems have been applied by various fields, leading to a lack of integration of the present work. However referring to Fairclough (2009, p. 143) their realization "is a multidisciplinary challenge for psychophysiologists, human factors professionals and computer scientists". Our SLR supports this debate by systematically structuring the scattered research results, analyzing 44 articles that explicitly refer to physio-adaptive systems. Our key goals are (1) to review the state-of-the-art of physio-adaptive systems research as well as (2) to recommend avenues for future research. Hereby, we formulate the following research question: "*What is the state-of-the art and future research directions of physio-adaptive systems?*" Following this introduction, we describe the foundations in section 2. In section 3, we introduce the research method of our SLR. The results of our article are presented in section 4. In section 5, we suggest avenues for future research. Lastly, section 6 concludes our article.

2 Foundations

The biocybernetic loop represents the core concept of physio-adaptive systems (Fairclough, 2009; Pope et al., 1995) that is derived from control theory (Wiener, 1948). The loop serves as a conceptual unit and also characterizes the data flow within the system along three different stages, namely (1) collection of physiological data, (2) state determination, as well as (3) system adaptation (see Figure 1).

The loop begins in the **first stage** with the collection of physiological data from the user via sensors (Fairclough, 2009). Within this stage, three knowledge components are generally suggested for the underlying architecture of a physio-adaptive system: (1) signal acquisition, (2) signal processing, and (3) signal storage. The signal acquisition component may support multiple sensor devices. Typically, scholars distinguish between ambulatory (Fairclough, 2009), remote (Anttonen and Surakka, 2005), or wireless sensors (Anttonen and Surakka, 2005; Strauss et al., 2005). When selecting the sensor device for a physio-adaptive system, its strengths and weaknesses must be carefully assessed with regards to accessibility, costs, labor- and time-intensity of data processing, level of artificiality/intrusiveness, and measurement problems/susceptibility (Lux et al., 2018; Dimoka et al., 2012). For instance, designers that rely on cardiovascular activity must weigh up the advantages (e.g., little impairment) and disadvantages (e.g., increased susceptibility through movement artefacts) of heart rate measurement through remote photoplethysmography (rPPG) against the advantages (e.g., high accuracy) and disadvantages (e.g., higher costs) of electrocardiogram (ECG) (Lux et al., 2018; Rouast et al., 2018).

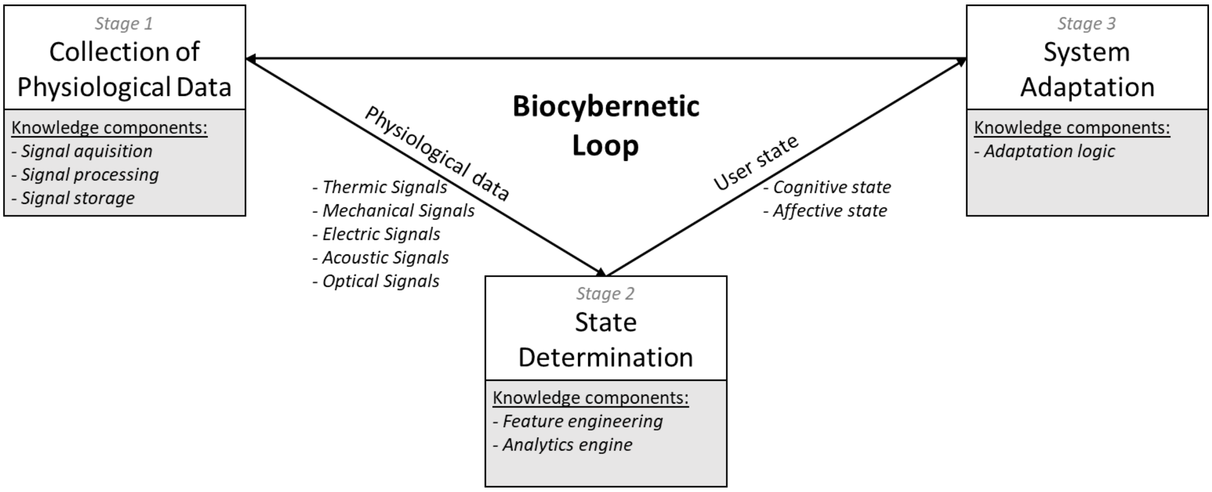

Figure 1. Scheme of the biocybernetic loop

In general, five different signal types can be distinguished. **Mechanical signals**, for instance, can include data from acceleration sensors (Badesa et al., 2016). **Thermic signals**, on the other hand, cover temperature data from skin thermometers that perform measurements either in the periphery or on the trunk of the body (Nasoz et al., 2010; Rani et al., 2005). Alternatively, disposable capsules can be used to measure the body temperature (Xu et al., 2013). In turn, **electric signals** include highly specialized voltage potentials, for instance, on the skin via electrodermal activity (EDA) sensors, from the heart via ECG sensors, on the eye utilizing electro oculography (EOG) sensors, in the brain using EEG sensors, or on muscles through electromyography (EMG) sensors (Rani et al., 2005; Ting et al., 2010; Wilson and Russell, 2007; Pope et al., 1995; Liu et al., 2009). For the measurement of **acoustic signals**, microphones close to the body are able to sample signals, such as acoustic data from the heart beats (Liu et al., 2009). Finally, **optical signals** can provide information about peripheral and near-brain pulses. Devices such as blood volume pulse (BVP) and functional near-infrared spectroscopy (fNIRS) sensors measure these signals and complete the physiological data collection (Rani et al., 2005; van der Vijgh et al., 2014).

Next, the acquired signals need to be processed. Depending on the number, type, and sampling rates of the sensors used, the implementation takes place via direct or interval-based means. Particularly, the processing of the acquired signals in real-time is an engineering challenge that requires the consideration of ordinary filters (Jacucci et al., 2015). For instance, for the processing of cardiovascular activity, research suggests a variety of filters in form of high-pass filters (Järvelä et al., 2016), low-pass filters (Yu et al., 2016), band-pass filters (Gervais et al., 2016), or the Butterworth filter (Xiong et al., 2013) to eliminate implausible frequencies from the signal created by movement or signal noise artifacts in order to derive the heart rate and related features from ECG signals (Lux et al., 2018). Finally, in the majority of cases a dedicated database for signal storage is used to supplement the first stage (Adam et al., 2014).

In the **second stage**, the physio-adaptive system analyses these data to quantify or label the corresponding user state (Fairclough, 2009). Hereby, one can observe a wide range of **cognitive** (e.g., mental workload - Teo et al., 2018, concentration - Saiwaki et al., 1996) and **affective** (e.g., frustration - Nasoz et al., 2010, fun - Conn et al., 2008) user states, which can be targeted by the system. Within this stage, two knowledge components are typically proposed for the underlying architecture of a physio-adaptive system: (1) a feature engineering component and (2) an analytics engine.

Feature engineering refers to the process of extracting meaningful features from data using domain knowledge and/or data preprocessing techniques. Physiological features allow conclusions to be drawn about complex physical processes and activities of the nervous system (Shaffer and Ginsberg, 2017). However, the extent of the features can vary depending on the amount of body-related information. In general, two different procedures are used (Fairclough, 2009). On the one hand, absolute (e.g., a specific threshold for the heart rate or blood pressure) or relative (e.g., changes in physiological data relative to the previous epoch or to a dedicated physiological baseline) criteria can be used for classification. For instance, in terms of temperature, it may be sufficient to use the temperature value itself, its mean or standard deviation as a feature. On the other hand, other signals contain much more body-related information (Novak et al., 2012). In this light, more-advanced features such as heart rate variability (HRV) require a more-complex course of action with regards to data preprocessing and outlier cleaning of the input data (Task Force of The European Society of Cardiology and The North American, 1996).

With regards to the analytics engine, two dominant approaches exist to determine the user state, namely rule-based and machine learning (ML) approaches (Fairclough, 2009). Whereas rule-based approaches incorporate expert and domain-specific knowledge within formalized rules, ML-algorithms such as neural networks and other discriminatory algorithms are trained for the detection of specific user states with suitable use case-specific data for whose selection and pre-processing domain knowledge is also required. Hereby, ML approaches seem to be in particular feasible for the recognition of complex physiological patterns (Fairclough, 2009). In summary, the extraction of meaningful features from physiological data as well as the choice of the underlying analytics engine determine the technical repertoire that can be used to classify the user state. Scholars emphasize the correct classification of the user's state as an important vehicle for user acceptance (Parasuraman and Miller, 2004; Lee and See, 2004).

Finally, in the **third stage**, the response of the system to the determined user state is triggered (Hettinger et al., 2003). Within this stage, the adaptation logic represents the central knowledge component for the underlying architecture of a physio-adaptive system. The objective is to offer adaptive responses to cognitive and affective states that are perceived as timely and intuitive by the user (Fairclough, 2009). The adaptive response of the system may either try to transform undesirable user states, such as frustration, into desirable ones (the so-called positive control dynamics) or to preserve desirable states, such as attention (the so-called negative control dynamics).

In general, literature defines three categories for adaptive responses (Gilleade et al., 2005). In particular, **emotion display** (e.g., Katmada et al., 2015) could draw users' attention to their emotional situation in order to foster positive emotions and/or alleviate negative ones. For instance, pilots can be given feedback on their individual engagement level in mentally less demanding phases of work, with the aim of avoiding inattention (Prinzel III et al., 2002). In turn, other physio-adaptive systems **offer assistance** (e.g., Rodriguez-Guerrero et al., 2017) in order to avoid user frustration when they are in a stuck situation or cannot continue the activity without support. For instance, Dorneich et al. (2005) proposed a physio-adaptive system capable of detecting arousal and stress based on physiological data. The system helps soldiers to focus on combat in stressful situations by adaptively reducing the amount of communication on the radio channel. Lastly, **challenge adaptation** (e.g., Wilson and Russell, 2007) requires system access to the difficulty or distribution of activities in order to adapt the challenge in a way that negative effects are avoided. If a user is bored the challenge of the corresponding activity could be increased. For instance, Haarmann et al. (2009) proposed a physio-adaptive system capable of adapting the challenge for pilots by controlling the level of automation of the flight-related systems based on their personal arousal level that is retrieved by physiological data. Compared to the study by Prinzel III et al. (2002), the pilots no longer need to take action themselves to keep their condition in the optimal range, but the system adjusts the demand level so that it is automatically reached and maintained.

3 Method

Following well-established guidelines presented by Kitchenham and Charters (2007) and Webster and Watson (2002), we conducted a SLR. Generally, literature reviews can be grouped along quantitative versus qualitative approaches (King and He, 2005). In particular, literature reviews can be classified as meta-analysis, vote counting, descriptive review, or narrative review (Guzzo et al., 1987). While narrative reviews primarily extract qualitative statements, meta-analyses in particular serve to concentrate on quantitative aspects of the literature examined (King and He, 2005). Our article applies a descriptive approach, which can be classified in between vote counting and a narrative review. The focus of descriptive reviews is on the collection of quantifications and identification of patterns from existing literature (Guzzo et al., 1987). To ensure generalizability, a descriptive review offers codes for all relevant articles and their characteristics within an area of interest (King and He, 2005). Hence, a descriptive literature review seems most suitable to develop a classification framework, which corresponds well to the purpose of our research, that is, offering a state-of-art overview of physio-adaptive systems.

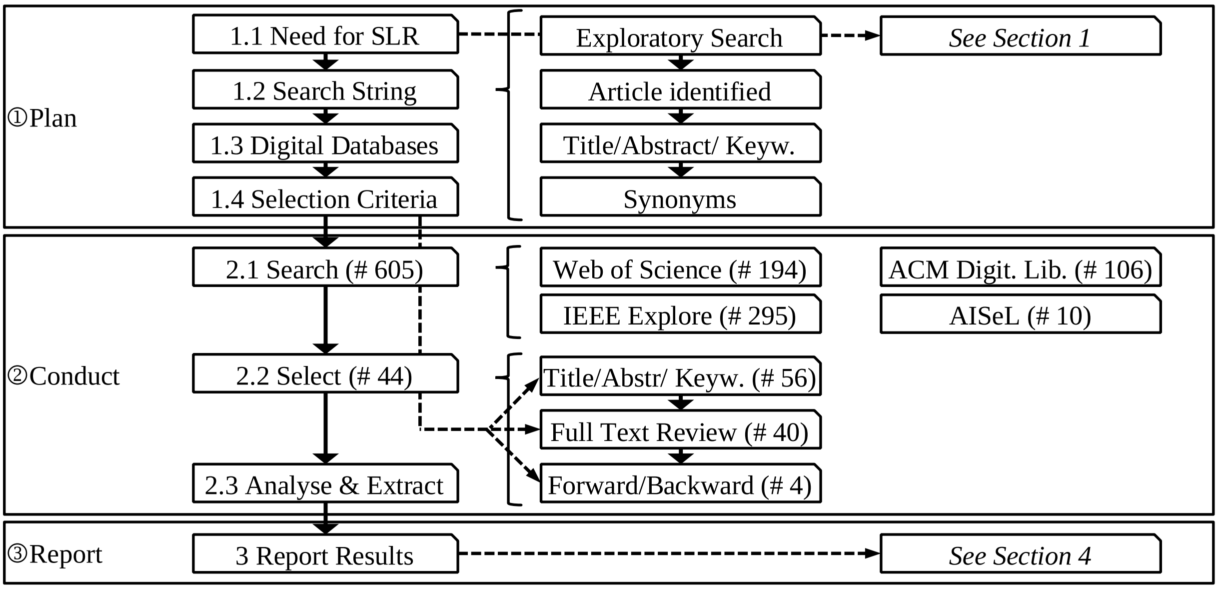

Figure 2. Stages of the SLR

As suggested by Kitchenham and Charters (2007), we organized our SLR along three stages (plan, conduct, and report, see Figure 2). In the plan stage, we identified a need for a SLR, developed a review protocol and evaluated it. Hereby, we developed a search string based on terms from highly cited articles in the field of physio-adaptive systems. Such an approach seems to be beneficial, since highly cited articles often shape the terminology and foundational concepts within the scientific discourse and typically help to integrate existing, not always congruent research approaches in the field. Thus, these types of articles offer an efficient basis for the derivation of a search string. Such course of action is also well established and has already been successfully applied by various SLRs in the field of Information Systems (e.g., Rissler et al., 2017). In the conduct stage, we carried out a databases search, selected relevant articles, and analyzed them. Lastly, within the report stage, we described our findings.

Plan. We created the search string in four steps. First, we conducted an exploratory search using Google Scholar with the search term “physiology AND adaptive systems”. Second, we reviewed the first 100 search results and identified 7 highly cited articles (Wilson and Russell, 2007; Rani et al., 2005; Ting et al., 2010; Liu et al., 2009; Pope et al., 1995; Fairclough, 2009; Novak et al., 2012). Third, we analyzed the full text of these articles for relevant concepts and terminology and extracted the terms “physiology” and “biocybernetic loop” as highly relevant to our SLR. In addition, we identified “psychophysiology” as relevant term for our search string. The terms “adaptive-system”, “adaptive-automation”, “bio-feedback”, “adaptive-interface”, and “adaptive-computing” were also included as they strongly relate to the concept of the “biocybernetic loop” (see section 2). Finally, we used wildcards and Boolean operators to create the final search string according to the two building blocks of physiology and adaptive systems: *(physiol* OR psychophysiol*) AND (adaptive-system* OR “adaptive-automation” OR adaptive-interface* OR “adaptive-computing” OR biocybernetic* OR “bio-feedback”).*

No.	Criterion Description
1	The article studies systems that adapt to human states.
2	The adaptation is based on physiological data.
3	The article is published in a peer reviewed outlet.
4	The article implements a prototype.

Table 1. Study selection criteria for the filter process

We have not limited our SLR to a specific time period in order to ensure a holistic search. Next, the databases Web of Science, ACM Digital Library, IEEE Explore, and AISeL were selected for our SLR as these databases are well-established and used by scholars as reliable sources for literature reviews (e.g., Bandara et al., 2015). All studies that met the following criteria were incorporated (see Table 1).

Conduct. The search was executed with the defined search string in the selected databases and 605 initial articles were identified (see Figure 2). 8 articles were found in more than one database and thus only counted once. Next, the selection criteria were applied on the title, abstract, and keyword section of the results, excluding 541 articles (56 remained) that did not meet the criteria 1-3. Due to the unclear definition of the article scope in the abstracts of various articles, selection criterion 4 could first be evaluated when the articles were fully read. As a result, 16 articles were excluded (40 remained). Following criteria 1-4, 4 further articles were included into the literature pool by conducting a forward and backward search. In sum, 44 relevant articles were identified.

In the following, the articles found are analyzed regarding their meta-information. In particular, the type of literature (journal versus conference article) and the research method used were evaluated.

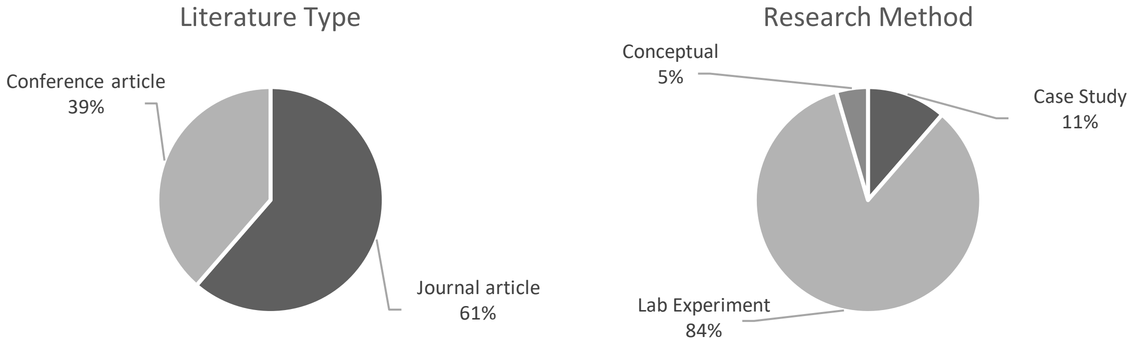

Figure 3. Overview of Meta-Information

A majority of articles (27 articles, 61%) were published in journals, while the remaining 17 articles (39%) were extracted from conference proceedings or conference workshops (see Figure 3). The research methods along the articles found were very unevenly distributed. Most of the articles (37 articles, 84%) dealt with a laboratory experiment, while only a small proportion was devoted to a case study (5 articles, 11%) or a conceptual study (2 articles, 5%).

4 Results

In the following, we describe the classification process of the framework before each (sub)category is explained along the publication results.

4.1 Classification Process

We applied a three-step approach for the classification process. In a **first step**, categories for our framework were created deductively (top-down) by focusing on extant concepts from physio-adaptive systems. First due to the broad range of application areas for physio-adaptive systems (e.g. Fairclough, 2009) we introduced the category “context”. Furthermore, we relied on the biocybernetic loop scheme as a theoretically grounded and well-established concept to setup a solid basis for the classification process (see section 2). Each stage (i.e., (1) collection of physiological data, (2) state determination, and (3) system adaptation) referred to one category in our classification framework.

Within the category “collection of physiological data”, we also introduced subcategories. As described in section 2, we relied on the (1.1) “type of signal” (i.e., mechanical, thermic, electric, acoustic, and optical) as one subcategory. Furthermore, we created a subcategory for (1.2) “dimensionality reduction”. Following Novak et al., 2012, this aspect is especially important for physio-adaptive systems leveraging ML approaches, since not all physiological feature classes always provide added value for condition classification, but large numbers of feature classes make it difficult to recognize patterns during training. Lastly, due to the complex and individual character of physiological data, we relied on the recommendations from Novak (2014) and added a subcategory (1.3) "normalization" because it seems relevant for both ML-based and rule-based approaches. Within the category "state determination", we relied on the subcategory (2.1) "algorithm" as the correct classification of the user's state represents an important vehicle for user acceptance. The relevance of this category was emphasized by several studies within the field of physio-adaptive systems (Parasuraman and Miller, 2004; Lee and See, 2004). In addition, as suggested by Fairclough (2009), we used an additional subcategory for the (2.2) "user state" in order to be able to describe the goal of the system's adaptive response. Lastly, we introduced three subcategories within "system adaptation": (3.1), adaptive delivery (i.e., implicit versus explicit), (3.2) adaptive type (i.e., proactive versus reactive), and (3.3) adaptive response (i.e., emotion displays, assistance offering, and challenge adaptation, as suggested by the biocybernetic loop scheme; see section 2). Adaptive delivery refers to how adaptive changes are made. According to Fairclough (2009), it is called explicit adaptation, in case that the user is aware of the adaptation. It is called implicit adaptation when the user does not notice it. The adaptive type rather investigates whether the system adapts before a certain state is reached (proactively) or whether the system only reacts to certain state changes (Fairclough, 2009).

In the **second step**, we used inductive reasoning (bottom-up) to analyze, whether all articles could be classified under the previously introduced (sub)categories. It became evident that changes on the initial framework were required to typecast all the different articles within the reviewed literature. In particular, the adaptive response is sometimes not only based on a cognitive or affective user state but also on the activity itself or a sleep stage (Korres et al., 2018; Nirjon et al., 2012). Against this backdrop, we differentiated between "cognitive", "affective", and "activity" states in our review. Furthermore, the "emotion display" was renamed to "state display" since this categorization so far lacks the possibility to classify solutions besides affective user states. However, several studies offer an explicit display for users on their cognitive state (e.g., Maior et al., 2018; Cao et al., 2016).

In the **third step,** the studies were assigned to the respective (sub)categories. Any discrepancy was discussed and resolved by two researchers. In particular, mismatches occurred concerning the subcategory "adaptive delivery". Some articles were unclear as to whether the participants perceived the adaptation or not. We solved the issue by specifying that the adaptation is considered explicitly when substantial changes are made, such as changing the user interface or drastically accelerating a game. Similarly, in the area of work, large speed changes or task omissions represented an obvious change in the task sequence and were therefore regarded as explicit adaptation (Takahashi et al., 1994; Yu et al., 2017). The physio-adaptive systems of all other articles, where the adaptation was more subtle and not explicitly or implicitly named, were classified as implicit (Fairclough and Gilleade, 2012). Furthermore, the assignment to the subcategory of "normalization" was difficult due to missing information. If the authors did not specify if they relied on normalization procedures, we assumed that no procedure was applied.

4.2 Classification Framework

This section explains the classification framework along each (sub)category. Besides the categories delivery and type, all categories are mutually exclusive. The total number of articles found for each (sub)category is summed up in the lower part of the classification framework (see Table 2, p. 9). For each category, the numerical distribution of the articles is illustrated.

4.2.1 Context

Work (22 articles / 50%) represented the most frequently named context for physio-adaptive systems. In particular, every second article referred to this context. Hereby, we were able to identify two main working contexts, namely aviation (16 articles) [1, 3, 5, 6, 12, 14, 15, 16, 17, 18, 19, 24, 31, 40, 42, 43] and military (4 articles) [7, 8, 23, 34]. Within the aviation field, articles investigated the adaptive automation of the control of breathing air parameters in a space capsule depending on the operator functional state of the pilot [3]. For instance, [18] examined the development of the individual engagement level of the pilot depending on the degree of automation during a complex observation task. In contrast, [5] manipulated aircraft speed and other complexity measures of a flight simulation based on the mental workload of the pilot in order to achieve an optimal task performance. In turn, articles in the military field tried to adapt the activated communication channels to the mental workload of the soldier [23]. However, only two articles [36, 39] within the working context did not address the aviation or military field. In particular, [36] focused on a general working context without mentioning a specific domain. The authors tried to examine the effects of a state display showing the stress level to employees during their work. In turn, [39] concentrated on the effects of an arousal meter showing the arousal level to the user in a trading dashboard during stock exchange trading activities.

Gaming (15 articles / 34%), on the other hand, was the second most frequently named context. 34% of the articles [2, 4, 9, 11, 20, 21, 25, 27, 28, 29, 32, 33, 37, 41, 44] addressed it. Various games domains were addressed. In [29], the difficulty of a Tetris game was changed in such a manner to keep the player in a desirable state. In turn, [28] manipulated the difficulty of a robotic basketball game, where the basket moves depending on the level of difficulty to improve the learning ability of children who suffer from autism. The **health** (3 articles / 7%) context was less frequently mentioned with a share of only 7% the reviewed articles [22, 26, 38]. [26] investigated an alarm system that adapts the signal type and time of alarm to the sleep state of the participants to avoid the disturbance of deep sleep states. Furthermore, [38] concluded that physio-adaptive systems can independently dose narcotic drugs depending on the depth of narcosis of the patient. [22] selected a different approach and supported the movement rehabilitation of mobility-impaired patients by modifying the complexity of the training based on the arousal and valance level classified by acceleration, temperature, EDA, and BVP. Finally, articles in the context of **traffic** (3 articles / 7%) [10, 13, 30] and **other** (1 articles / 2%) [35] were only named three times respectively once. In particular, [10] addressed the problem of fatigue during vehicle driving, providing adaptive warning messages depending on decreasing levels of vigilance, while [13] showcased the adaptive provision of solutions and advices to problematic driver states such as provision of jokes in frustrating situations or a calm down advice in situations of high anger. In turn, [30] adaptively increased the seating comfort of car drivers depending on potholes in combination with a system that provides feedback on changes in driving behavior (e.g., abrupt accelerations or braking) based on the individual’s emotional and cognitive state. Within the other context, the article referred to the adaptation of the music type according to the level of activity (e.g., providing fast music during jogging or slow relaxing beats during calm phases) [35].

Author	Context	Data collection																	State determination			System adaptation						
		Type of Signals										Dimensionality Reduction					Norm.		Alg.		Target State	Deliv.		Type		Response		
		M	T	E					A	O																		
		ACC	TEMP	EDA	EOG	ECG	EMG	EEG	HS	fNIRS	BVP	PCA	SFS	FP	LDA	TH	BL	BLF	ML	RB	Cognitive/ Affective / Activity state	Implicit	Explicit	Proactive	Reactive	SD	AO	CA
[1] (Wilson and Russell, 2007)	Work	-	-	-	X	X	-	X	-	-	-	-	-	X	-	-	-	-	X	-	Mental workload (c)	-	X	-	X	-	-	X
[2] (Rani et al., 2005)	Game	-	X	X	-	X	X	-	-	-	X	-	-	-	-	-	X	-	X	-	Anxiety (a)	-	X	-	X	-	-	X
[3] (Ting et al., 2010)	Work	-	-	-	X	X	-	X	-	-	-	-	-	-	-	-	-	-	-	X	OFS (c)	X	-	-	X	-	X	-
[4] (Liu et al., 2009)	Game	-	X	X	-	X	X	-	X	-	X	-	-	-	-	X	X	-	X	-	Anxiety (a)	-	X	-	X	-	-	X
[5] (Pope et al., 1995)	Work	-	-	-	-	-	X	X	-	-	-	-	-	-	-	-	-	-	-	X	Engagement (c)	-	X	-	X	-	-	X
[6] (Di Flumeri et al., 2019)	Work	-	-	-	-	-	-	X	-	-	-	-	-	-	X	-	-	-	X	-	Vigilance (c)	-	X	-	X	-	-	X
[7] (Teo et al., 2018)	Work	-	-	-	-	X	-	X	-	X	-	-	-	-	-	-	X	-	-	X	Mental workload (c)	-	X	-	X	-	X	-
[8] (Rusnock and Geiger, 2017)	Work	-	-	-	-	X	-	-	-	-	-	-	-	-	-	-	X	-	-	X	Mental workload (c)	-	X	-	X	-	X	-
[9] (Ewing et al., 2016)	Game	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	-	X	Mental workload (c)	X	-	-	X	-	-	X
[10] (Cao et al., 2016)	Traffic	-	-	-	X	-	-	X	-	-	-	X	-	-	X	-	X	-	X	-	Vigilance (c)	-	X	-	X	X	-	-
[11] (van der Vijgh et al., 2014)	Game	-	-	X	-	X	-	X	-	-	X	-	-	-	-	-	X	-	-	X	Stress (a)	X	-	-	X	-	-	X
[12] (Christensen and Estepp, 2013)	Work	-	-	-	X	X	-	X	-	-	-	-	-	X	-	-	X	-	X	-	Mental workload (c)	-	X	-	X	-	-	X
[13] (Nasoz et al., 2010)	Traffic	-	X	X	-	X	-	-	-	-	-	-	-	-	-	-	X	X	X	-	Neutrality (a), Panic/Fear (a), Frustration/Anger (a), Boredom/Fatigue (a)	-	X	-	X	X	X	-
[14] (Haarmann et al., 2009)	Work	-	-	X	-	X	-	-	-	-	-	-	-	-	-	-	X	-	-	X	Arousal (a)	X	-	-	X	-	-	X
[15] (Bailey et al., 2006b)	Work	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	-	X	Engagement (c)	-	X	-	X	-	-	X
[16] (Prinzel III et al., 2003)	Work	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	-	X	Engagement (c)	-	X	-	X	-	-	X
[17] (Prinzel III et al., 2002)	Work	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	-	X	Engagement (c)	-	X	-	X	X	X	-
[18] (Freeman et al., 2000)	Work	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	-	X	Engagement (c)	-	X	-	X	-	-	X
[19] (Prinzel et al., 2000)	Work	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	-	-	-	X	Engagement (c)	-	X	-	X	-	-	X
[20] (Saiwaki et al., 1996)	Game	-	-	X	-	X	-	X	-	-	-	-	-	-	-	-	-	-	X	-	Concentration (c), Nervous-ness (a), Comfort, Boredom (a)	X	-	-	X	-	-	X
[21] (Takahashi et al., 1994)	Game	-	-	X	-	X	-	-	-	-	-	-	-	-	-	-	-	-	X	-	Mental workload (c)	X	-	-	X	-	-	X
[22] (Badesa et al., 2016)	Health	X	X	X	-	-	-	-	-	-	X	-	-	-	-	-	X	-	-	X	Arousal / Valence (a)	-	X	-	X	-	-	X
[23] (Dorneich et al., 2005)	Work	-	-	-	-	X	-	X	-	-	-	-	-	-	-	-	-	-	-	X	Mental workload (c) / Executive load (c)	X	-	-	X	-	X	X
[24] (Ting et al., 2007)	Work	-	-		X	X	X	X	-	-	-	-	-	-	-	-	-	-	-	X	OFS (c)	-	X	-	X	-	-	X
[25] (Katmada et al., 2015)	Game	-	X	X	-	-	-	-	-	-	X	-	-	-	-	-	-	-	X	-	Anxiety (a)	-	X	-	X	X	-	-
[26] (Korres et al., 2018)	Health	X	-	-	-	-	-	X	-	-	-	-	-	-	-	-	-	-	X	-	Sleep stage (act)	X	-	-	X	-	-	-
[27] (Yannakakis, 2009)	Game	-	-	X	-	-	-	-	-	-	X	-	X	-	-	-	-	-	X	-	Entertainment value (a)	X	-	-	X	-	-	X
[28] (Conn et al., 2008)	Game	-	X	X	-	X	X	-	-	-	-	-	-	-	-	-	X	-	X	-	Liking (a)	-	X	-	X	-	-	X
[29] (Fairclough and Gilleade, 2012)	Game	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	-	X	Flow (c), Engagement (c), Overload(c), Boredom (c)	X	-	-	X	-	-	X
[30] (Serbedzija and Fair-clough, 2012)	Traffic	-	-	-	-	X	X	-	-	-	-	-	-	-	-	-	-	-	-	-	Emotional states (a)	X	-	-	X	-	X	-
[31] (Maior et al., 2018)	Work	-	-	-	-	-	-	-	-	X	-	-	-	-	-	-	X	-	-	X	Mental workload (c)	-	X	-	X	X	-	-
[32] (Muñoz et al., 2018)	Game	-	-	-	-	-	-	-	-	-	X	-	-	-	-	-	X	-	-	X	Enjoyment (a)	X	-	-	X	-	-	X
[33] (Salminen et al., 2018)	Game	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	-	X	Empathy (affective interde-pendence) (a)	-	X	-	X	X	-	-
[34] (Afergan et al., 2014)	Work	-	-	-	-	-	-	-	-	X	-	-	-	-	-	-	X	-	X	-	Workload (c)	X	-	-	X	-	-	X
[35] (Nirjon et al., 2012)	Other	X	-	-	-	-	-	-	X	-	-	-	-	-	-	-	X	-	X	-	Activity level (act)	X	-	-	X	-	-	-
[36] (Yu et al., 2017)	Work	-	-	-	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	Stress (a)	-	X	-	X	X	-	-
[37] (Potts et al., 2019)	Game	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	-	-	-	X	Relaxation, self-awareness (c)	-	X	-	X	X	-	-
[38] (Bailey et al., 2006a)	Health	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	X	-	Anesthesia depth (c)	X	-	-	X	-	-	-
[39] (Lux et al., 2015)	Work	-	-	X	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	X	Arousal (a)	-	X	-	X	X	-	-
[40] (Freeman et al., 1999)	Work	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	X	-	-	X	Engagement (c)	X	-	-	X	-	-	X
[41] (Parnandi and Gutierrez-Osuna, 2015)	Game	-	-	X	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	X	Arousal (a)	X	-	-	X	-	-	X
[42] (Aricò et al., 2016)	Work	-	-	-	-	-	-	X	-	-	-	-	-	-	X	-	-	-	X	-	Mental workload (c)	X	-	-	X	-	-	X
[43] (Zhang et al., 2017)	Work	-	-	-	X	X	X	X	-	-	-	-	-	-	-	-	X	-	X	-	Cognitive Load (c)	X	-	-	X	-	-	X
[44] (Rodriguez-Guerrero et al., 2017)	Game	-	X	X	-	X	-	-	-	-	-	-	-	-	-	-	X	-	-	X	Dominance, Arousal (a)	X	-	-	X	-	X	-
	∑	3	7	14	6	18	7	24	2	3	8	1	1	2	3	1	26	1	19	25	act:2, a: 17, c: 26	20	24	0	44	9	8	27

M = Mechanical signals; **T =** Thermal signals; **E =** Electrical signals; **A =** Acoustic signals; **O =** Optical signals; **ACC** = Acceleration; **TEMP** = Temperature;
EDA = Electrodermal activity; **EOG** = Electro oculography; **EEG** = Electroencephalography; **EMG** = Electromyography; **HS** = Heart sound;
fNIRS = Functional near-infrared spectroscopy; **BVP** = Blood volume pulse; **PCA** = Principal component analysis; **SFS** = Sequential forward selection; **FP** = Fisher projection;
LDA = Linear discriminant analysis; **TH** = Thresholding; **BL** = Baseline; **BLF** = Baseline as feature **IND** = Individual normalization procedure; **ML** = Machine learning algorithm;
SD = State display; **AO** = Assistance offering; **CA** = Challenge adaptation; **RB** = Rule based; **OFS** = Operator functional state

Table 2. Concept matrix for identified articles targeting physio-adaptive systems

4.2.2 Data collection

Type of Signals. Overall reviewed articles an average of 2.09 signal types from the subcategories mechanical, thermal, electrical, acoustic, and optical signals were used per article. However, most of the articles (38 articles / 86%) used at least one signal from **electrical signals**. Within this category, 24 articles relied on signals from EEG [1, 3, 5, 6, 7, 9, 10, 11, 12, 15, 16, 17, 18, 19, 20, 23, 24, 26, 29, 33, 37, 38, 40, 42, 43], 18 articles used signals from ECG [1, 2, 3, 4, 7, 8, 11, 12, 13, 14, 20, 21, 22, 23, 24, 25, 27, 28, 32, 36, 43, 44], 14 articles leveraged signals from EDA [2, 4, 11, 13, 14, 20, 21, 22, 25, 27, 28, 39, 41, 44], whereas 7 articles utilized signals from EMG [2, 4, 5, 24, 28, 30, 43], and only 6 articles used the signals derived from EOG [1, 3, 10, 12, 24, 43]. It is worth noting that 13 articles exclusively relied on EEG signals within the electrical signals' subcategory. Interestingly, 7 of the 13 articles that exclusively used EEG as data source classified the construct engagement.

11 articles (25%) used features from **optical signals**. Most articles (8) [2, 4, 11, 22, 25, 27, 32, 36] relied on BVP signals, whereas only 3 articles [7, 31, 34] used the relatively new technique fNIRS for their investigations. 7 out of the 44 reviewed articles [2, 4, 13, 22, 25, 28, 44] collected **thermic signals**. Each approach used a sensor to collect skin temperature. However, none of the articles mentioned disposable capsules as a temperature sensor, although they can determine the body temperature more precisely than sensors in the periphery, which are sensitive to deviations due to outside temperature differences and peripheral vasoconstriction. For **mechanical signals**, a total of 3 articles [22, 26, 35] used an acceleration sensor in their studies. For instance, [35] relied on an acceleration sensor to determine the speed and type of an activity. The articles [4] and [35] collected among others **acoustic signals** from their participants. Both articles evaluated the heart sound by equipping their users with a microphone close to the body. While [4] tried to integrate as many different features as possible for the state determination, [35] followed the approach to detect the heart rate via the heart sound, since no ECG or BVP sensor has been used in this article.

Dimensionality Reduction. With regard to dimensionality reduction, only 7 articles (16%) mentioned the use of such procedures. Of these articles, only one [10] relied on several methods to reduce dimensionality, namely a Principle Component Analysis (PCA) and a Linear Discriminant Analysis (LDA). The goal of the PCA is to reduce the number of features by identifying uncorrelated features that explain the highest variance in the data by calculating the covariance matrix and eigenvalues. While the PCA ignores the class labels, LDA considers the class labels and focuses on the separability of these classes. For this reason, the literature includes the PCA among the unsupervised and the LDA among the supervised dimensionality reduction algorithms. However, all other articles used only one procedure or did not apply a dimensionality reduction at all. Over all articles, the LDA was most frequently mentioned with 3 articles [6, 10, 42], followed by the Fisher Projection (FP) with 2 articles [1, 12], which is methodologically related to the LDA. The PCA [10] and the Sequential Forward Selection (SFS) [27] – a greedy search algorithm that tries to find the optimal subset of features by selecting features iteratively based on the underlying classifier performance – were only applied once.

Normalization. 26 articles (59%) described that a baseline survey has been carried out. Physiological data are complex, individual, and dependent on the individual's daily form. For the identification of physiological patterns across individuals, it seems useful to cleanse the physiological data by a so-called baseline (Ewing et al., 2016; Picard et al., 2001). However, a total of 17 articles [1, 3, 5, 6, 19, 20, 21, 23, 24, 25, 26, 27, 30, 36, 37, 39, 41, 42] did not describe a procedure for data normalization or explicitly refrained from baseline surveys. For instance, [41] decided to drop the baseline survey altogether due to technical problems in the simultaneous measurement of the EDA features skin conductance level and skin conductance responses. In contrast, [13] not only collected a physiological baseline at rest, but also used it explicitly as a feature for the corresponding ML algorithms that performed the normalization.

4.2.3 State determination

Algorithm. At the technical level, we were able to identify two basic types. 18 articles (41%) [1, 2, 4, 6, 10, 12, 13, 20, 21, 25, 26, 27, 28, 34, 35, 38, 42, 43] applied ML algorithms for state recognition, while in slightly more than half of the articles (26 articles / 59%) [3, 5, 7, 8, 9, 11, 14, 15, 16, 17, 18, 19, 22, 24, 29, 30, 31, 32, 33, 36, 37, 39, 40, 41, 44] rule-based approaches were used. While ML algorithms are qualified to identify complex non-linear patters in the physiological data, rule-based approaches focus on specific thresholds and ranges. It is also worth mentioning that only 2 articles, namely [4, 13], relied on more than one ML algorithm. Such approach seems valuable because no ML algorithm has an inherent advantage over other ML algorithms for all problems. Thus, for a given problem, there is always a need to try many different ML algorithms. In particular, [4] showcased that Support Vector Machines (SVM) perform slightly better (88.9%) than regression trees (88.5%) to determine anxiety based on physiological data. Furthermore, the SVM was also considerably better than the K-Nearest Neighbor (80.4%) or Bayesian Networks (80.6%).

Target State. More than half of the articles (26 articles / 59%) [1, 3, 5, 6, 7, 8, 9, 10, 12, 15, 16, 17, 18, 19, 20, 21, 23, 24, 29, 31, 34, 37, 38, 40, 42, 43] targeted cognitive user states. Mental and cognitive workload (10 articles) [1, 7, 8, 9, 21, 23, 24, 31, 42, 43] are most often investigated, followed by engagement (8 articles) [5, 15, 16, 17, 18, 19, 29, 40] and the operator functional state (2 articles) [3, 24]. One prominent case, for example, referred to [17], in which the participants received real-time feedback on their personal engagement level during an aviation task in order to keep their concentration high in a self-controlled manner.

In turn, for affective states (17 articles / 39%), [2, 4, 11, 13, 14, 20, 22, 25, 27, 28, 30, 32, 33, 36, 39, 41, 44] the states arousal (5 articles) [14, 22, 39, 41, 44], anxiety (3 articles) [2, 4, 25], and boredom (3 articles) [13, 20, 29] were most frequently mentioned. For instance, one prominent case referred to [21] where the difficulty of a computer game was adaptively changed to keep the mental effort of the participants within the target range.

The activity category comprises a total of 2 articles (5%) [26, 35]. Hereby, the state of sleep [26] and the state of activity [35] are targeted, respectively. [35] showcased that the personal activity level can be estimated by the heart sound obtained from acoustic sensors and acceleration-related data.

4.2.4 System adaptation

Adaptive Delivery. Implicit adaptation was performed in a total of 20 of the 44 articles examined (43%) [1, 2, 3, 4, 9, 11, 21,23, 26, 27, 29, 32, 34, 35, 38, 40, 41, 42, 43, 44], while the explicit adaptation was investigated in 23 papers [5, 6, 7, 8, 10, 12, 13, 14, 15, 16, 17, 18, 19, 20, 22, 24, 25, 28, 31, 33, 36, 37, 39]. In particular, implicit adaptation was realized by slight manipulations of the automation level in air traffic management tasks [42]. In contrast, explicit adaptations concentrated on a direct user feedback of the determined user state [10] or noticeable manipulations of the experimental task [17].

Adaptive Type. All 44 reviewed articles adapted reactively to the user state. [29] adapted the difficulty of a Tetris game to avoid participants getting overloaded or bored by the game. Others like [13] offered user state-related assistance to car drivers by considering their levels of stress, anger, or frustration.

Adaptive Response. The largest number of articles were assigned to challenge adaptation (27 papers, 61%) [1, 2, 4, 5, 6, 9, 11, 12, 14, 15, 16, 18, 19, 20, 21, 22, 23, 24, 27, 28, 29, 32, 34, 40, 41, 42, 43], while the state display subcategory accounted for the second largest number of articles (9 papers, 20%) [10, 13, 17, 25, 31, 33, 36, 37, 39], followed by the assistance offering subcategory with only 8 articles (18%) [3, 7, 8, 13, 17, 23, 30, 44]. Most physio-adaptive systems (41) contained a single type of adaptive response. However, 3 of the articles integrated a total of two different adaptive responses. In [13, 17] a state display was given, and adaptive assistance was provided. For instance, [17] investigated whether a direct state feedback during an aviation task leads to better task performance than an automatic adaptation of the challenge. The relationship between physiological sensors and the type of adaptation appears interesting in the articles studied. With one exception, BVP sensors are exclusively used in articles with challenge adaptation. Only [25] used BVP for a state display. In contrast, according to the number of articles, ECG and EEG sensors are distributed widely among the respective system adaptation. Heart sound [4], movement [22], and EMG [2, 4, 5, 24, 28, 30, 43] were used exclusively in articles with challenge adaptation. Temperature is mentioned in 2 articles with state display [13, 25] and assistance offering [13, 44], as well as in 4 articles with challenge adaptation [2, 4, 22, 28]. In addition, EOG was used more often for challenge adaptation [5, 12, 23, 36] than for state display [10] or assistance offering [6]. Lastly, fNIRS was only applied once in each adaptation type.

5 Future work

In this section, we present avenues for future research on physio-adaptive systems. In close accordance with our classification framework and based on findings from the meta-data of the articles examined, a total of 7 gaps are identified within this field of research. We believe that our classification framework represents a valuable baseline for further investigations as it provides a systematic overview about what has not been researched yet, facilitating avenues for future work. Thus, we would like to call the researchers' attention to the following gaps as a promising starting point:

(1) **Lack of field studies concerning physio-adaptive systems.** Our analysis of the literature on physio-adaptive systems revealed that none of the articles found in the SLR tested a physio-adaptive system in the field. The relevance of laboratory studies is indisputable and especially appropriate to achieve high internal validity by keeping extraneous variables, such as noise, lighting, and temperature constant (Mitchell and Jolley, 2013). Still, scholars like Fairclough (2009) point out that the conditions created in laboratory setups only partly correspond to the conditions of a real-world operating environment of a physio-adaptive system. Thus, field studies seem particularly fitting to achieve high external validity, in other words, the degree to which the findings of the executed laboratory study can be generalized to the field (Mitchell and Jolley, 2013). Future research could therefore consider testing physio-adaptive systems in the field leading to valuable insights into practical problems and design principles that have not yet been considered during the development and implementation stage of these systems.

(2) **Proactive physio-adaptive systems not yet developed.** None of the articles examined in our SLR has considered the development of proactive physio-adaptive systems. But proactive adaptation offers great potentials. For instance, the avoidance of undesirable states, such as uncertainty, frustration, or anxiety could be prevented with these approaches even before their occurrence (Fairclough, 2009). Also other use cases, for instance, in the area of adaptation to the operator's functional state (Ting et al., 2007; Ting et al., 2010), appear particularly promising against the background of proactive avoidance of overstrain states. Thus, future work in the field of physio-adaptive systems could investigate the feasibility of proactive physio-adaptive systems in general and, if applicable, develop and evaluate first prototypes of these systems.

(3) **Lack of studies in the work context beyond aviation and military.** Considering the context of the articles reviewed in this SLR, it became apparent that the majority of them are conducted in highly controlled working tasks, specifically designed for the domains of aviation or military. These contexts are relevant, but they share also domain-specific requirements, which limits the applicability of the developed systems. Thus, investigating physio-adaptive systems in more unstructured working contexts seems promising as one could optimize desirable user states, such as engagement, attention, or flow, as they are supposed to improve employees' working outcomes (e.g., Spurlin and Csikszentmihalyi, 2017). Due to the complex requirements in such contexts (e.g., structure and challenge of the activity), specifically the advances on NeuroIS suggest interesting avenues for supportive physio-adaptive systems in this regard (Adam et al., 2014).

(4) **Cognitive states beyond mental workload scarcely researched.** Most physio-adaptive systems in our SLR that target cognitive states concentrated on mental workload (e.g., Wilson and Russell, 2007), engagement (e.g., Pope et al., 1995), or cognitive load (Zhang et al., 2017). However, scholars call for research to design and implement physio-adaptive systems for other cognitive states (Rissler et al., 2018). One prominent example refers to the cognitive state of flow (Fairclough and Gilleade, 2012). Flow refers to the experience in which people are fully focused on an activity (Csikszentmihalyi, 1990). It seems a desirable state to be integrated into a physio-adaptive system as it is supposed to improve human task performance and well-being (Rissler et al., 2018). Thus, maintaining or promoting cognitive states (beyond mental workload, engagement, or cognitive load) by means of physio-adaptive systems appears to be an interesting avenue for future research.

(5) **Dimensionality reduction procedures rarely used.** Only 16% of all investigated articles relied on dimensionality reduction to decrease the number of physiological data and features in order to recognize the user state. However, the selection of suitable features for state recognition is particularly important for ML, since a large space of features with low information content only increases the search space but does not contribute to more-effective pattern recognitions (Novak et al., 2012; Novak, 2014). Thus, future research should examine the use and influence of dimensionality reduction procedures on state recognition and consider their integration into physio-adaptive systems.

(6) **Multidimensional state adaptation scarcely explored.** Only 8 articles tried to adapt more than one user state. For instance, Fairclough and Gilleade (2012) adapted the difficulty of a Tetris game along the states of flow, engagement, boredom, and overload. In particular, the difficulty remained stable during the states of engagement and flow, whereas increases (respectively decreases) were triggered in case of boredom (respectively overload). Although the complexity increases with the number of classified states, the integration and recognition of a broader set of user states can improve the psychological validity of a physio-adaptive system (Fairclough, 2009). However, there seems to be a trade-off looming. On the one hand, the amount of required data to train ML classifiers for higher dimensional problems has to be larger in order to achieve acceptable results. On the other hand, the validity and rigor of the classification is typically considerably higher by integrating and combining adjacent user states. Future research should therefore investigate the feasibility of multidimensional state adaptation for the development of physio-adaptive systems.

(7) **Lack of investigation of the suitability of decision trees for state determination.** While considering the different approaches being used to determine the user state, various ML approaches could be identified (e.g., SVM - Liu et al., 2009, ANN - Wilson and Russell, 2007, KNN - Nasoz et al., 2010). Still, one exception refers to classification trees as none of the articles was based on such ML approach. However, research has showcased that classification trees have been successfully applied within multiple domains, including physiological data (Chaudhuri et al., 2018; Wen et al., 2014). Furthermore, classification trees are able to successfully handle datasets with even small sample sizes and high feature spaces. Thus, future research should test this promising approach within physio-adaptive systems and evaluate its performance.

6 Conclusion

In our article, we offered a state-of-the-art overview of the field of physio-adaptive systems in the form of a SLR along the following contributions. First, by developing a classification framework, we performed a step towards structuring the state-of-the-art of physio-adaptive systems research. Second, based on this overview, we derived seven research gaps as a grounding for future research to be well-directed. Third, the integration of the state-of-the-art summarizes scattered research results in area of physio-adaptive systems. Still, we are aware that our article comes with limitations. Any bias in the search string might bias the reviewed articles. To reduce this possibility, we applied established methodological recommendations (i.e., Kitchenham and Charters, 2007; Webster and Watson, 2007). Moreover, all decisions during the plan, conduct, and report stages are made explicit. We hope that this article can serve as a reference in the broader field of physio-adaptive systems and the (sub)categories that should be considered when designing related solutions.

References

Adam, M. T. P., H. Gimpel, A. Maedche and R. Riedl (2014). "Stress-Sensitive Adaptive Enterprise Systems: Theoretical Foundations and Design Blueprint". In F. D. Davis (ed.) *Proceedings Gmunden Retreat on NeuroIS 2014*, pp. 39–41.

Afergan, D., E. M. Peck, E. T. Solovey, A. Jenkins, S. W. Hincks, E. T. Brown, R. Chang and R. J.K. Jacob (2014). "Dynamic difficulty using brain metrics of workload". In: *CHI 2014, one of a CHInd. Conference proceedings : Toronto, Canada, April 26 - May 1, 2014 ; the 32nd Annual ACM Conference on Human Factors in Computing Systems*. Ed. by M. Jones, P. Palanque, A. Schmidt, T. Grossman. New York, NY: Assoc. for Computing Machinery, pp. 3797–3806.

Agarwal, R. and E. Karahanna (2000). "Time Flies When You're Having Fun: Cognitive Absorption and Beliefs about Information Technology Usage" *MIS Quarterly* 24 (4), 665.

Anttonen, J. and V. Surakka (2005). "Emotions and heart rate while sitting on a chair". In: *CHI 2005, technology, safety, community. Conference proceedings : Conference on Human Factors in Computing Systems, Portland, Oregon USA I April 2-7, 2005 00*. Ed. by W. Kellogg. New York: ACM Press, p. 491.

Aricò, P., G. Borghini, G. Di Flumeri, A. Colosimo, S. Bonelli, A. Golfetti, S. Pozzi, J.-P. Imbert, G. Granger, R. Benhacene and F. Babiloni (2016). "Adaptive Automation Triggered by EEG-Based Mental Workload Index: A Passive Brain-Computer Interface Application in Realistic Air Traffic Control Environment" *Frontiers in human neuroscience* 10, 539.

Badesa, F. J., R. Morales, N. M. Garcia-Aracil, J. M. Sabater, L. Zollo, E. Papaleo and E. Guglielmelli (2016). "Dynamic Adaptive System for Robot-Assisted Motion Rehabilitation" *IEEE Systems Journal* 10 (3), 984–991.

Bailey, J. M., W. M. Haddad, J. J. Im, T. Hayakawa and P. A. Nagel (2006a). "Adaptive and neural network adaptive control of depth of anesthesia during surgery". In: *American Control Conference, 2006. 14 - 16 June 2006, [Minneapolis, MN*. Piscataway, NJ: IEEE Operations Center, 6 pp.

Bailey, N. R., M. W. Scerbo, F. G. Freeman, P. J. Mikulka and L. A. Scott (2006b). "Comparison of a brain-based adaptive system and a manual adaptable system for invoking automation" *Human factors* 48 (4), 693–709.

Bandara, W., E. Furtmueller, E. Gorbacheva, S. Miskon and J. Beekhuyzen (2015). "Achieving Rigor in Literature Reviews: Insights from Qualitative Data Analysis and Tool-Support" *Communications of the Association for Information Systems* 37.

Bastarache-Roberge, M.-C., P.-M. Léger, F. Courtemanche, S. Sénécal and M. Fredette (2015). "Measuring Flow Using Psychophysiological Data in a Multiplayer Gaming Context". In F. D. Davis, R. Riedl, J. vom Brocke, P.-M. Léger and A. B. Randolph (eds.) *Information systems and neuro science. Gmunden retreat on neurois 2015*, pp. 187–191: Springer.

Cao, L., J. Li, Y. Xu, H. Zhu and C. Jiang (2016). "A Hybrid Vigilance Monitoring Study for Mental Fatigue and Its Neural Activities" *Cognitive Computation* 8 (2), 228–236.

Chaudhuri, T., D. Zhai, Y. C. Soh, H. Li and L. Xie (2018). "Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology" *Energy and Buildings* 166, 391–406.

Christensen, J. C. and J. R. Estepp (2013). "Coadaptive aiding and automation enhance operator performance" *Human factors* 55 (5), 965–975.

Conn, K., C. Liu, N. Sarkar, W. Stone and Z. Warren (2008). "Affect-sensitive assistive intervention technologies for children with autism: An individual-specific approach". In: *The 17th IEEE International Symposium on Robot and Human Interactive Communication, 2008. RO-MAN 2008 ; 1 - 3*

Aug. 2008, Technische Universität München, Munich, Germany. Piscataway, NJ: IEEE, pp. 442–447.

Csikszentmihalyi, M. (1990). *Flow*. *The psychology of optimal experience.* New York: Harper and Row.

Di Flumeri, G., F. de Crescenzio, B. Berberian, O. Ohneiser, J. Kramer, P. Aricò, G. Borghini, F. Babiloni, S. Bagassi and S. Piastra (2019). "Brain-Computer Interface-Based Adaptive Automation to Prevent Out-Of-The-Loop Phenomenon in Air Traffic Controllers Dealing With Highly Automated Systems" *Frontiers in human neuroscience* 13.

Dimoka, Davis, Gupta, Pavlou, Banker, Dennis, Ischebeck, Müller-Putz, Benbasat, Gefen, Kenning, Riedl, vom Brocke and Weber (2012). "On the Use of Neurophysiological Tools in IS Research: Developing a Research Agenda for NeuroIS" *MIS Quarterly* 36 (3), 679.

Dorneich, M. C., P. M. Ververs, S. Mathan and S. D. Whitlow (2005). "A Joint Human-Automation Cognitive System to Support Rapid Decision-Making in Hostile Environments". In: *Proceedings, the International Conference on Systems, Man and Cybernetics*. *Waikoloa Hilton Village, Waikoloa, Hawaii, USA, October 10-12, 2005*. Piscataway, N.J: Institute of Electrical and Electronics Engineers, pp. 2390–2395.

Ewing, K. C., S. H. Fairclough and K. Gilleade (2016). "Evaluation of an Adaptive Game that Uses EEG Measures Validated during the Design Process as Inputs to a Biocybernetic Loop" *Frontiers in human neuroscience* 10, 223.

Fairclough, S. and K. Gilleade (2012). "Construction of the biocybernetic loop". In: *Proceedings of the 14th ACM international conference on Multimodal interaction*. Ed. by L.-P. Morency. New York, NY: ACM, p. 571.

Fairclough, S. H. (2009). "Fundamentals of physiological computing" *Interacting with Computers* 21 (1-2), 133–145.

Fairclough, S. H. and K. Gilleade (2014). *Advances in Physiological Computing.* London: Springer London.

Forrester Research Inc (2017). *Midyear Global Tech Market Outlook For 2017 To 2018*. URL: https://www.forrester.com/report/Midyear+Global+Tech+Market+Outlook+For+2017+To+2018/-/E-RES140272 (visited on 08/20/2019).

Freeman, F. G., P. J. Mikulka, L. J. Prinzel and M. W. Scerbo (1999). "Evaluation of an adaptive automation system using three EEG indices with a visual tracking task" *Biological Psychology* 50 (1), 61–76.

Freeman, F. G., P. J. Mikulka, M. W. Scerbo, L. J. Prinzel and K. Clouatre (2000). "Evaluation of a psychophysiologically controlled adaptive automation system, using performance on a tracking task" *Applied psychophysiology and biofeedback* 25 (2), 103–115.

Gervais, R., J. Frey, A. Gay, F. Lotte and M. Hachet (2016). "TOBE: Tangible out-of-body experience". In: *Proceedings of the TEI '16 Tenth International Conference on Tangible, Embedded, and Embodied Interaction*. Ed. by S. Bakker, C. Hummels, B. Ullmer, L. Geurts, B. Hengeveld, D. Saakes, M. Broekhuijsen. New York, NY: ACM, pp. 227–235.

Gilleade, K. M., A. Dix and J. Allanson (2005). "Affective videogames and modes of affective gaming: assist me, challenge me, emote me." *Proceedings of the 2005 DiGRA International Conference: Changing Views: Worlds in Play*.

Guzzo, R. A., S. E. Jackson and R. A. Katzell (1987). "Meta-analysis analysis" *Research in Organizational Behavior* 9, 407–442.

Haarmann, A., W. Boucsein and F. Schaefer (2009). “Combining electrodermal responses and cardiovascular measures for probing adaptive automation during simulated flight” *Applied Ergonomics* 40 (6), 1026–1040.

Hettinger, L. J., P. Branco, L. M. Encarnacao and P. Bonato (2003). “Neuroadaptive technologies: Applying neuroergonomics to the design of advanced interfaces” *Theoretical Issues in Ergonomics Science* 4 (1-2), 220–237.

Jacucci, G., S. Fairclough and E. T. Solovey (2015). “Physiological Computing” *Computer* 48 (10), 12–16.

Järvelä, S., J. Kätsyri, N. Ravaja, G. Chanel and P. Henttonen (2016). “Intragroup Emotions: Physiological Linkage and Social Presence” *Frontiers in psychology* 7, 105.

Katmada, A., M. Chatzakis, H. Apostolidis, A. Mavridis and S. Panagiotis (2015). “An adaptive serious neuro-game using a mobile version of a bio-feedback device”. In: *Proceedings of 2015 International Conference on Interactive Mobile Communication Technologies and Learning (IMCL). Date and venue: 19-20 November 2015, Thessaloniki, Greece*. Piscataway, NJ: IEEE, pp. 416–420.

King, W. R. and J. He (2005). “Understanding the Role and Methods of Meta-Analysis in IS Research” *Communications of the Association for Information Systems* 16.

Kitchenham, B. and S. Charters (2007). “Guidelines for performing Systematic Literature Reviews in Software Engineering”.

Korres, G., C. Birgitte Falk Jensen, W. Park, C. Bartsch and M. Eid (2018). “A Vibrotactile Alarm System for Pleasant Awakening” *IEEE transactions on haptics* 11 (3), 357–366.

Labonté-LeMoyne, É., P.-M. Léger, B. Resseguier, M.-C. Bastarache-Roberge, M. Fredette, S. Sénécal and F. Courtemanche (2016). “Are We in Flow Neurophysiological Correlates of Flow States in a Collaborative Game”. In: *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. Ed. by J. Kaye, A. S. I. G. o. C.-H.M. Interaction. [Place of publication not identified]: ACM, pp. 1980–1988.

Lee, J. D. and K. A. See (2004). “Trust in automation: designing for appropriate reliance” *Human factors* 46 (1), 50–80.

Liu, C., P. Agrawal, N. Sarkar and S. Chen (2009). “Dynamic Difficulty Adjustment in Computer Games Through Real-Time Anxiety-Based Affective Feedback” *International Journal of Human-Computer Interaction* 25 (6), 506–529.

Lux, E., M. T. P. Adam, V. Dorner, S. Helming, M. T. Knierim and C. Weinhardt (2018). “Live Biofeedback as a User Interface Design Element: A Review of the Literature” *Communications of the Association for Information Systems* 43 (1), 257–296.

Lux, E., F. Hawlitschek, M. T.P. Adam and J. Pfeiffer (2015). “Using Live Biofeedback for Decision Support: Investigating Influences of Emotion Regulation in Financial Decision Making”. In *ECIS 2015 completed reseaech papers*. AIS Electronic Library.

Maior, H. A., M. L. Wilson and S. Sharples (2018). “Workload Alerts—Using Physiological Measures of Mental Workload to Provide Feedback During Tasks” *ACM Transactions on Computer-Human Interaction* 25 (2), 1–30.

Mitchell, M. L. and J. M. Jolley (2013). *Research design explained.* Eighth edition, International edition. [Belmont, California]: Wadsworth Cengage Learning.

Muñoz, J. E., M. Cameirão, S. Bermúdez i Badia and E. R. Gouveia (2018). “Closing the Loop in Exergaming - Health Benefits of Biocybernetic Adaptation in Senior Adults”. In: *Proceedings of the 2018 Annual Symposium on Computer-Human Interaction in Play*. Ed. by F. F. Mueller, D. Johnson, B. Schouten. New York: ACM, pp. 329–339.

Nasoz, F., C. L. Lisetti and A. V. Vasilakos (2010). "Affectively intelligent and adaptive car interfaces" *Information Sciences* 180 (20), 3817–3836.

Nirjon, S., R. F. Dickerson, Q. Li, P. Asare, J. A. Stankovic, D. Hong, B. Zhang, X. Jiang, G. Shen and F. Zhao (2012). "MusicalHeart". In: *Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems*. Ed. by R. Eskicioglu. Toronto, Ontario, Canada: ACM, p. 43.

Novak, D. (2014). "Engineering Issues in Physiological Computing". In S. H. Fairclough and K. Gilleade (eds.) *Advances in Physiological Computing*, pp. 17–38. London: Springer.

Novak, D., M. Mihelj and M. Munih (2012). "A survey of methods for data fusion and system adaptation using autonomic nervous system responses in physiological computing" *Interacting with Computers* 24 (3), 154–172.

Parasuraman, R. and C. A. Miller (2004). "Trust and etiquette in high-criticality automated systems" *Communications of the ACM* 47 (4), 51.

Parnandi, A. and R. Gutierrez-Osuna (2015). "A comparative study of game mechanics and control laws for an adaptive physiological game" *Journal on Multimodal User Interfaces* 9 (1), 31–42.

Picard, R. W., E. Vyzas and J. Healey (2001). "Toward machine emotional intelligence: analysis of affective physiological state" *IEEE Transactions on Pattern Analysis and Machine Intelligence* 23 (10), 1175–1191.

Pope, A. T., E. H. Bogart and D. S. Bartolome (1995). "Biocybernetic system evaluates indices of operator engagement in automated task" *Biological Psychology* 40 (1-2), 187–195.

Potts, D., K. Loveys, H. Ha, S. Huang, M. Billinghurst and E. Broadbent (2019). "ZenG". In: *Proceedings of the 2019 on Creativity and Cognition - C&C '19*. Ed. by S. Dow, M. L. Maher, A. Kerne, C. Latulipe. New York, New York, USA: ACM Press, pp. 583–590.

Prinzel, L. J., F. G. Freeman, M. W. Scerbo, P. J. Mikulka and A. T. Pope (2000). "A closed-loop system for examining psychophysiological measures for adaptive task allocation" *The International Journal of Aviation Psychology* 10 (4), 393–410.

Prinzel III, L. J., F. G. Freeman, M. W. Scerbo, P. J. Mikulka and A. T. Pope (2003). "Effects of a psychophysiological system for adaptive automation on performance, workload, and the event-related potential P300 component" *Human factors* 45 (4), 601–613.

Prinzel III, L. J., A. T. Pope and F. G. Freeman (2002). "Physiological Self-Regulation and Adaptive Automation" *The International Journal of Aviation Psychology* 12 (2), 179–196.

Rani, P., N. Sarkar and C. Liu (2005). "Maintaining Optimal Challenge in Computer Games through Real-Time Physiological Feedback". In *CHI 2005*.

Riedl, R. and P.-M. Léger (2016). *Fundamentals of NeuroIS*. *Information Systems and the Brain.* 1st ed. 2016. Berlin, Heidelberg: Springer.

Rissler, R., M. Nadj, M. Adam and A. Mädche (2017). "Towards an integrative theoretical framework of IT-mediated interruptions". In *Proceedings of the 25th European Conference on Information Systems (ECIS)*. Guimarães.

Rissler, R., M. Nadj, M. X. Li, M. T. Knierim and A. Maedche (2018). "Got Flow?". In: *Extended abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*. Ed. by R. Mandryk, M. Hancock. New York: Association for Computing Machinery, pp. 1–6.

Rodriguez-Guerrero, C., K. Knaepen, J. C. Fraile-Marinero, J. Perez-Turiel, V. Gonzalez-de-Garibay and D. Lefeber (2017). "Improving Challenge/Skill Ratio in a Multimodal Interface by Simultaneously Adapting Game Difficulty and Haptic Assistance through Psychophysiological and Performance Feedback" *Frontiers in neuroscience* 11.

Rouast, P. V., M. T. P. Adam, R. Chiong, D. Cornforth and E. Lux (2018). "Remote heart rate measurement using low-cost RGB face video: a technical literature review" *Frontiers of Computer Science* 12 (5), 858–872.

Rusnock, C. F. and C. D. Geiger (2017). "Simulation-Based Evaluation of Adaptive Automation Revoking Strategies on Cognitive Workload and Situation Awareness" *IEEE Transactions on Human-Machine Systems* 47 (6), 927–938.

Saiwaki, N., H. Togashi, H. Tsujimoto and S. Nishida (1996). "An adaptive interface based on physiological indices". In: *1996 IEEE International Conference on Systems, Man and Cybernetics*. Piscataway: IEEE, pp. 2793–2798.

Salminen, M., S. Järvelä, A. Ruonala, J. Timonen, K. Mannermaa, N. Ravaja and G. Jacucci (2018). "Bio-adaptive Social VR to Evoke Affective Interdependence". In: *IUI 2018. Proceedings of the 23nd International Conference on Intelligent User Interfaces ; March 7-11, 2018, Tokyo, Japan*. Ed. by S. Berkovsky. New York, New York, USA: ACM Press, pp. 73–77.

Serbedzija, N. and S. Fairclough (2012). "Reflective pervasive systems" *ACM Transactions on Autonomous and Adaptive Systems* 7 (1), 1–19.

Shaffer, F. and J. P. Ginsberg (2017). "An Overview of Heart Rate Variability Metrics and Norms" *Frontiers in public health* 5, 258.

Shearer, P. B. (2016). "Physiological detection of flow". Ph.D Dissertation. University of South Dakota (USD).

Shen, L., M. Wang and R. Shen (2009). "Affective e-Learning: Using "Emotional" Data to Improve Learning in Pervasive Learning Environment" *Journal of Educational Technology & Society* 12 (2), 176–189.

Spurlin, S. and M. Csikszentmihalyi (eds.) (2017). *Flow at Work:* Routledge.

Strauss, M., C. Reynolds, S. Hughes, K. Park, G. McDarby and R. W. Picard (2005). "The HandWave Bluetooth Skin Conductance Sensor". In J. Tao, T. Tan and R. W. Picard (eds.) *Affective computing and intelligent interaction. First International Conference, ACII 2005 : Beijing, China, October 22-24, 2005 : proceedings*, pp. 699–706. Berlin: Springer.

Takahashi, M., A. Tsuyoshi, O. Kuba and H. Yoshikawa (1994). "Experimental study toward mutual adaptive interface". In: *RO-MAN. 3rd IEEE International Workshop on Robot and Human Communication, July 18-20, 1994, Nagoya*. Piscataway, NJ: Institute of Electrical and Electronics Engineers, pp. 271–276.

Task Force of The European Society of Cardiology and The North American (1996). "Heart rate variability: standards of measurement, physiological interpretation and clinical use. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology" *Circulation* 93 (5), 1043–1065.

Teo, G., L. Reinerman-Jones, G. Matthews, J. Szalma, F. Jentsch and P. Hancock (2018). "Enhancing the effectiveness of human-robot teaming with a closed-loop system" *Applied Ergonomics* 67, 91–103.

Ting, C.-H., M. Mahfouf, D. A. Linkens, A. Nassef, P. Nickel, G. Robert, J. Hockey and A. C. Roberts (2007). "Towards on-line supervision and control of operational functional state (OFS) for subjects under mental stress". In: *IEEE/NIH Life Science Systems and Applications Workshop, 2007. LISA 2007 ; Bethesda, MD, 8 - 9 November 2007*. Piscataway, NJ: IEEE Service Center, pp. 77–80.

Ting, C.-H., M. Mahfouf, A. Nassef, D. A. Linkens, G. Panoutsos, P. Nickel, A. C. Roberts and G. R. J. Hockey (2010). "Real-Time Adaptive Automation System Based on Identification of Operator Functional State in Simulated Process Control Operations" *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans* 40 (2), 251–262.

van der Meulen, R. and W. Bamiduro (2018). *Gartner Says Global IT Spending to Grow 6.2 Percent in 2018.* URL: https://www.gartner.com/en/newsroom/press-releases/2018-04-09-gartner-says-global-it-spending-to-grow-6-percent-in-2018 (visited on 08/21/2019).

van der Vijgh, B., R. J. Beun, M. van Rood and P. Werkhoven (2014). "GASICA: generic automated stress induction and control application design of an application for controlling the stress state" *Frontiers in neuroscience* 8, 400.

Webster, J. and R.T. Watson (2002). "Analysing the past to prepare for the future: Writing a literature review" *MIS Quarterly* 26 (2), xiii–xxiii.

Wen, W., G. Liu, N. Cheng, J. Wei, P. Shangguan and W. Huang (2014). "Emotion Recognition Based on Multi-Variant Correlation of Physiological Signals" *IEEE Transactions on Affective Computing* 5 (2), 126–140.

Wiener, N. (1948). *Cybernetics or Control and Communication in the Animal and the Machine.* New York & Paris: John Wiley & Sons, Inc.

Wilson, G. F. and C. A. Russell (2007). "Performance enhancement in an uninhabited air vehicle task using psychophysiologically determined adaptive aiding" *Human factors* 49 (6), 1005–1018.

Xiong, M., R. He, L. Ji and J. Wu (2013). "A Biofeedback System for Mobile Healthcare Based on Heart Rate Variability". In D. Zeng, C. C. Yang, V. S. Tseng and C. Xing (eds.) *Smart Health. International Conference, ICSH 2013, Beijing, China, August 3-4, 2013. Proceedings*, pp. 84–95. Berlin/Heidelberg: Springer Berlin Heidelberg.

Xu, X., A. J. Karis, M. J. Buller and W. R. Santee (2013). "Relationship between core temperature, skin temperature, and heat flux during exercise in heat" *European journal of applied physiology* 113 (9), 2381–2389.

Yannakakis, G. N. (2009). "Game adaptivity impact on affective physical interaction". In: *3rd International Conference on Affective Computing and Intelligent Interaction and workshops, 2009. ACII 2009 ; Amsterdam, Netherlands, 10 - 12 Sept. 2009*. Piscataway, NJ: IEEE, pp. 1–6.

Yu, B., N. Bongers, A. van Asseldonk, J. Hu, M. Funk and L. Feijs (2016). "LivingSurface: Biofeedback through Shape-changing Display". In: *Proceedings of the TEI '16 Tenth International Conference on Tangible, Embedded, and Embodied Interaction*. Ed. by S. Bakker, C. Hummels, B. Ullmer, L. Geurts, B. Hengeveld, D. Saakes, M. Broekhuijsen. New York, NY: ACM, pp. 168–175.

Yu, B., M. Funk, J. Hu and L. Feijs (2017). "StressTree". In: *DIS'17. Proceedings of the 2017 ACM Conference on Designing Interactive Systems : June 10-14, 2017, Edinburgh, United Kingdom*. Ed. by O. Mival, M. Smyth, P. Dalsgaard. New York, New York: The Association for Computing Machinery, pp. 333–337.

Zhang, J., Z. Yin and R. Wang (2017). "Design of an Adaptive Human-Machine System Based on Dynamical Pattern Recognition of Cognitive Task-Load" *Frontiers in neuroscience* 11, 129.