Physiology-based personalization of persuasive technology

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Physiology-based personalization of persuasive technology: a user modeling perspective

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Abstract

Persuasive technology (PT) can assist in behavior change. PT systems often rely on user models, based on behavior and self-report data, to personalize their functionalities and thereby increase efficiency. This review paper shows how physiological measurements could be used to further improve user models for personalization of PT by means of bio-cybernetic loops and data-driven approaches. Furthermore, we outline the advantages of using physiological measures for personalization compared to self-report and behavior measurement. Additionally, we show how two types of physiological information—physiological states and physiological reactivity—can be relevant for PT adaptations. To illustrate this, we present a model with two types of physiology-based PT adaptations as part of a bio-cybernetic loop; state-based and reactivity-based. Next, we discuss the implications of physiology-aware PT for persuasive design and theory. And lastly, because of the potential impact of such systems, we also consider important ethical implications of physiology-aware PT.

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1 Introduction

Physiology as input to user models is increasingly studied (Janssen et al. 2012; Oliver and Kreger-Stickles 2006; Van Der Zwaag et al. 2013). However, few insights on the use of physiology to personalize *persuasive technology* (PT) are available. This paper aims to fill this gap in the literature. PT systems are intentionally designed to change a person's attitude and/or behavior (IJsselsteijn et al. 2006, p. 1). Thereby these systems foster for example healthier or more sustainable lifestyles and reduce ill health, human suffering, and high costs on individuals and society (World Health Organization 2018). PT comes in many forms, for example, mobile phone applications, wristbands, smart lights, or computers, and can operate in various contexts, such as health care, education, or environmental sustainability (Masthoff et al. 2014; Samsung US Newsroom 2021). These technologies develop rapidly due to emerging trends in the industry and society.

1.1 Goal of this work

The goal of this work is (1) to provide a concise overview of persuasive technology research, and (2) to propose physiological measurements as additional input to user models in PT systems. This paper presents the output of a literature study that explores the emerging field of personalization in persuasive technology. Specifically, it ventures into the recent trend of using physiological information for personalization. This paper will argue that (psycho)physiological assessments can deliver an important contribution to user models in PT systems.

Attempts at persuasion are most effective when personalized to the user (Markopoulos et al. 2015; Meschtscherjakov et al. 2016). In personalized PT systems, user models are used to adapt system features to the users' emotional, cognitive or behavioral characteristics (Markopoulos et al. 2015), for example, by sending an authority-based message to a user that self-reported a high susceptibility to the persuasion principle of authority (Cialdini 2007; Kaptein et al. 2012). It is clear that users can have emotional and cognitive reactions to persuasion attempts (Cialdini 2007; Miron and Brehm 2006; Perloff 2008), and physiological activity is known to reflect these emotional and cognitive processes (Kreibig 2010; Picard 1995), and thus potentially also persuasion-related processes. Furthermore, state-of-the-art sensor technologies enable unobtrusive continuous measurement of related nervous system features. As a consequence, we were interested to study the literature on psychophysiological reactions to persuasion, to find (a) whether psychophysiological assessments might provide a further understanding of the user's psychological persuasion-related processes during PT usage, and (b) whether such insights can inform personalization of persuasive interventions. For example, previous research has indicated that affective meta-data can enhance the performance of content-based recommender systems (Tkalčič et al. 2010). If so, psychophysiological assessments can potentially enrich the user models currently employed by PT systems and thereby their efficiency. We aim to identify important future directions and ethical considerations concerning the usage of physiology in PT systems. The outcome of this literature review can help PT researchers and designers further integrate physiology in PT in a responsible, thoughtful way.

This paper sets out to answer the following question: How can insights from physiology be used to personalize persuasive technology? It will start with describing PT systems, their functionalities, and introducing physiology as a measure of persuasion-related processes. We will present a system architecture to illustrate the use of physiology to personalize PT systems.

1.2 Relation to existing work

The use of physiology as input for personalization is not new. Various scholars have created personalized music players that use physiological states to coach people towards certain moods (Janssen et al. 2012; Van Der Zwaag et al. 2013) or fitness levels (Oliver and Kreger-Stickles 2006). In these systems, the target objective, for example, mood or fitness level, was represented by a certain physiological state. These systems recommended a song with an energy just above or below the current physiological state of the user (Janssen et al. 2012; Oliver and Kreger-Stickles 2006; Van Der Zwaag et al. 2013). In that sense, these systems describe state adaptation where physiology serves as both the input signal as well as the target state.

The architecture we will present differs from previous user-modeling research on three points: (1) It is focused on persuasion and physiology, (2) the objective is to change behavior or motivational state, and (3) this system accounts for both slow and fast changes in physiology, that is state as well as reactivity adaptation. Furthermore, the paper includes an examination of the implications and ethics of physiology-aware PT systems.

1.3 Methodology

For finding relevant research, this paper used a backward and forward snowballing procedure (Wohlin 2014). Key references for this topic come from different fields, not all of which use the same terminology. With the snowballing method, we hope to include also high-quality sources from unexpected locations. The tentative starting set consisted of papers from several literature searches supplemented by relevant papers from the authors' libraries. It included papers on persuasive technology, personalization of persuasion, physiological computing, user modeling, and ethics. For reliability purposes, we only included peer-reviewed papers with a reasonable number of citations per year depending on the field of research. The second requirement was handled more loosely if the paper was very on-topic. To be included, papers had to focus on persuasive technology, some form of system adaptation with a closed-loop, persuasion-related processes, or psychophysiological responses to persuasion attempts. During the synthesis phase, we standardized terms describing the same phenomenon. Then, the essential information from the included papers was summarized in tables and figures and organized to form the storyline (of the rest) of this paper.

2 Introducing Persuasive Technology

Originally, persuasion specified the process by which one person tried to influence another person (Perloff 2008). Persuasive approaches have been effectively used to change the perspectives on topics such as health behaviors (Perloff 2008), shopping (Cialdini 2007), or politics (Brader 2005). Since people attribute social characteristics to personal information systems (e.g. computers or smartphones) (Fogg 2003; Nass and Moon 2000), persuasion can also occur via a technology–human interaction (Meschtscherjakov et al. 2016; Mitchell et al. 2020). This resulted in the rise of *persuasive technology* (PT), which is "*a computerized software or information system designed to reinforce, change or shape attitudes or behaviors or both without using coercion or deception*" (Oinas-Kukkonen and Harjumaa 2008).

Recent technological developments have changed attempts at persuasion from mass to individualized influence since they enable a more complex, subtle, and calculative form of persuasive communication (Perloff 2008). Persuasion attempts to promote certain behavior have come a long way from crusades against binge drinking in the 1800s (Perloff 2008, p. 5) to contemporary smartphone applications with push notifications (Kaptein et al. 2012; Samsung US Newsroom 2021). Contemporary PT comes in many forms, that is computers (Vroege et al. 2014; Wijsman et al. 2013), wristbands (Westerink et al. 2014), mobile phone applications (Garnett et al. 2019), ambient lighting (Maan et al. 2011) or even in virtual reality (Chionidis and Powell 2020). It can be used for various objectives, for example, stimulating users to take a small break during computer work (Ham et al. 2011), encouraging physical exercise (Herrmann and Kim 2017; Spelt et al. 2019b), promoting healthy eating (Kaptein et al. 2012; Maimone et al. 2018; Orji et al. 2014), conserving energy (Ham and Midden 2014), supporting waste management (Nkwo 2019), promoting weight-loss (Karppinen et al. 2018), or reducing alcohol intake (Garnett et al. 2019).

PT will likely continue to evolve. People voluntarily use PT because it can provide support in their pursuit to change their behavior in a direction they wish to achieve. Contemporary PT is to a great extent shaped by the role and development of modern information systems in the last few decades (IJsselsteijn et al. 2006). Information systems have become omnipresent in our society (Iyengar et al. 2018) and most people see their personal information systems, such as a smartphone or a computer, as indispensable or even as an extension of themselves. The technology behind these devices enabled growth in the number of persuasive communications with messages traveling faster than ever before (Iyengar et al. 2018; Perloff 2008). For instance, Natural Language Generation has been used to automate the creating of personalized persuasive messages on a large scale (Guerini et al. 2007; Maimone et al. 2018; Pan and Zhou 2014). The recent trends of applying artificial intelligence to information systems (Iyengar et al. 2018) and reliable biosensors to wearable technology (van Lier et al.

2020) further expand PT's potential, for example, by creating an immersive, all-round experience with continuous dialogues.

3 Personalizing persuasion

Persuasion, the main goal of PT, is a communicative process in which an entity (e.g. a computer, poster, or television) influences a person to change his or her perspective on a particular subject or their behavior, while the person still has a free will to do or think otherwise (Perloff 2008). In this paper, we make a distinction between persuasion, an attempt at persuasion, and persuasion-related processes. An attempt at persuasion concerns the effort that tries to persuade someone, for example, a message or video. Persuasion-related processes are the related psychological processes evoked by that persuasion attempt. Persuasion is when attitude, intentions, and/or behavior are successfully changed by an attempt at persuasion.

There is no one-size-fits-all approach to (successful) persuasion. Persuasion can be achieved using a variety of strategies (Armstrong 2010; Michie et al. 2013; Rhoads 2007). Differences in susceptibility to persuasion attempts come from a variety of dispositional characteristics. To start with, a person has to be motivated and able to perceive and process a persuasive attempt for it to be effective (Petty and Cacioppo 1986). This process can be restricted by emotional (DeSteno et al. 2004; Rosselli et al. 1995) or situational states (Kitchen et al. 2014; Petty and Cacioppo 1986). Also, personality traits can influence people's susceptibility to specific persuasive strategies, like need for cognition (Cacioppo et al. 1986), behavioral motivation (Hirsh et al. 2012; Sherman et al. 2006), gamer type (Orji et al. 2014), or the big five characteristics (Alkiş and Taşkaya Temizel 2015). And finally, demographic variables, such as age or educational level, can affect susceptibility to persuasive information in general (Orji et al. 2015). In addition, susceptibility to persuasive messages can vary over situations, because a person's susceptibility to persuasive appeals can change depending on characteristics of the person's situation.

The idea behind personalization is that when the persuasive information does not fit with the state of the user, this causes the likelihood of persuasion to decrease. This misfit can be mitigated with a better comprehension of the user and their context. Therefore, technologies that try to persuade should tailor themselves to the user with information from, among others, *self-report, behavior* or *contextual measures* (Markopoulos et al. 2015; Oinas-Kukkonen and Harjumaa 2009). Table 1 and Table 2 present an overview of known measures for the personalization of PT. Information from all these measures can be used to adapt features of the system, such as the persuasive strategies used, the end-goals that are set, the content of the messages, and the timing of the prompts (Table 2). Adapting these system features to user characteristics fosters persuasion (Hirsh et al. 2012). For instance, messages are more persuasive when their framing as a gain or as a loss is adapted to the receiver's personality traits (Hirsh et al. 2012).

Table 1 Overview of information from measures for the personalization of persuasive technology

Measures	Features used for adaptation	Examples
Self-report	Questionnaires can be used to obtrusively measure (Markopoulos et al. 2015): Demographic state, which can influence users' motivations, opportunities, and abilities to perform a certain behavior (Michie et al. 2011; Orji et al. 2015) Personality traits, which relate to the user's tendency to comply with distinct persuasion strategies (Alkiş and Taşkaya Temizel 2015; Cacioppo et al. 1986; Hirsh et al. 2012; Kaptein et al. 2012; Sherman et al. 2006) Reflections on the user's own affective or cognitive state, which can influence motivation and ability to comply (DeSteno et al. 2004; Kitchen et al. 2014; Petty and Cacioppo 1986; Rosselli et al. 1995) Self-reported (target) behavior	Age, gender, education Big-Five, need for cognition PANAS Food diary
Behavior	Behavior measures can be used to unobtrusively measure: The target behavior in relation to persuasive features, which can reveal susceptibility to those persuasive features (Markopoulos et al. 2015) Expressions of user states in behavioral responses, which can reveal mental states (Barral et al. 2016; Moshfeghi and Jose 2013)	Accelerometry, energy usage, user-system interaction Keystroke force, dwell time
Context	Contextual measures can reveal the activities a user is involved in to assure that a persuasive prompt is delivered when the user is receptive, can process it and there is room for action, and thereby how the context might influence susceptibility (Van Dantzig et al. 2018)	Geolocation, calendar, time
Physiology	Physiological activity holds information about the emotional and cognitive states of a person (Cacioppo et al. 2007). Physiological state can reveal whether the user is in a receptive mood, whereas physiological reactivity reveals the impact of a persuasion attempt	Heart rate (variability), respiration rate, skin conductance level, facial muscle activity

Table 2 Overview of adaptable system features for the personalization of persuasive technology

Adaptable system-features	Explanation	Examples
Persuasive strategy	Various strategies can be used to achieve persuasion (Cialdini 2007; Michie et al. 2011; Rhoads 2007)	Authority, action-planning, gain-framing, controlling language
Goals	People use a PT to achieve a preferably self-set goal. The system determines several measurable sub-goals adapted to the user's capabilities to help achieve that goal	Active minutes per day, calorie intake, screen time
Content	Persuasive messages that include user-specific information are perceived as more personal. User-system interaction improves when the system's interactions are in line with the characteristics of the user	Nicknames, behavioral history, culture, age,
Timing	Attempts at persuasion are most effective when delivered just in time. Prompts can have different functions, such as reminding or motivating, depending on the time at which the user receives them (Fogg 2009)	Spark prompts, facilitator prompts, signal prompts

4 Physiology during persuasion-related processes

Recently researchers have explored an additional measure of persuasion-related processes in the form of physiology (Barraza et al. 2015; Cacioppo et al. 2017; Correa et al. 2015; Falk and Scholz 2018). It is known that certain mental states correspond with activation of physiology, for example, heart rate and skin conductance were found to change 20 minutes before a person becomes aggressive (Looff et al. 2019). This might also be the case in persuasion-related processes. An attempt at persuasion is likely to influence someone's mental state: A person goes through several experiences before the exposure to the persuasive cue is translated into an actual change of motivation or behavior. For example, the processing of persuasive information requires attention and further compliance asks for self-regulation. In addition, a person can have a range of feelings, such as annoyance or frustration when it is not easy to comply or if the message feels confrontational. We can also expect a drive and determination when someone is eager to comply. As psychological and physiological processes interact (Cacioppo et al. 2007), the mental processes activated by a persuasion attempt are expected to result in varying levels of physiological activity. Studying these variations in physiological activity can therefore generate insights into the psychological mechanisms of persuasion. Moreover, if physiology indeed reflects persuasion-related processes, physiological assessment could serve as additional adaptation input in personalized persuasive technology (Table 1).

To support the above line of thought, we will provide some background on how psychological mechanisms can produce physiological responses: Psychological states and processes activate brain areas, such as the prefrontal cortex, limbic system, or thalamus (Gazzaniga et al. 2009; Posner et al. 2005). In turn, these brain areas can further activate the nervous system (Fairclough et al. 2014; Jänig 2003; Kreibig 2010; Picard et al. 2001; Thayer and Lane 2009). The autonomic nervous system innervates bodily processes via its sympathetic and parasympathetic branches. Via the sympathetic branch, the body is activated and prepared for action (sometimes in response to an emotional experience), whereas the parasympathetic branch is responsible for relaxation (Jänig 2003). The interplay between the two branches determines the activity in the various physiological subsystems (Cacioppo et al. 2007; Jänig 2003), such as the *cardiovascular*, *electrodermal*, *respiratory,* and *facial muscle systems*. As such these systems are known to reflect different parts of emotional (Jänig 2003; Kreibig 2010; Picard et al. 2001) and cognitive processes (Boucsein 2012; Fairclough and Mulder 2011). Changes in the cardiovascular, electrodermal, and respiratory systems are predominantly associated with arousal levels, ranging from calm to excited, and can be related to certain affective states like anger or stress (Brouwer et al. 2018; Looff et al. 2019). Facial muscle activity, on the other hand, can reflect valence, ranging from negative to positive emotions (van Boxtel 2010).

Peripheral physiology comprises all parts of the nervous system outside the brain and spinal cord, including the *cardiovascular*, *electrodermal*, *respiratory,* and *facial muscle systems* mentioned above. Peripheral physiological changes are often easily measurable with wearable technologies and thereby incorporable in PT systems. These subsystems, their main functions and measurable features are presented in Table 3 (see Jänig 2003; Kreibig 2010 for a full review).

Since peripheral physiology can be influenced via the nervous system by emotion- or cognition-related brain activity, changes in physiology are taken to have psychological meaning. These physiological changes become especially meaningful when considering the timing of the physiological change in the process, which is; before the persuasion attempt, during the persuasion attempt, during the evoked persuasion-related processes, during new behavior, and after new behavior. The specifics of the psychophysiological relationship in persuasion are not yet clear. Among others, it is not known whether persuasion consists of only one or a mix of psychological processes, and which physiological parameters covary with the phenomenon. This latter issue is part of the *multi-mapping problem* (Cacioppo et al. 2007, Chapter 1; Fairclough 2009), which describes how one specific physiological reaction does not necessarily pinpoint one specific psychological state but can result instead from various different psychological phenomena (one-to-many specificity). Nevertheless, several studies (Barraza et al. 2015; Cacioppo et al. 2017; Cascio et al. 2015; Correa et al. 2015; Falk and Scholz 2018; Lewinski et al. 2016; Spelt et al. 2019c; Spelt et al. 2020) indicated that persuasion-related cognitive and affective processes are reflected in physiology to some extent. Section 6.2 will further describe the findings of these studies.

Table 3 Main functions, important measurable features, and interpretations of activity changes of the cardiovascular, electrodermal, respiratory, and facial psychophysiological systems

Physiological subsystem	Measurable features	Psychological meaning
The cardiovascular system is responsible for blood flow throughout the body. Its main functions are the supply of oxygen and the disposal of waste. The system is under hormonal and nervous system control (Cacioppo et al. 2007)	*Heart rate (HR)* is measured as the number of beats per minute. Sympathetic and parasympathetic activity can increase and decrease HR, respectively (Camm et al. 1996) *Heart rate variability (HRV)* reflects the beat-to-beat variability in HR and thereby the interplay between the sympathetic and parasympathetic nervous systems	HR increases in states with higher arousal levels, for example, joy, fear, or cognitive demands. It decelerates in passive emotions and resting states, such as affection, or contentment (Jänig 2003; Kreibig 2010; Looff et al. 2019) HRV indicates adaptive emotion regulation in both pleasant and unpleasant emotions. Reduced HRV indicates emotional dysregulation, such as anxiety, stress, or depression (Jänig 2003; Kreibig 2010)
The electrodermal system involves sweat gland activity. The system is solely innervated by the sympathetic branch of the nervous system (Boucsein 2012; Cacioppo et al. 2007)	*Skin conductance level (SCL)* is the tonic component of skin conductance *Skin conductance responses (SCRs)* are rapid phasic components. SCRs are measured as the number or magnitude of the skin conductance peaks	Electrodermal activity can reflect affect, attentional reactions, or effort. SCL elevates during experiences that call for action or evoke stress (Brouwer et al. 2018) SCRs can arise in response to a stimulus and their magnitude reflects emotional levels independent of the valence of the stimuli. The presence of SCRs can indicate reward focus or decision-making
The respiratory system consists of all organs involved in breathing. Its primary task is oxygen supply and carbon dioxide depletion. Breathing can occur both automatically and intentionally (Cacioppo et al. 2007)	*Respiration rate (RR)* can be measured via mechanical movement of the diaphragm and rib muscles	Changes in RR relate to cognitive demands, for example, high task difficulty or working memory load, as well as emotional processing, for example breathing rate is faster in disgust or sadness, slower in relief, and stops in surprise

Table 3 (continued)

Physiological subsystem	Measurable features	Psychological meaning
The facial muscles are skeletal muscles on the face and are used to control conscious and unconscious facial expressions (Boxtel 2010)	*Zygomaticus major (EMG-ZM)* activity is measured from the muscles located between the cheekbones and lip corners *Corrugator supercilii (EMG-CS)* activity is measured from the muscles located at the medial end of the eyebrows	EMG-ZM activity causes the lip corners to go up. This is known as smiling and is associated with psychological states of positive valence EMG-CS activity causes frowning and is associated with negative emotions, for example, anger or sadness. Frowning also occurs with increased cognitive demands, for example reading or thinking

5 Measures for the personalization of persuasion attempts

That physiology might be used as a measure of persuasion-related processes offers significant benefits for the personalization of PT. This is mainly due to how physiological measures relate to the contemporaneous measures of self-report, and behavior.[1] Self-report, behavior, and physiological measurements differ in characteristics (Table 4) and can thereby complement each other when personalizing PT.

For personalization, the system needs to understand the state of the user, as this state is critical for the perception and thereby the success of an attempt at persuasion. Each measure reflective of persuasive processes captures a different facet of this user state. The measures try to apprehend the process at different moments in time; during persuasion (physiology), shortly before and after (self-report), or later in time (behavior). This has consequences for when they can be used to measure persuasion effectiveness.

As remarked before, persuasion is a complex, often multi-phased, process (Oinas-Kukkonen and Harjumaa 2009): Various mental steps or even persuasive attempts might be needed to affect behavior. Asking for self-reports after each and every step in the process of being persuaded or for each persuasive message is annoying. Especially since the (targeted) behavior is only expected to change after a cascade of persuasive messages, and not after a single message. With physiology, however, the reaction to each individual message can be measured and interpreted. This yields data with a high temporal resolution, and in a continuous data-trace even small changes in physiology might be meaningful. Physiology thus can be used for event detection (Maimone et al. 2018), and captures an instantaneous psychology-related reaction that can be used for real-time tailoring of the PT-user communication.

[1] Contextual measures are not discussed in this analysis, as context-aware coaching in persuasive systems (Van Dantzig et al., 2018) is a relatively new phenomenon.

Table 4 Characteristics of self-report, behavioral and physiological measurements used for personalization of persuasive technology

	Self-report measurement	Behavior measurement	Physiological measurement
Representation	User's conscious reflections on affective and cognitive states (constructs)	Consequences of affective and cognitive states (behavior)	Derivatives of conscious and unconscious affective and cognitive processes (physiology)
User control	Overt controlled responses	Overt semi-controlled responses	Covert uncontrollable responses
Nature	Retrospective, obtrusive	Continuous, unobtrusive	Continuous, unobtrusive
Pitfalls	Introspection, non-response, (short-term) illness, signal loss	Faulty usage, illness, signal loss	Physical exercise, situational stressors, (short-term) illness, signal loss
Function	**Predictive**: Helps narrow down PT features that increase susceptibility for this user	**Process tracking:** Tracks changes in user behavior	**Predictive:** Helps identify which timing, strategy & content is most appropriate for this user
	Success assessment: Measures whether user's behavior & underlying motivations have changed	**Success assessment:** Tracks whether behavior reached set goals	**Process tracking:** Tracks user's reactions to PT prompts

In addition, these measures differ in the extent to which the user is aware of the measurement and/or the responses being captured. To start, physiological measures collect information without the need to disturb the user. This unobtrusiveness results in direct and unhindered information related to the user's mental state. Although at the start the user might be aware of the system that performs the physiological or behavioral measurements, the user might forget it as time progresses. In contrast, completing a questionnaire cannot remain unnoticed: The user must deliberately answer and knows which answers they have given (Maimone et al. 2018). Obtrusive questionnaires might reduce the persuasiveness of the system, as they can reveal the persuasive strategies that the system aims to use. As for behavior, whether or not the user was aware of the mental processes that caused it, the user can be aware of the behavior itself. A physiological sensing device might pick up hidden states or reactions which a behavior or self-report measure might have missed (Picard 1995). Additionally, people have no control over their physiological responses, as they are under autonomic nervous system control, which contrasts with self-report and to some extent with behavior measures. In theory,

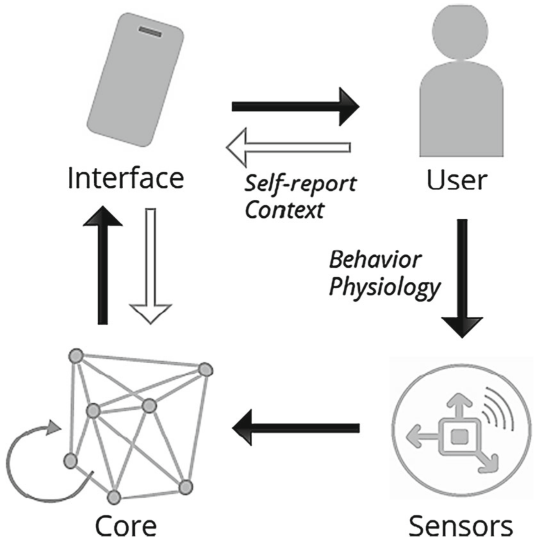

Fig. 1 Hypothetical persuasive technology system involving a biocybernetic loop in black. Figure based on Fairclough (2009)

physiological measurement enables the analysis of mental states when the user is not consciously aware of them. Maybe precisely because the user is often unaware of physiological responses and has no control over them, they can function as an implicit measure of the mind (Picard 1995).

Each measure has its own pitfalls (Table 4). Persuasion-related processes can happen automatically and outside of the user's awareness making them difficult to capture with traditional measures (Falk and Scholz 2018); the traditional measures are often limited to conscious introspection, thereby lacking measurement of potentially relevant unconscious processes. Physiology has a wider range of possible inconveniences for assessing persuasion effectiveness: One difficulty is signal quality. Although the development of biosensors is ongoing, currently, the quality of measurement can vary between people or situations. It is important that analyses only include reliable points in a physiological trace for responsible personalization of the system. Future research must indicate which methods can assure sufficient quality of the physiological signal. Additionally, inter-personal physiological activity levels can vary depending on static characteristics as age, gender, or health (Shaffer and Ginsberg 2017), but are less relevant in subject-specific systems employing PT. In addition, dynamic influences on intra-personal physiological activity levels, such as exercise, situational stressors, or illness, could lead to false positives and be detrimental to the efficiency of PT. For example, the system might interpret a sudden change in physiological activity as a reaction to a persuasive feature of the system, whereas in reality, the user's love interest walked in at the exact same moment. This issue, however, becomes less problematic as time progresses due to repeated exposure: The encounter with a love interest and exposure to a persuasive feature will not always coincide. Considering the information in this section thus far, we conclude that self-report, behavior and physiological measures each have their own function when personalizing PT systems.

6 Biocybernetic loops in Persuasive Technology

Now that the potential benefit of the physiological assessment of persuasion-related processes has been identified, this section reports on physiology-based approaches for PT personalization. Adapting a system based on physiology is known as *physiological computing*. The core component in physiological computing is the *biocybernetic loop* (Fairclough 2009). The loop aims at extracting user states from physiology using biosensors and providing (real-time) system adaptations. Physiological computing applications are used in various contexts, such as military task performance (John et al. 2004), mental workload (Fairclough 2009), vitality (Westerink et al. 2014), or gaming (Mandryk and Atkins 2007; Tijs et al. 2008).

PT systems can potentially function as biocybernetic loops as presented in Fig. 1. The interface could be any type of device that communicates with the user, for example, a smartphone, a wristband, a computer, or a smart lamp. The user employs the system to achieve a self-set or advised behavior change. The sensors register overt and covert user reactions using bio- and behavior sensors. The core is an algorithm that chooses the persuasive features that will increase the likelihood of persuasion. User information is fed to the core via the interface (white arrows) or the sensors (black arrows). The core analyzes this information and adapts the interaction accordingly, which closes the loop.

The interaction between the core and biosensors can be discussed in more detail when considering two types of physiological information relevant for personalization: *physiological state* and *physiological reactivity*. In a certain *physiological state,* activity is relatively stable for a brief period. It can reflect emotional or cognitive states, such as relaxation or anxiety (Picard et al. 2001). This information is relevant for PT as a user's emotions can change the perception of a message and influence the likelihood of persuasion (DeSteno et al. 2004; Picard 2003; Rosselli et al. 1995). For example, people in fearful or anxious states are more susceptible to frightening information in fear appeals (DeSteno et al. 2004; Rogers 1983). Emotions can also dissuade. For example, anger leads to a lower level of information processing and thereby to no or a less persistent change in attitude (Brehm 1966; Petty and Cacioppo 1986). Moreover, emotions can influence the effectiveness of persuasion attempts even when they are incidental and do not relate to the persuasion objective (DeSteno et al. 2004; Petty and Cacioppo 1986). Even if feelings of anger were evoked by something unrelated to the persuasive attempt itself, the attempt's effect is still limited due to lower levels of information processing. In general, messages with an emotional framing that is in line with the state of the user are most persuasive (DeSteno et al. 2004): Rational messages, for example, are more effective in neutral than positive moods (Rosselli et al. 1995). Therefore, knowing the physiological state of the user and having insight into their emotions before the PT acts might increase the likelihood of persuasion.

Physiological reactivity is the second type of relevant information for PT personalization. Physiological reactivity can indicate a rapid change in activity following (or during) exposure to something (Cacioppo et al. 2007). The magnitude of these activity changes can reveal information about the user's psychological reaction to this something. A sudden change in cardiovascular, electrodermal, or respiratory activity often indicates induced arousal (Cacioppo et al. 2007), whereas facial muscle activity can be related to valence (van Boxtel 2010). A classic example of this phenomenon is the startle response (Lang et al. 1990), where the sudden increase in arousal reveals how shocked a person is by what he/she just saw. Reactivity can therefore be insightful in case of an attempt at persuasion. For example, a message might engage the user, resulting in a distinct physiological pattern with elevated heart rate and skin conductance levels. In addition, physiological reactivity might reveal the success rate of a persuasive appeal: high levels of reactivity can relate to active processing and elaborating on information (Thayer et al. 2009), potentially resulting in behavior change. However, it can also indicate that the person is feeling reactant to the message, that is, highly aroused and dismissive (Sittenthaler et al. 2015), whereas no or low levels of reactivity could hint at the indifference of the user.

6.1 The concept of physiology-based adaptation

We argue that physiological state and reactivity information enable two types of physiology-contingent adaptation in PT: *State and reactivity adaptation.* In state adaptation, the system adapts to the stable physiological state of the user. In reactivity adaptation, the user's physiological reactivity to for example a message is used to tailor the system. Figure 2 presents these adaptations in the biocybernetic loop as determined by the core on the basis of input of biosensors. Traditional motivational state adaptation (red lines in Fig. 2) is not explained further as this is considered out of the scope of this paper. It basically consists of linking the presentation of a persuasive message with its impact in terms of (the absence of) a change in motivational state and/or behavior to generate knowledge. The next sections discuss both types of adaptations in detail.

State adaptation starts with a measurement of the person's physiological state using biosensors (see the blue path in Fig. 2). The core of the system filters the physiological data, interprets the psychophysiological state, and finds appropriate persuasive features that will increase the likelihood of persuasion in this state. For these steps, the core can use existent knowledge from literature or potentially application-specific knowledge from extensive testing with the system. Existent knowledge consists of, among others, which type of messaging is suited for an emotional state (DeSteno et al. 2004; Van Den Broek et al. 2006). For example, users with a low arousal state might be served best with a message triggering a moment of reflection, while during high arousal an energetic persuasive appeal might be an extra motivational push. System features subject to state adaptation could include persuasive strategy, content, and timing. For example, using kind words when the user is tired.

After the state-adapted messages have been sent, their effects on the motivations and behavior of each individual user can be measured via self-report or, if possible, behavioral sensors. Linking physiological states with persuasive features and persuasion effectiveness can result in user-specific insights on which new rules can be defined. Activity levels and their accompanying psychological states may affect the persuasive impact of an appeal differently depending on the user. Even when activity patterns appear to reflect a distinct state, the degree of susceptibility to a persuasive cue depends on the person's appraisal of the situation.

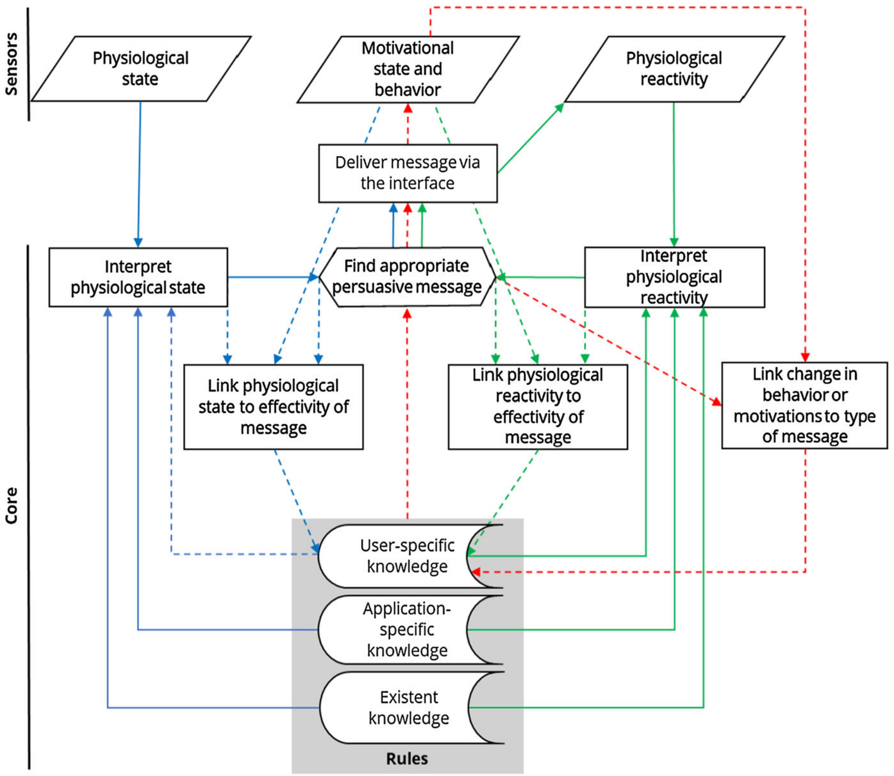

Fig. 2 Architecture and detailed steps of three types of PT system adaptation: Physiological state (blue), physiological reactivity (green), and normal motivational state or behavior adaptation (red). Each box depicts a different process: A parallelogram stands for data, a hexagon marks a preparation phase, and a half-cylinder indicates storage of rules based on knowledge. The dashed lines apply only to systems that can monitor motivational state and/or behavior

In addition, *reactivity adaptations* can be done based on physiological reactivity to a persuasive message (see green paths in Fig. 2). The biosensors can measure the magnitude of the reactivity response. The core can interpret the (absence of a) reaction in terms of susceptibility based on existent knowledge in the literature or on application-specific knowledge and decide whether to send a second message or use similar messaging in the future. Optionally this step can be repeated for the second message. In that sense, reactivity responses can be used to fine-tune PT-user interaction and predict the success rate of a message. Reactivity information becomes even more meaningful when linked to consequent behavior or motivational state. Sensors can monitor consequent changes in motivational state and behavior. This information can then be used to specify further rules based on user-specific knowledge and optimize future interactions.

To find appropriate messages, physiological state and reactivity can be quantified in terms of valence and arousal (Bradley and Lang 1994; Russell 1980). This quantification can be deciphered in terms of psychology, for example, low arousal means relaxation. Or this quantification can be related to (a change in) behavior directly, for example, low arousal and high valence indicate susceptibility to a message. The system might start with psychology labels in order to use existent persuasion knowledge and prevent a cold start,[2] while it moves towards linking physiology directly to behavior. Persuasive processes are individual-dependent, meaning that not all knowledge will apply to each user. How to interpret physiological reactions to persuasive features in terms of a specific user's susceptibility to them is something the PT can learn: over time, the system can gain user-specific insights by reinterpreting physiological states and their impact on susceptibility as measured by motivation and/or behavior change.

Perhaps, the system's network can function as a black box or use machine learning and adapt to the user's feedback to personalize its models. Therefore, it is important to characterize message features and analyze the user's reactions to those features multiple times. These iterations ensure that the right conclusions are drawn about the persuasiveness of a specific message in a particular state or the meaning of reactivity in terms of susceptibility. Consequently, the PT can be personalized based not only on physiological activity but also on user-specific inferences from that physiological activity: The insights gained from coaching one behavior might be transferred to coaching a second behavior. This is especially useful when behavioral or self-report data for the second behavior are not available or hard to measure, for example, food intake. With a persuasion profile per user, we might no longer need to measure behavior, but only physiology. This approach of combining physiological with self-report and behavior measures could enable optimal persuasion in PT by delivering the right message, at the right time, with the right content (Fischer 2001; Fogg and Eckles 2007).

6.2 To date validation of physiology-based adaptation

This section relates empirical findings from previous psychophysiological persuasion research to the steps in the model presented in Fig. 2. To date, little proof exists for state-based adaptations (i.e., the blue path). Most findings relate to the reactivity-based adaptation path in the model (i.e., the green path). The first step of physiological reactivity adaptation is measuring the *physiological reactivity* during exposure to a persuasion attempt. Several studies indicated that physiology could indeed change during an attempt at persuasion. The findings relate to activity in several physiological subsystems including neural (Cacioppo et al. 2017; Cascio et al. 2015; Chua et al. 2011; Falk and Scholz 2018; Vezich et al. 2017), cardiovascular, electrodermal, and respiratory arousal (Spelt et al. 2020), as well as facial activity (Lewinski et al. 2016).

Next, the system *interprets this physiological reactivity* to provide a prediction of the user's susceptibility to that message based on existent or application-specific knowledge. This step is also supported by earlier research, although results may depend on (limitations in) experimental design: Neuroscientific studies describe different neural correlates for message-induced persuasion (Cascio et al. 2015; Chua et al. 2011; Falk et al. 2015; Falk and Scholz 2018), perceived persuasiveness (Cacioppo et al. 2017),

[2] The phrase *cold start* has been used for situations where a system has to start making recommendations while knowing very little of the user (Schein et al. 2002).

and persuasion-induced behavior change (Cooper et al. 2018; Falk et al. 2010; Falk and Scholz 2018; Pegors et al. 2017; Vezich et al. 2017). Cardiovascular and electrodermal arousal can indicate the success of narrative persuasion, namely heart rate variability lowered and skin conductance level and the number of responses increased in persuaded participants (Barraza et al. 2015; Correa et al. 2015). Peripheral physiology can also reveal psychological reactance to a persuasive message (Lewinski et al. 2016; Sittenthaler et al. 2015; Spelt et al. 2019a), that is when a person becomes motivated to reject it.

Earlier findings by these authors (Spelt et al. 2020) indicate that assessing physiology during an attempt at persuasion even has merit for predicting behavior change in the near future, even when the characteristics of that specific individual are also considered: Variation in persuasion effectiveness is best explained with physiology and self-report measures combined. Thus, if this relationship also holds within individuals, the physiological reactivity to a particular message is informative about its likely success and suggests that this message could be used more often in order to persuade the user. Additionally, physiological activity during a persuasion attempt seems to be able to inform the system about the personality traits of the user (Spelt et al. 2019c): During persuasion attempts, electrodermal activity can be related to susceptibility to persuasion and smiling to extraversion. Also, physiology during persuasion attempts might indicate how much effort is needed to make that person reach the persuasion objective: Physiology in combination with persuasion effectiveness seems to reveal how well an attempt fits the person. That is if a user (repeatedly) shows more physiological activity during unsuccessful persuasion attempts advocating a certain goal than to other goals, this particular objective might be too misaligned with the user's motivations regarding that objective. In such a case, it may be advisable to adjust the persuasion objective towards the person's motivations. These types of information about the user might serve as input for the next reactivity adaptation step; *finding an appropriate persuasive message*.

7 Discussion

7.1 Implications of physiology-aware persuasive technology

Considering the above, physiology-contingent personalization of persuasion has several implications for persuasive systems design. The first and foremost advantage is that a physiology-contingent personalized and data-driven persuasive system may simply be a more effective persuasive system. Therefore, physiology-aware PT systems can support people in achieving their self-set goals better than normal PT systems. Not only is this pleasant for the user, but it can also relieve the burden on, among others, the healthcare system, in case of health-related coaching, or the earth's resources, in case of environment-related coaching. The reason for the increased effectiveness is that such a system is more user-centered by adapting to physiology and user-specific insights about that physiology. Because of the relationship between emotional and cognitive processes and peripheral physiology, the system responds to psychological processes by adapting to physiological processes. Therefore, physiology-aware

PT systems are perceived to have higher *emotional intelligence* than normal systems, defined as *"the ability to recognize, express and have emotions, coupled with the ability to regulate these emotions, harness them for constructive purposes, and skillfully handle the emotions of others"* (Pantic and Rothkrantz 2003, p. 1370). A technology has emotional intelligence when it can recognize and adapt to overt and covert states of a user (Pantic and Rothkrantz 2003; Picard 1995).

Other advantages come from the large amount of data physiological measurements yield, especially when compared to periodic self-report measures. Physiological measures have a high temporal resolution, making them sensitive to small changes in the persuasion process as well, thus potentially picking up information that would have been missed by traditional measures. This continuous flow of data enables that, in addition to making decisions based on existent knowledge, the system can also engage in data-driven approaches for decision-making. For example, pattern recognition by sophisticated algorithms could yield additional insights in persuasion in general, and for the specific user.[3] Approaches can be similar to classifying emotion from physiological measures using cross-validated linear discriminants (Agrafioti et al. 2012; Picard et al. 2001) or other methods as e.g. neural nets, fuzzy logic (Mandryk and Atkins 2007), temporal multimodal (Nakisa et al. 2020) or preference deep learning (Martinez et al. 2013). That is if during user-PT interaction certain patterns in physiology coincide repeatedly with specific events or patterns in behavior and/or context this suggests a connection worth investigating (in the general population). Thereby, these data-driven approaches might advance the field of persuasion[4] and Persuasive Technology. In that sense, physiological data not only improves the functioning of PT, but also the understanding of core mechanisms and assumptions of persuasion. The use of big data to gain insight into psychological processes is also known as psychological computing (see Zhang 2019 for a full explanation).

7.2 Limitations and future research

This paper aims to demonstrate the potential of physiological measurement to personalize PT systems. However, the work on the psychophysiology of persuasion and its use for PT is subject to limitations. Some limitations are inherently known in the related research fields, such as the multi-mapping problem in psychophysiology (see Sect. 4). We highlight limitations that specifically relate to research on the psychophysiology of persuasion.

Potential difficulties relate to the ability to establish a realistic persuasion process. Persuasion is known as a communicative process in which one person influences another (Perloff 2008). However, in the experiments that study physiology while simulating this process little of this intention remains: Psychophysiological studies ask for a

[3] Bearing in mind that (1) emotions and cognitions do not stand on their own, and thus additional information from self-report, context, or behavioral measures is needed to interpret physiological arousal as described in Sect. 5. Also, (2) these data-driven approaches are subject to bias, as they are often highly specialized to the data that is fed.

[4] Data-driven approaches might bypass shortcomings in existing knowledge. For example, current psychological models are descriptive in nature and fail to pinpoint underlying mechanisms of persuasion (Kitchen et al. 2014), because they lack temporal and spatial resolution (Zhang 2019).

rigid setup in an unnatural environment to ensure measurement reliability. Often these studies take place in a lab room using a bunch of sensors (e.g. Barraza et al. 2015; Correa et al. 2015) or an fMRI machine (Falk et al. 2011, p. e.g.; Vezich et al. 2017). Also, the manipulation may consist of timed persuasive stimuli and does not allow human-system communication. Although this rigid setup yields important advantages, such as reliable stimulus–response linking and assessing many physiological features at once, it might decrease the likelihood of persuading the participants. Future research into the psychophysiology of persuasion-related processes might benefit from creating a lifelike communicative experiment setting, perhaps with less restricting physiological sensors and a human persuader.

Participant recruitment affects the generalizability of the results. People often chose to participate in these studies voluntarily. Therefore, it could be that people participated because they were already interested in the topic. This might affect the generalizability of the results to people with other interests or motivations. Current findings primarily stem from studies examining health behaviors (Falk et al. 2015; Spelt et al. 2020; Vezich et al. 2017). These results might not be generalizable, as different behaviors are differently ingrained in our psychology and our physiology therewith. Persuasive attempts on for example meat consumption might yield different psychophysiological results as moral psychology is wired differently as health beliefs. Therefore, future research might benefit from persuading a diverse set of people over a range of behaviors or attitudes.

Other shortcomings relate to the common use of cross-subjects correlational analyses. Firstly, these relational tests assume a linear or monotonic relationship, whereas it could be that the psychophysiological relationship of interest is actually an alternative shape such as an (inversed) parabola (Aggarwal and Ranganathan 2016), similar to for example the hypnotized U-shaped relationship between self-value and neural activity (Bartra et al. 2013). Secondly, human processes are most likely non-ergodic[5] due to limitations in their individual variability. This impedes the generalizability of group results to individual cases ("ecological fallacy", Fisher et al. 2018). To circumvent this issue, psychophysiology researchers often employ multi-level models accounting for individual differences. This approach has, however, two shortcomings. First, the individual differences in the models are based on aggregated results (intercepts and slopes), instead of real individual variation (Molenaar 2005). Second, the results are obtained using group-models that accounted for individual differences, instead of individual models (Fisher et al. 2018). For the latter, some variables, such as subject as random effect, might be no longer relevant whereas other variables, such as time of the day, might be. Thus, results of psychophysiological studies become more meaningful when comparing the central tendency and variation of the intra- and inter-individual data sets as well as considering true individual variation (Fisher et al. 2018) using longitudinal studies. These limitations arise from reflections on current research. The psychophysiology of persuasion is a relatively new area of research in which much remains unclear.

[5] Ergodicity refers to the notion that the behavior in a subset of a dynamic system is approximately identical to the average behavior overall states that the system can be in (see Molenaar 2004 for a full explanation).

The main limitation of the model presented in this paper is therefore that—to date—only part of the presented model can be validated with existing publications. But although earlier findings cover only a small portion of the model, these initial results are compelling and encourage further research. Future studies might investigate if physiology can be used for the remaining steps of physiological reactivity adaptation (Fig. 2). It would be interesting if more studies could underline that *physiological reactivity links to the effectivity of the message* and that this assessment generates useful *user-specific knowledge* that can optimize future interactions. Also, the possibilities of physiological state adaptation and the interaction between the various types of adaptation might be interesting to explore. Furthermore, future field studies should validate if the psychophysiological relationships associated with persuasion are strong enough to use in real-life situations and withstand external interferences that influence physiology.

Research on physiology-aware persuasive technology systems is still in its infancy. A push in this area is expected considering ongoing technology developments in data-driven solutions, biosensors, and affective computing. Additional forces pushing PT development are people's tendencies towards personal information systems, the focus on user-centric design, and the need to relieve human suffering from detrimental behavioral patterns. With upcoming technological developments, it is only a matter of time before physiology is integrated into PT, but it is important to do this in a thoughtful, responsible way. An issue that needs clarification is whether PT systems that—in addition to self-report and behavior measures—also personalize on physiology are any better than traditional systems employing only self-report and behavior measures. Results from previous work as described in Sect. 6.2 suggest that physiology gives a real-time indication of whether persuasive information affects a person and can improve the prediction of persuasion effectiveness when added to self-report data. Further assessment of the added value of physiology-based adaptation to traditional personalization methods is an interesting direction for future research. The third area of uncertainty is the potential impact of such physiology-aware persuasive systems on humanity and society. Does physiology-aware persuasive technology make the world a better place? Is this a direction we want to go? These ethical aspects are discussed in the next section.

7.3 Ethics of physiology-aware persuasive technology

Physiology-aware PT promises to provide morally valuable benefits, such as reduction in the burdens of disease or increase in sustainable behavior. Along with these benefits, several potential ethical risks should also be highlighted and considered in the design of such PT systems. A growing literature discusses ethical issues surrounding PT (Berdichevsky and Neunschwander 1999; Davis 2009; Frank and Nickel 2017; Jacobs 2019; Smids 2012; Spahn 2012; Yetim 2011). In the future, other ethical considerations should also be evaluated in relation to physiological measurements, such as the effects of the system's costs on distributive justice (Smids 2018), the threat of deskilling (Frank 2020; Nickel 2012), the contribution to the moralization of health behaviors (Swierstra 2015; Swierstra and Waelbers 2012; Verbeek 2006), and the relation with user vulnerability (Jacobs 2019). The following is by no means an exhaustive account of the relevant ethical issues surrounding these technologies; rather we draw attention to two sets of concerns - user autonomy and trustworthiness - that are intensified with the use of physiology-aware PT.

Although ethics is discussed in the final section of this article, these considerations should take place at the beginning of an actual design process in order to construct PT that takes into account relevant values. The methodology of value-sensitive design is relevant, as it comprises an iterative design process that explicitly takes values and stakeholder concerns into the design process from the beginning (Friedman et al. 2002). Importantly raising questions about the potential ethical risks of using physiology-aware PT, does not mean that the status quo—less efficient PT—is not ethically problematic in and of itself.

7.3.1 Autonomy

For any PT—physiology-aware or not – the central ethical question has to do with autonomy (Smids 2018; Spahn 2012) and whether or not the behavior change they induce is voluntary (Smids 2012). Indeed, the most widely accepted definition of PT excludes the use of coercion or misinformation (Fogg 2003). The use of physiological data to persuade users at the right time, in the right way, and in an increasingly personalized manner can be understood as heightening the concerns about autonomy and voluntariness for at least two reasons: 1) Physiological data are more out of individual control than self-reports or behavior data. The user will not always, presumably rarely, be consciously aware of the physiological measurements being taken. Nor can the user reflect on and make decisions about the specific information that they want to feed into the physiology-aware PT after the initial adoption of the device. 2) In theory, physiological data can reveal the affective states of the user before or without the user being aware of it. Thus, potentially bypassing the user's conscious awareness of the states to which the PT is responding.

Informed consent is the standard way to ensure voluntary use of technology that collects a person's data and attempts to influence their behavior (White 2013). However, physiology-contingent adaptations challenge some of the traditional methods of obtaining and conceptualizing informed consent. To obtain morally justified consent, it must be specified exactly to which element of the PT a user is consenting. Jacobs (2019) points out four distinct elements of PT to which consent could apply: *"First, the goals and intended behavioral outcomes. Second, persuasive tools that a PT utilizes. Third, the types of individual interactions of the PT with the user. Fourth, the use and storage of data."*[6] (Jacobs 2019, p. 6). However, personalization, as a persuasive tool, is more prominent in physiology-aware PT compared to normal PT. The interactions between a PT system and the user are partially based on interpretations of automatic responses by the user. When signing the consent, the details of the interpretations are not yet clear. Even more importantly, physiology-aware PT systems are more likely to adopt deep learning approaches. As a result, the rules for personalization

[6] Physiological measurements produce, store, and analyze a large amount of personal data, some of it potentially sensitive, but this is not a unique privacy concern raised by physiology-aware PT.

might change as time progresses making one-time consents insufficient. The ethical and legal challenges of informed consent to artificial intelligent applications must be solved before such deep-learning approaches can be used in any type of PT system. Future research should indicate which alternative models of consent are most appropriate for physiology-aware PT systems, for example, dynamic consent (Kaye et al. 2015) or temporally distributed consent (Loosman 2020).

7.3.2 Reliability and trustworthiness

The reliability and trustworthiness of physiology-aware PT are of ethical concern because physiological data can be seen as a kind of biomedical data. Biomedical data, as well as the algorithms used for analysis, is perceived to be much more complex than what we humans can understand (Callebaut 2012, p. 70), and, thereby, rated as more objective, scientific, and closer to medicine (Crawford et al. 2014; Mittelstadt and Floridi 2016) than, for example, self-reports. The assumption is that these data represent an objective truth, without the need for human interpretation (Mittelstadt and Floridi 2016). In reality, all data undergoes various human-imposed transformations before interpretation,[7] such as noise elimination, filtering, sub-setting, et cetera. In the context of PT informed by physiology, the danger is that users may overestimate the reliability and objectivity of the technology by thinking that physiological assessment is error-free and free from interpretation.

Users tend to put trust in PT systems (Nickel 2012), as their functionalities are expected to contribute to their well-being. However, the complexity of physiology-based systems complicates user's perceptions of the system's trustworthiness in at least two ways: First, users may not understand the functioning of the system, its limitations, or capabilities. For example, which information can be derived from physiological data and how does this change the system's behavior? Users might lose confidence if they do not understand why something is measured or feel like the system is measuring more things than needed. Second, an issue of trust arises if users do understand the limitations of the system. To illustrate, complexity from the multi-mapping problem in psychophysiology (Cacioppo et al. 2007) can make the user wonder whether the psychophysiological interpretations obtained by the system are valid. The limitations of complex systems can make that the user wonder whether or not the system is adapting properly. Given that the precise psychophysiological relationship in persuasion is not yet established, we must consider whether or not and to what extent it is morally acceptable to draw inferences from these less-than-perfect representations of mental states (Fairclough 2009) and give feedback or attempt to persuade based on such representations. In either of the above scenarios, users may end up over-or under-trusting the system (Weitz et al. 2019). Both situations have costs: With over-trust, the user perceives the system as more accurate and persuasive than it is. This might result in being too confident in the functionalities of the system and not using his or her own resources, such as self-regulation or intrinsic motivation, to achieve the wanted change

[7] Which data is important differs depending on the question that needs to be answered (Mittelstadt and Floridi 2016) and on *"what data is recognized, how that data is collected, and by whom"* (Crawford et al. 2014, pp. 1669–1670). The rather complex processing of data limits the transparency of the operation of such technologies for a user.

in behavior. This is undesirable, as a PT can never fully understand the user and their context. Therefore, the user needs to keep ownership of their progression towards a certain goal. When users under-trust the system users may not take the system seriously. Perceived persuasiveness is lower than actual persuasiveness, which will make the user abandon the system. The risk here is that the user does not accomplish the self-set behavior goal.

The presence of these medical data issues and physiology-inference challenges does not mean that such a system should not be developed—future research might resolve some of these issues—but it does mean that physiology-aware PT is not error-free or without risks. Thus, without precautions and sufficient information, an attitude of blind trust towards physiology-aware PT is not justified. To ensure trustworthiness, PT systems should communicate their capabilities and limitations to the users. For this, we propose several options: (1) Explain the problem of unreliability of measurements and ambiguity of inferences before usage in the informed consent.[8] (2) Provide a real-time measure of unreliability to the user while using the system. (3) Enable the user to provide continuous feedback on the experienced relevance and correctness of the physiological inferences. And (4) show how physiological assessment increases the confidence of the system to guide you. Additionally, the system should convey which physiological features it measures, how these are interpreted, and in which system adaptations these interpretations result (Picard 1995). The user has to be aware of changing functionalities due to learning phases[9] and should be able to indicate their resilience against misclassifications. That way the user can know when the system is more or less reliable and decide whether that is desirable.

8 Conclusion

Persuasive technology (PT) can be used to help achieve behavior change. PT systems employ user models to enable the communication of "*the right message, at the right time, in the right way*" (Fischer 2001). While these user models normally are based on self-report and behavior measures, we described a model that allows a PT system to adapt its features to a person's physiological state and reactivity: Physiology-aware PT. Existing research suggests that physiology can hold information about persuasion-related processes: Physiological assessment gives a real-time indication of whether persuasive information affects a person and can significantly improve a prediction of persuasion effectiveness that is only based on self-report. Thereby, it can be a means to the personalization of persuasive technology.

As such, physiology-aware PT systems have the potential to support people better in their desired behavior change. As an important asset, physiology can be assessed in real-time with a high-temporal resolution, while the user does not have to take any

[8] Trust is related to explainability—if the system can be more explicit about why it gives certain recommendations, people may be able to better assess its recommendations in a given context, and may be able to better adjust the system settings or goals to fit their own needs and capabilities (Cutillo et al. 2020).

[9] Many recommender systems suffer from a cold start (Schein et al. 2002). Before a system can offer personalization based on user-specific (physiological) inferences, it needs a learning phase and a large amount of data. As a result, the system will have fewer functionalities when the user first adopts it.

explicit actions. The lack of user control or awareness, however, also might entail ethical objections, especially when used outside research in for example consumer products that use PT. Thus, further research is needed to develop physiology-aware PT systems that can help to change behavior that is detrimental to health, sustainability or leads to other negative effects.

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