
Volume 21, issues 1–2, January 2009
ISSN 0953-5438
ELSEVIER
BCS
Interacting with Computers
The Interdisciplinary Journal of Human-Computer Interaction
Double Special Issue:
Enactive Interfaces Edited by Chris Raymaekers
and Physicality & Interaction Edited by Devina Ramduny-Ellis, Alan Dix, Joanna Hare & Steve Gill
Available online at
ScienceDirect
www.sciencedirect.com

Interacting with Computers 21 (2009) 133–145

Contents lists available at ScienceDirect

Interacting with Computers

journal homepage: www.elsevier.com/locate/intcom

Fundamentals of physiological computing

Stephen H. Fairclough *

School of Natural Sciences and Psychology, Liverpool John Moores University, 5-21 Webster Street, Liverpool L3 2ET, UK

A R T I C L E I N F O

Article history:
Received 16 May 2008
Received in revised form 23 October 2008
Accepted 24 October 2008
Available online 8 November 2008

Keywords:
Physiological computing
Affective computing
Human factors
Psychophysiology
System adaptation
Intelligent systems

A B S T R A C T

This review paper is concerned with the development of physiological computing systems that employ real-time measures of psychophysiology to communicate the psychological state of the user to an adaptive system. It is argued that physiological computing has enormous potential to innovate human–computer interaction by extending the communication bandwidth to enable the development of 'smart' technology. This paper focuses on six fundamental issues for physiological computing systems through a review and synthesis of existing literature, these are (1) the complexity of the psychophysiological inference, (2) validating the psychophysiological inference, (3) representing the psychological state of the user, (4) designing explicit and implicit system interventions, (5) defining the biocybernetic loop that controls system adaptation, and (6) ethical implications. The paper concludes that physiological computing provides opportunities to innovate HCI but complex methodological/conceptual issues must be fully tackled during the research and development phase if this nascent technology is to achieve its potential.

1. Introduction

Communication between humans and computing systems may be described as purposeful and overt; the intentions of the user are relayed to the operating system via keyboard and mouse. This standard mode of human–computer interaction (HCI) is asymmetrical with respect to information exchange (Hettinger et al., 2003). In other words, the computer is capable of providing a wealth of information with respect to the internal state of the system (e.g., hardware capabilities, memory usage etc.), contrasting sharply with the paucity of data available to the computer about the psychological state of the user (e.g., cognitions, motivations and emotions). The absence of context provides little opportunity for the computer system to adapt in a dynamic fashion to the fluid, idiosyncratic needs of the user, a state of affairs that has led some to describe conventional HCI as two monologues rather than a dialogue (Norman, 2007). The realisation of a symmetrical HCI, where the computer system is aware of covert and overt behavioural cues from the user, is a prerequisite for the development of adaptive systems that are capable of responding to the needs of the user in real-time.

1.1. Physiological computing as a means of providing user context

Physiological computing represents an innovative mode of HCI where system interaction is achieved by monitoring, analysing and responding to covert psychophysiological activity from the user in real-time (Allanson, 2002; Allanson and Fairclough, 2004). These systems operate by transforming psychophysiological data into a control signal (or an input to a control signal) without a requirement for any overt response from the user (Byrne and Parasuraman, 1996). Physiological computing captures spontaneous and subconscious facets of user state, opening up bandwidth within the HCI by enabling "an additional channel of communication from the user to the computer, albeit a largely unconscious one" (Hettinger et al., 2003, p. 228). In this way, information exchange between human and computer is rendered symmetrical as the physiological computing system constructs, consults and responds to a dynamic representation of the user.

The next generation of 'smart' technology will be characterised by increased autonomy and adaptive capability (Norman, 2007). Smart technology covers a range of application domains, such as: adaptive automation on the flightdeck or in the vehicle, robotics, telemedicine, computer-based learning, domestic systems, computer games, computerised control of the ambient environment (See Norman (2007) for further examples). These 'smart' systems must be capable of responding proactively and implicitly, e.g., ambient intelligence (Aarts, 2004). For example, to activate an auto-pilot facility or intelligent cruise control system in order to reduce the mental workload of the pilot/driver without jeopardising safe performance, or to activate context-specific help information if a user is frustrated by a task or interface, or to make the computer game more challenging if the player is bored. The physiological computing approach provides one means of monitoring, quantifying and representing the context of the user to the system in order to enable proactive and implicit adaptation in real-time. This approach delivers not only a means of monitoring the user,

* Tel.: +44 0 151 2314199; fax: +44 0 151 2314245.
E-mail address: s.fairclough@ljmu.ac.uk

0953-5438/$ - see front matter
doi:10.1016/j.intcom.2008.10.011

but also a method for assessing the impact of an adaptive response on the user. This reflexive quality of physiological computing provides a means by which the system may 'fine-tune' an adaptive response to the preference of the individual user. Physiological computing does not only enable a computer system to adapt in a 'smart' way, it also provides a means by which the system can learn about the preferences of the user. As technology develops in this direction, the interaction between users and machines will shift from a master–slave dyad towards a collaborative, symbiotic relationship that requires the computer to extend awareness of the user in real-time (Klein et al., 2004; Pantic et al., 2007).

Each interaction between person and computer is characterised by unique properties generated by a wide range of influences (e.g., the person, the system, the environment). The purpose of dialogue design is to create an optimal interface with respect to maximising performance efficiency or safety, which represents a tacit attempt to "standardise" the dynamic of the HCI. Similarly, human factors and ergonomics research has focused on the optimisation of HCI for a generic 'everyman' user. Physiological computing represents a challenge to the concepts of a standard interaction or a standard user. Interaction with a physiological computing system contains an improvisatory element as both user and system respond to feedback from the other in real-time. In addition, physiological computing interactions are tailored to the specific individual in a defined place at a precise time. This shift from the general to the specific attributes of the user has been called individuation (Hancock et al., 2005), which is "directed to explore ways through which each and every individual can customize his or her tools to optimize the pleasure and efficiency of his or her personal interaction" (p. 12).

1.2. Applications of physiological computing

Physiological computing systems may be designed to promote performance efficiency (by monitoring cognitive psychophysiology) or to maximise the pleasure associated with HCI (by monitoring affective psychophysiology). For example, recording continuous signals from the electroencephalogram (EEG) has been used to control adaptive automation in laboratory-based studies (Bailey et al., 2006; Freeman et al., 1999, 2000; Pope et al., 1995; Prinzel et al., 2003, 1995). In this case, automation was activated only when EEG signals from the operator indicated engagement with the task; if the person disengaged from the task, automation was deactivated and the operator was forced to re-engage with task activity via manual control. A similar approach was demonstrated by Wilson et al. (2007) using EEG in combination with a number of autonomic variables (e.g., heart rate, respiration rate) to characterise the mental workload of the operator. This system used an artificial neural net to categorise the level of mental workload and to automate elements of the task when the operator was assessed to be in a state of "overload." Wilson et al. (2007) reported substantial improvements of performance when adaptive automation was controlled by psychophysiology. The physiological strand of affective computing research (Picard, 1997) draws from original experiments on the psychophysiology of emotion (Cacioppo et al., 1993), where emotions are induced in a laboratory and the resulting psychophysiological changes used to classify distinct emotional states, e.g., anger, happiness, sadness, surprise. A number of studies purposefully degraded the quality of the HCI in order to induce and to detect negative user emotions using psychophysiology (Partala and Surrakka, 2004; Scheirer et al., 2002; Ward and Marsden, 2003). The detection of negative emotions may be particularly relevant for computing applications designed to aid learning (Picard et al., 2004), i.e., to offer assistance when negative emotions are detected. Research on affective computing has also explored how psychophysiological activity from the user may be used to inform the response of an interactive agent or avatar within the context of a telemedicine application (Lisetti et al., 2003). This is a particularly interesting application area as physiological signals may also be used for rudimentary medical monitoring, e.g., blood pressure, heart rate, body temperature. It has been suggested that psychophysiology is used alongside other indicators (facial expression, verbal expression, haptic measures) to generate empathetic avatars as well as providing a diagnosis of the patient's emotional state for the benefit of a physician (Lisetti and LeRouge, 2004; Lisetti et al., 2003). Psychophysiology has been used to objectively evaluate cognitive activity (Yamada, 1998), emotional responses (van Reekum et al., 2004) and cognitive-emotional states (Mandryk and Atkins, 2007) during interaction with computer games. This application of physiological computing is directly relevant to hedonomics (Hancock et al., 2005; Helander and Tham, 2003), i.e., designing technology that maximises the enjoyment and pleasure experienced by the user. For example, detection of player frustration due to the experience of repeated failure might lead to automated assistance or a downward adjustment of game difficulty (Gilleade and Dix, 2004; Gilleade et al., 2005). Similarly, Rani et al. (2005) used a range of psychophysiological measures to index anxiety and adapted a Pong game to respond accordingly, i.e., the game was made easier in response to the detection of high anxiety and vice versa. Physiological computing represents a conduit for existing research on affective computing (Picard, 1997) and the emerging area of hedonomics (Hancock et al., 2005; Helander and Tham, 2003) as researchers in both domains use psychophysiology to index and enhance the positive emotional experiences of computer users.

An argument has been made that psychophysiological measures may be insufficient for the recognition of internal psychological states, such as emotions, due to (1) the absence of sufficient correspondence between the experienced state and associated physiological changes, (2) the enormous range of psychological states cannot be represented by physiology, (3) the lack of clear differentiation between psychological states, and (4) the variable and idiosyncratic experience of psychological states (see Picard (2003) for further detail and discussion of this point). One fundamental problem for psychophysiology is the complex relationship between experienced states and their expression via the central nervous system; this issue is discussed in detail in Section 2.1. This issue is occasionally confused by those outside of the discipline who believe that psychophysiological measurement provides a literal, isomorphic representation of a given thought, intention or emotion. This is not so; psychophysiological measures represent an operationalisation of internal states, the quality of which may vary from measure to measure, and between different states. If we accept that psychophysiology provides a less-than-perfect representation of internal states, the important question is this: are psychophysiological operationalisations of internal psychological states sufficiently sensitive and diagnostic to realise this category of technology? Questions surrounding the adequacy of psychophysiology as a basis for adaptive technology must be considered in the context of a specific application and a defined range of function.

1.3. Biocybernetic adaptation

The biocybernetic loop (Pope et al., 1995) is the core component of a physiological computing system. The loop functions as a conceptual entity derived from control theory (Wiener, 1948) that also describes the flow of data within the system. The loop is initiated by the collection of psychophysiological data from the user via ambulatory (Wilhelm, 2002), remote (Anttonen and Surakka, 2005) or wireless (Strauss et al., 2005) sensors. These data are filtered and quantified to operationalise relevant psychological constructs, e.g., frustration, user engagement, alertness. The system subsequently analyses these data in order to quantify or label the state of the user. An assessment of user state may be made with reference to absolute (e.g., heart rate exceeds 80% of normal baseline) or relative criteria (e.g., heart rate has risen 20% since the previous data collection epoch); alternatively, the assessment provided by the system may be categorical in nature (e.g., pattern of heart rate activity and skin conductance level indicate that the person is in a negative rather than a positive emotional state). This assessment may be achieved via the development of discriminant algorithms (Liu et al., 2005) or neural networks (Gevins et al., 1998; Laine et al., 2002). The magnitude of change or specific label applied to the user representation determines an appropriate response from the adaptive system. For example, the detection of frustration may prompt the system to provide help information. The final stage of the loop is represented by any second-order change in user state that may occur in response to system adaptation and elicit a second-order response from the system and so on.

The functional goal of the biocybernetic loop is to derive real-time adaptations to cognitions, motivations and emotions that appear both timely and intuitive from the users' perspective. The loop may be designed to detect and respond to undesirable user states (e.g., frustration, anxiety, cognitive disengagement). The adaptive response of the system to an undesirable user state may be grouped into three broad categories (Gilleade et al., 2005):

(a) By offering *assistance* if the user is frustrated (Gilleade and Dix, 2004; Kapoor et al., 2007; Partala and Surrakka, 2004; Scheirer et al., 2002) or in a state of "stuck" (Burleson and Picard, 2004) or unable to perform the task due to excessive mental workload (Wilson, 2003).
(b) By adapting the level of *challenge* to sustain or increase task engagement if the user is bored or demotivated by the task (Rani et al., 2005; Scerbo et al., 2003).
(c) By incorporating an *emotional* display element into the user interface to reinforce positive emotions and mitigate negative emotions (Ahn et al., 2007; Klein et al., 2002; Lisetti and LeRouge, 2004; Prendinger et al., 2005).

Physiological computing has the potential to extend the communication bandwidth of HCI and enable a dynamic, individualised dialogue between user and system, however, research remains at an early stage and faces a number of obstacles. The purpose of this paper is to outline a number of high-level issues for future research via a review and synthesis of existing research. This review is not concerned with low-level fundamental issues surrounding physiological computing, such as: signal normalisation, baselining and correcting for individual differences. Interested readers are referred to Picard (1997) and Picard et al. (2001), Allanson and Fairclough (2004), or Mandryk et al. (2006) for discussion of these issues.

2. Fundamental issues

The development of physiological computing remains at an early stage and research efforts converge on a number of fundamental issues. The purpose of this section is to articulate issues that have a critical bearing on the development and evaluation of physiological computing systems.

2.1. Psychophysiological inference

The complexity of the psychophysiological inference (Cacioppo and Tassinary, 1990; Cacioppo et al., 2000) represents an obstacle for the design of physiological computing systems. The rationale for the biocybernetic loop rests on an assumption that the psychophysiological measure (or array of measures) is an accurate and sensitive representation of a relevant psychological element or dimension, e.g., frustration, task engagement. This assumption is often problematic because the relationship between physiological measures and psychological meaning is complex.

2.1.1. Mapping physiological measures to psychological states

Cacioppo and colleagues (1990, 2000) described four possible categories of relationship between physiological measures and psychological elements:

- One-to-one (i.e., a physiological variable has a unique isomorphic (i.e., one-to-one) relationship with a psychological element).
- Many-to-one (i.e., two or more physiological variables are associated with the relevant psychological element).
- One-to-many (i.e., a physiological variable is sensitive to one or more psychological elements).
- Many-to-many (i.e., several physiological variables is associated with several psychological elements).

The unique one-to-one relationship between psychology and physiology is ideal for biocybernetic control but instances of isomorphic correspondence that have been fully tested in the field as well as the laboratory are very rare in the psychophysiological literature relative to the three remaining categories. In the many-to-one case, an investment of mental effort for example, may be only be fully represented by a psychophysiological response pattern that incorporates several measures, such as: cortical activity from the frontal lobes (Smith et al., 2001), increased systolic blood pressure (Richter and Gendolla, 2006) and changes in heart rate variability (Fairclough et al., 2005). This pattern is inverted in the one-to-many relationship, e.g., systolic blood pressure may increase when a person is excited, frustrated or stressed (Cacioppo and Gardner, 1999). In the many-to-many case, a mixture of increased mental effort and stress may combine to exert multiple, overlapping paths of influence over both systolic blood pressure and heart rate variability.

2.1.2. The specificity of the psychophysiological inference

These mappings between physiological measure and psychological constructs describe the one aspect of the psychophysiological inference, but the relation between physiology and psychology can also vary in terms of specificity and generality (Cacioppo and Tassinary, 1990; Cacioppo et al., 2000). For example, a laboratory experiment designed to elicit task engagement may reveal a series of physiological changes, e.g., increased systolic blood pressure, increased heart rate, increased respiration rate, elevated skin conductance. This many-to-one relationship may be described as an *outcome* relationship, i.e., there is a basic association between a pattern of physiological change and increased task engagement in that specific laboratory situation. If we investigate this relationship further by running a further series of experiments in the laboratory (i.e., using different ways to engage the participant such as raising task difficulty or offering cash incentives), we may find that increased systolic blood pressure is the only physiological variable that responds to increased task engagement across all manipulations. This context-specific, one-to-one *marker* relationship describes the unique isomorphic relationship between blood pressure and task engagement in the laboratory. If we performed a different series of experiments to investigate anger, we may induce anger in the lab and subsequently study the experience of anger in the field by asking participants to wear ambulatory monitoring apparatus whilst reporting episodes of anger in a diary. If we uncovered a core set of variables, e.g., elevated skin conductance, increased respiration, increased heart rate, associated with the experience of anger in both the laboratory and the field, this context-independent, many-to-one relationship would be described as a psychophysiological *concomitant*. It is important that candidates for physiological computing attain this level of specificity and are transferable between the laboratory and the field. The highest level of psychophysiological specificity is described by an *invariant* relationship where we have an isomorphic (one-to-one) relationship that is independent of the testing context, i.e., elevated blood pressure is associated with task engagement but not anger regardless of whether this relationship is tested in the laboratory or the field.

2.1.3. Implications for physiological computing

The implications of this analysis for the design of physiological computing systems should be clear. The one-to-many or many-to-many categories that dominate the literature represent psychophysiological links that are neither exclusive nor uncontaminated. This quality is captured by the *diagnosticity* of the psychophysiological measure, i.e., the ability of the measure to target a specific psychological concept and remain unaffected by related influences (O'Donnell and Eggemeier, 1986). It is important that biocybernetic control or adaptation is based on a psychophysiological inference that is sufficiently diagnostic. For example, imagine an auto-tutoring system that relies on systolic blood pressure to infer frustration levels and offers assistance as an adaptive response. Feelings of frustration or anger increase blood pressure (Bongard and Al'Absi, 2005) but increased systolic blood pressure may also represent a state of positive challenge (Gendolla and Richter, 2006), e.g., a one-to-many relationship. This many-to-many linkage may cause the system to inadvertently offer help when the learner is positively engaged with the task.

Whilst it is important to maximise the diagnosticity of those measures underlying a physiological computing system, it is difficult to translate this general requirement into specific guidelines. The requisite level of diagnostic fidelity required for physiological computing will vary for different systems. For example, is the system required to distinguish gross difference between anger and happiness or stress and relaxation? Or does the system require a finely tuned diagnosis between states of anger and fear or stress and excitement? Alternatively, the system may be required to differentiate four distinct states (happiness, sadness, tiredness, alertness), which could be assessed absolutely (with reference to a 'neutral' state) or relatively with reference to one another, i.e., happiness vs. sadness, tiredness vs. alertness. It is essential for the system designer to define the requisite level of diagnostic fidelity before choosing which psychophysiological measures should be incorporated into the system.

The *sensitivity* of the psychophysiological inference is a vital attribute to enable a physiological computer system to respond in a timely and appropriate fashion to changes in user state. Sensitive variables are those that are capable of differentiating meaningful levels along a psychological dimension, i.e., to distinguish low levels of frustration from high levels of frustration (a two-class problem) or discriminate between low, medium, high and extremely high levels of frustration (a four-class problem). The sensitivity criterion (O'Donnell and Eggemeier, 1986) refers to the level of correspondence between psychophysiological reactivity and fluctuations along a psychological dimension. This criterion is particularly important for physiological computing systems designed to respond to a single psychological continuum, e.g., Wilson and Russell (2007) on mental workload. The sensitivity of the psychophysiological inference captures a complex relationship between the physiological reaction, the relationship of that reaction to an underlying psychological dimension and the temporal relationship of both to the response from the system. In terms of design, it is important to establish the range of response that may be meaningfully expressed by the psychophysiological inference. For example, if the response of the corrugator muscle of the face is used to index negative affect (Larsen et al., 2003), can this response be classified to distinguish between high and low levels of negative affect? Or is it possible to classify the response of the corrugator muscle on a finer level of detail, to distinguish between low and medium and high levels of negative affect?

With respect to the generality of the psychophysiological inference, it is important for the relation between psychological construct and physiological measure to be consistent with respect to inter- and intra-individual differences, i.e., the relationship must hold across individual users and across individual sessions. This aspect of the psychophysiological inference is captured by the *reliability* criterion (O'Donnell and Eggemeier, 1986). One important feature that distinguishes an outcome/marker from a concomitant/invariant relation is the consistency of the psychophysiological inference across laboratory and field settings; this is a particularly important measurement criterion for psychophysiological candidates to achieve if they are to be used as part of real-time adaptive system in a work or domestic environment.

Both diagnosticity and sensitivity define the precision of the psychophysiological inference; reliability captures the generality of this relationship across people, sessions and environments. These measurement characteristics also determine the accuracy of user representation that lies at the heart of the biocybernetic loop. Furthermore, it is the fidelity of the user representation that effectively defines the maximum number of levels or modes of adaptive response that a system can deliver to the user (see Section 2.3 for further discussion of this point).

2.2. Psychophysiological validity

Once levels of diagnosticity, sensitivity and reliability have been defined for any given system, the designer must develop a protocol to validate the psychophysiological inference. Validating the inference is important during the early phase of system development. As a first step, careful selection of psychophysiological variables based on a review of existing literature should ensure a degree of content validity, i.e., that a precedent exists (theoretically or experimentally) for specific variables to tap those psychological constructs targeted by the system designer. The next stage is to establish the concurrent validity of the psychophysiological inference. Concurrent validity represents the degree to which a particular psychophysiological measure (or groups of measures in a many-to-one case) can be demonstrated to predict the target psychological element or dimension. Testing this relationship is important because the designer must have confidence in the psychophysiological inference in both a general and a specific sense. With respect to the latter, the designer should establish the reliability of the psychophysiological inference across a range of representative test conditions (e.g., high vs. low levels of operator stress), test environments (laboratory vs. field) and individual differences within the desired population.

2.2.1. Validating psychophysiological states via exposure to media

Psychophysiological validity may be tested under laboratory conditions where the state of the user is manipulated by exposure to emotional media, for example: movie clips (Lisetti and Nasoz, 2004), music (Etzel et al., 2006) and standardised media such as the International Affective Picture System (IAPS) (Lang et al., 2005). The latter has been used by Haag et al. (2004) to induce changes in valence as well as activation associated with emotion. It is important to have confidence that the selected media clips have a strong link with desired emotional states. The IAPS, with its long and proven research record, is the strongest candidate in this respect; all 956 IAPS images have been rated by 100 adults (half female) to generate normative scores for both valence (happy–sad) and activation (alert–tired). This approach is flawed in the sense that it is essentially a passive experience for the participant and the emotional experience may not generalise to active tasks such as interacting with a computer system.

2.2.2. Validating psychophysiological states with experimental tasks

In order to examine psychophysiological relations with active behaviour, researchers have used standardised tasks adapted from experimental psychology (e.g., mental arithmetic, problem-solving) or task manipulations with "known" consequences. With respect to the former, participants have been asked to solve anagrams of increased complexity (Rani et al., 2003) in order to induce anxiety. Others have adopted applied tasks such as computer-based problem-solving and introduced a manipulation intended to frustrate the participant, such as a delay in the mouse response (Partala and Surrakka, 2004; Scheirer et al., 2002) or requesting participants to re-enter information during a form-filling exercise (Dennerlein et al., 2003). Like the preceding category, these types of manipulations are dependent on strong and unambiguous linkage between the task manipulation and the target psychological construct in order to be effective. For example, a mouse delay during a problem-solving task is obviously frustrating because this kind of error threatens the ability of the person to perform the task, however the link between solving anagrams and anxiety inducement is perhaps more tenuous. Experimental manipulations with known outcomes have been employed that closely correspond to real-life situations. For example, Ward and Marsden (2003) compared the psychophysiological responses to poorly designed and well-designed versions of the same webpage; Mandryk and Atkins (2007) used psychophysiology to distinguish between competition with a friend vs. competition with a stranger during a computer game. These realistic manipulations are laudable from the perspective of ecological validity (i.e., the correspondence between test conditions and real-life situations), however, the absence of experimental control may make it difficult to assess which psychological construct is being captured by these manipulations, i.e., several psychological constructs could play an influential role when we play a computer game against a stranger as opposed to a friend (self-consciousness, ego-threat, extrinsic motivation, anxiety).

2.2.3. Validating psychophysiological states using subjective measures

Subjective self-report measures are collected as manipulation checks in order to demonstrate the effectiveness of the experimental manipulation. The association between subjective self-report variables and psychophysiological measures is also used to index concurrent validity. This is a logical approach since the private psychological experience of the individual is the target variable for the biocybernetic loop and self-report data capture is the obvious candidate to capture subjective experience. However, this link is often problematic as subjective self-report measures are based on a conscious act of introspection whereas the psychophysiological response reflects the influence of both conscious and unconscious processes. Subjective self-report is also prone to bias due to personality or memory limitations (Nisbett and Wilson, 1977; Villon and Lisetti, 2006), and the correspondence of these measures with psychophysiological activity is often erratic (Cacioppo et al., 1993). Despite these disadvantages, subjective self-reports represent the best available approximation of the private experience of the individual (see Section 2.5), but establishing concurrent validity in this way runs the risk of (a) interfering with the target behaviour by expecting participants to self-report, (b) creating physical artifacts in the psychophysiological data record, and (c) 'blunting' the sensitivity of the psychophysiological response by only studying the correspondence between physiology and those psychological states that may be consciously verbalised or recorded.

2.2.4. Validating psychophysiological states using observable behaviour

The validity of the psychophysiological inference may also be tested with recourse to another category of data collection besides subjective self-report; this tactic represents the establishment of concurrent validity with reference to other dependent behavioural variables. One approach is to validate the inference by measuring the relationship between psychophysiology and overt, behavioural markers. As psychophysiological variables seek to represent private psychological events, a number of overt markers may be used to operationalise the same target psychological state. For example, facial expressions may be observed and coded into distinct categories of emotion, and the ability of the psychophysiological variable to predict group membership employed as an index of concurrent validity. Similarly, observable behavioural expressions such as fidgeting, head shakes (Kapoor et al., 2007), changes in body posture (Mota and Picard, 2003) or pressure exerted to manipulate input control devices (Dennerlein et al., 2003) could be used as independent indicators of user state for the purposes of validation. This approach is hindered by the fact that that psychophysiological change may occur in the absence of any corresponding expression of overt behaviour. In addition, when behavioural markers do occur, they may represent discrete and sporadic events that occur at low level of temporal fidelity relative to psychophysiological data.

2.2.5. The challenge of psychophysiological validity

The establishment of concurrent psychophysiological validity represents a significant challenge for the development of a physiological computing system because there is no "gold standard" or "ground truth" to establish the psychophysiological inference. In addition, there are several possible routes by which the researcher can assess psychophysiological validity, which suffer from similar flaws (a) mood induction by media or standard task may be context-specific and not generalise to other task contexts or different participant population, (b) the specific technique used to induce a particular user state is often incorrectly identified with generic user states, e.g., frustration in response to a demanding maths test may not be synonymous with frustration due to a delayed mouse response or a poorly designed web page, and (c) "black box" approaches, such as neural networks and decision trees are often reported as successfully differentiating generic emotional states; what these algorithms actually do is successfully distinguish between a range of experimental manipulations, which may be context-specific and grossly dissimilar.

The 'titration' procedure described by Wilson and Russell (2007) offers an alternative approach whereby participants were exposed to a wide range of task demands (from simple to extremely difficult) prior to taking part in the experiment. The authors captured a subjective rating of difficulty from each participant to each level of task demand (from easy to impossible) and then used these ratings in order to define easy/medium/hard/impossible levels of task demand for that particular individual. The 'titration' approach involves using subjective self-reports in order to personalise and standardise the experience of each individual participant. This approach may not be possible for all types of manipulation but it has the advantages of testing and tailoring the effectiveness of the task manipulation or mood induction to each individual prior to validation.

2.3. The representation of the user

Once psychophysiological validity has been established, the designer may consider how the psychological state of the user should be operationalised by the system. This is an important aspect of system design that determines the range of adaptive strategies available to biocybernetic loop, and ultimately, the level of "intelligence" exhibited by the system.

The biocybernetic loop encompasses the decision-making process underlying software adaptation. In its simplest form, these decision-making rules may be expressed as simple Boolean statements; for example, IF frustration is detected THEN offer help. The loop incorporates not only the decision-making rules, but also the psychophysiological inference implicit in the quantification of those trigger points used to activate the rules. In our study (Fairclough et al., 2006) for example, this information took the form of a linear equation to represent the state of the user (e.g., subjective mental effort = x_1 * respiration rate – x_2 * eye blink frequency + constant) as well as the quantification of trigger points, e.g., IF subjective effort > y THEN adapt system. Other studies have also used linear modelling techniques and more sophisticated machine learning approaches systems to characterise user state in terms of the psychophysiological response, e.g. (Liu et al., 2005; Mandryk and Atkins, 2007; Rani et al., 2002; Wilson and Russell, 2003).

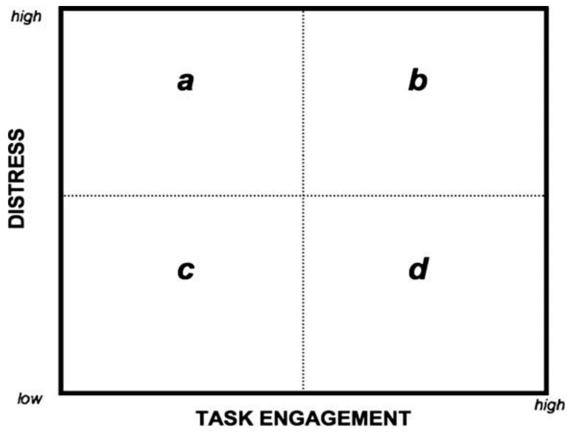

Fig. 1. Two-dimensional representation of psychophysiological state of the user.

2.3.1. The complexity of the user representation

The psychological state of the user has been represented as a one-dimensional continuum, e.g., frustration (Gilleade and Dix, 2004; Kapoor et al., 2007; Scheirer et al., 2002), anxiety (Rani et al., 2005), task engagement (Prinzel et al., 2000), mental workload (Wilson and Russell, 2007). Other research has elected to represent user state in terms of: distinct categories of emotion (Healey and Picard, 1997; Lisetti and Nasoz, 2004; Lisetti et al., 2003), two-dimensional space of activation and valence (Kulic and Croft, 2005, 2006) and distinct emotional categories based upon a two-dimensional analysis of activation and valence (Mandryk and Atkins, 2007) As stated earlier, reliance on a one-dimensional representation of the user may restrict the range of adaptive options available to the system. This may not be a problem for simple system adaptation, but complex systems will require an elaborated representation of the user in order to deploy a large repertoire of adaptive responses.

One straightforward way of moving beyond a one-dimensional representation of the user is to model psychological state in two-dimensional space, e.g., Mandryk and Atkins (2007). Matthews and colleagues at Dundee University developed a subjective tool called the Dundee Stress State Questionnaire (DSSQ) to assess three meta-factors linked to cognition, motivation and emotion (Matthews et al., 2002). It has been suggested that two DSSQ factors, Task Engagement and Distress, could be combined to create a generic representation of the user state (Fairclough, 2007; Fairclough and Venables, 2006). Task Engagement was defined as an "effortful striving towards task goals", which increased during a demanding cognitive task and declined when participants performed a sustained and monotonous vigilance task (Matthews et al., 2002). The Distress meta-factor was characterised by "an overload of processing capacity" which increased when participants experienced a loss of control over performance quality (Matthews et al., 2002). The combination of engagement and distress permits us to consider the state of the user as a point in the two-dimensional space shown in Fig. 1.

Fig. 1 partitions the psychological state of the user in four quadrants or 'zones'. This analysis is similar to Csikszentimihalyi's (1990) concept of flow states, particularly zone *b—the* stretch zone. Zone *a* represents an undesirable state of high distress in combination with low task engagement. In this case, the user is overloaded from a cognitive perspective as well as being disengaged from the task. When engagement and distress are both high (zone *b*), users occupy a "stretch" zone, remaining highly engaged but also feeling overwhelmed by the task. This state may tolerated for short periods, particularly during a learning phases or a demanding but rewarding period of performance. In zone *c*, the user is fundamentally bored as indicated by low levels of distress and engagement. The user may disengage from the task due to disinterest if this state persists for a sustained period. When the user is comfortable with the level of demand yet remains motivated by the task, they fall into zone *d* (low distress and high task engagement). This state may subside into boredom (zone *c*) if the task lapses into monotony or give way to a learning phase (zone *b*) if demand increases appropriately. This two-dimensional representation (Fig. 1) allows the adaptive controller to make a distinction between two states of low engagement, both of which require different categories of adaptive response, e.g., in zone *a*, task demand should be reduced or the adaptive aiding provided whereas zone *c* may require task demand to be increased. This complex representation of the user provides the adaptive controller with greater specificity in order to target the adaptive response.

2.3.2. Multimodal representation of the user

Measures from other available sources, such as performance, may be amalgamated with psychophysiology to increase the complexity of the user representation. This multimodal representation of the user may be achieved by combining the psychophysiological characterisation of user state with a representation of progress within the "task-space" or "problem-space." This representation provides a useful context for the diagnosis of user state produced by psychophysiological monitoring that may be expressed in a simple or complex fashion. For an auto-tutoring system, the system may simply monitor user progress through a problem space by capturing time spent on each sub-task compared to a normative database. Alternatively, a complex and generic representation of "task-space" may be adopted to deliver a sophisticated representation of task context. An existing model of mental workload (Hancock and Caird, 1993) is used to illustrate this point. This model provides a two-dimensional representation of mental workload (1) distance from the desired goal and (2) time remaining to complete the desired goal. Like the scheme illustrated in Fig. 1, this two-dimensional space may be expressed as four quadrants with one section that is inherently undesirable (high distance from goal, low time remaining). An assessment of psychophysiological state (Fig. 1) in combination with a sensitive representation of task space provides a rich representation of the user state in the context of performance. The combination of psychophysiology and observable behaviours used by Kapoor et al. (2007) to index frustration provides a nice example of the same approach where behavioural markers (fidgeting) are reinforce a psychophysiological diagnosis (in effect, this is the same strategy as using dependent variables as a source of concurrent validity described in Section 2.2.4). If we extend the number of variables or dimensions used to represent the user, we gain a more complex representation of the HCI. This complexity is inherently beneficial provided that the system can deal with dissociation between different measures that becomes increasingly likely if the number of data capture channels are increased.

Early examples of physiological computer systems will rely on one-dimensional representations of the user and be capable of relatively simple adaptive responses. The full potential of this technology will only be realised when systems draw from an extended repertoire of precise and timely adaptations. It is anticipated that timeliness and sophistication of the adaptive response will be perceived by the user as the level of "intelligence" exhibited by the system. Furthermore, the precision and intricacy of the user representation delivered by the monitoring technology will determine the adaptive capability of the system as a whole.

2.4. Awareness and interaction design

2.4.1. Self-awareness vs. the computerised representation of self

Physiological computer systems operationalise the psychological state of the user by monitoring and analysing psychophysiology in real-time. This approach represents a machine analogue of the neurological process of interoception (Cameron, 2001; Critchley, 2004) whereby autonomic responses to cognitive or emotional stimuli generate the expression of feelings and emotions in the brain (Churchland, 2002; Damasio, 1999). Psychophysiological data is analysed along parallel tracks by the person and the machine during an interaction with a physiological computing system. In the first case, this is an inherently fuzzy process wherein physiological activity provides one source of data input among others (e.g., context, beliefs) and expression of these data with respect to self-awareness is vulnerable to the vagaries of self-perception and selective attention (Craig, 2004; Critchley et al., 2004; Dolan, 2002). By contrast, the adaptive controller subjects physiological data to an explicit collection of mathematical procedures in order to generate an objective, tangible representation of a psychological concept or dimension.

2.4.2. Perceptions of system error

It is unsurprising that computerised assessment of psychophysiological activity will differ markedly from human perception of the same activity. The significant issue for physiological computing is how divergent appraisals of the same activity influence users' perception of system accuracy. High levels of accuracy are critical attributes for the acceptance of physiological computing systems, given that this technology seeks a degree of autonomous functionality as well as access to a private and personal data (see Section 2.6). The perception of accuracy is an important determinant of system reliability that influences the level of trust in an adaptive system (Lee and See, 2004; Muir and Moray, 1996; Parasuraman and Miller, 2004). Mismatches between user and system perceptions of psychological state may fall into one of two categories (1) a 'false alarm' when the system detects a specific state or a change of psychological state that is imperceptible to the user and (2) a 'miss' when the system fails to detect a state or change in a state that has been perceived subjectively by the user. Both types may undermine the credibility of the system, but false alarms are potentially the most pernicious, particularly if their occurrence leads to unwelcome or inappropriate adaptation at the interface.

A physiological computing system is capable of delivering two categories of adjustment at the interface, explicit and implicit adaptations, which occur, respectively, in the attentional foreground and background (Ju and Leifer, 2008). Explicit system adaptations are consciously registered by the user. The appearance of an avatar offering help information is a source of conspicuous feedback that the system has detected a degree of distress or confusion or that the user is in a state of 'stuck' (Burleson and Picard, 2004). Instances of implicit adaptation may not be consciously registered by the user. These adaptations may be subtle, such as adjusting an aspect of the visual display or may be completely undetectable (e.g., updating software without any feedback to the user): this category of implicit adaptation is characteristic of so-called 'calm' technology (Weiser and Brown, 1997) and ambient intelligence (Aarts, 2004).

2.4.3. Explicit and implicit system adaptation

The delivery of explicit adaptation from a physiological computing system will often prompt an act of introspective self-assessment. The appearance of an avatar to offer assistance might incline the user to ponder "am I stuck?" or "do I need help?" The results of self-examination is compared to the diagnosis of the system, which yields either affirmation or a false alarm in the case of disagreement. This tendency of explicit adaption to prompt self-appraisal creates an enormous potential for false alarms, particularly because this type of system is capable of high-fidelity monitoring, i.e., where system diagnoses are relatively frequent and even a small false alarm rate may translate into a large absolute number of misdiagnoses (Parasuraman and Hancock, 1999). The size of this problem may be curtailed by designing explicit adaptations to intervene in an infrequent basis or in a relatively conservative fashion. On a positive note, the presentation of explicit adaptation has a potential advantage of entraining the user and enhancing self-awareness of moods, emotions and other psychological states (Picard and Klein, 2002). There is also some evidence that explicit feedback based on psychophysiology may function as a tacit source of biofeedback to entrain physiological self-regulation (Pope and Palsson, 2001).

The capacity of the system to produce false alarms is effectively avoided if adaptation of the interface is implicit and passes unnoticed by the user in the attentional background (Ju and Leifer, 2008). This is also the primary mechanism for physiological computing to extend conventional HCI bandwidth by enabling the user to communicate at an unconscious level (Hettinger et al., 2003). In this case, we may consider a completely subconscious mode of HCI where both user and system interact without any awareness on the part of the former. Computer gaming applications are a good starting point to consider this possibility due to the complexity of the software environment (permitting a range of subtle, ambient adaptations) and the demands on selective attention (creating a substantial background in which implicit interactions could occur). A physiologically adaptive computer game may alter game play by increasing the intelligence of computer-generated opponents or speeding up the tempo of background music, i.e., "emote me" adaptations (Gilleade et al., 2005) as explored in the study by Dekker and Champion (2007). Unfortunately, little is known about the efficacy of these implicit interactions in terms of provoking desirable changes in user state. Using the representation of user state shown in Fig. 1, we may question whether implicit adaptation has sufficient potency to prevent boredom (zone *c*) or avoid disengagement and distress (zone *a*). Given that implicit adaptations should not produce false alarms, this kind of adaptation may be utilised liberally by the system, resulting in frequent adaptations that may yield a pronounced, cumulative effect on user state. In practice, it may be difficult to design adaptations that affect psychological change whilst remaining completely undetected by the user (see Ju and Leifer, 2008, for more detailed discussion). Aside from ethical issues (see Section 2.6), there is one other caveat on the use of implicit adaptation. Under conditions of extreme frustration or distress, it is likely that the user would expect a physiologically adaptive system to present a tacit acknowledgement of this negative state in the form of an explicit adaptation or intervention. A conscious and salient experience of distress that passes without recognition by the system would be categorised as a "miss" from the perspective of the user.

The design of explicit and implicit system adaptations for physiological computer systems must cater to the strengths and weaknesses of both approaches. Explicit adaptation brings the potential to create false alarms that damage the credibility of the system, and for this reason, should be deployed conservatively. However, the conspicuity of explicit adaptation at the interface is possibly the more potent technique to directly influence the psychological state of the user. Implicit adaptations represent subtle changes at the interface that may be used frequently without creating the potential for false alarms. It is assumed that implicit adaptations may be difficult to design in practice, as their purpose is to influence the state of user in a completely unobtrusive fashion. It is also argued that implicit adaptations may not impact on users' psychological state to the same extent as explicit system adaptation, but this latter point remains pure speculation in absence of available evidence.

2.5. The dynamics of the biocybernetic loop

The design of a physiological computing system is based upon the biocybernetic control loop (Fairclough and Venables, 2004; Pope et al., 1995; Prinzel et al., 2000). The biocybernetic loop defines the *modus operandi* of the system and is represented as a series of contingencies between psychophysiological reactivity and system adaptation.

2.5.1. The goals of the biocybernetic loop

The rules of the biocybernetic loop are formulated to serve a meta-goal or series of meta-goals to provide the system with a tangible and objective rationale. The meta-goals of the biocybernetic loop must be carefully defined and operationalised to embody generalised human values that protect and enfranchise the user (Hancock, 1996). For example, the physiological computing system may serve a preventative meta-goal, i.e., to minimise any risks to the health or safety of the operator and other persons. Alternatively, meta-goals may be defined in a positive way that promotes pleasurable HCI (Hancock et al., 2005) or states of active engagement assumed to be beneficial for both performance and personal well being. The definition of the meta-goal is also determined by the context of system operation. A biocybernetic loop operating within a desktop system may focus on positive cognitive-affective states that promote productivity and emotional well being (Picard and Klein, 2002), which serves a protective function for health in the long term (Kiecolt-Glaser et al., 2002). In the context of a safety–critical systems such as autonomous functions in the aircraft or automobile, preserving performance effectiveness in order to minimise the risk of accident or injury is the top priority for the loop (Prinzel, 2002).

The biocybernetic loop is equipped with an array of adaptive interventions to promote the meta-goals of the system, e.g., to provide help, to give emotional support, to manipulate task difficulty (Gilleade et al., 2005). The implementation of these interventions is controlled by the loop in order to 'manage' the psychological state of the user. Correspondingly, the way in which person responds to each adaptation is how the user 'manages' the biocybernetic loop. This is the improvisatory crux that achieves human–computer collaboration by having person and machine respond dynamically and reactively to responses from each other. It may be useful for the loop to monitor how users respond to each intervention in order to individualise (Hancock et al., 2005) and refine this dialogue.

This generative and recursive model of HCI emphasises the importance of (a) accurately monitoring the psychological state of the user (as discussed in the previous sections) and (b) equipping software with a repertoire of adaptive responses that covers the full range of possible outcomes within the human–computer dialogue over a period of sustained use. The latter point is particularly important for 'future-proofing' the physiological computing system as user and machine are locked into a co-evolutionary spiral of mutual adaptation (Fairclough, 2007).

Research into motivation for players of computer games has emphasised the importance of autonomy and competence (Ryan et al., 2006), i.e., choice of action, challenge and the opportunity to acquire new skills. This finding begs the question of whether the introduction of a biocybernetic loop, which 'manages' the HCI according to preconceived meta-goals, represents a threat to the autonomy and competence of the user? Software designed to automatically help or manipulate task demand runs the risk of disempowerment by preventing excessive exposure to either success or failure. This problem was articulated by Picard and Klein (2002) who used the phrase 'computational soma' to describe affective computing software that effectively diffused and neutralised negative emotions. Feelings of frustration or anger serve as potent motivators within the context of a learning process; similarly, anxiety or fatigue are valuable psychological cues for the operator of a safety–critical system. It is important that the sensitivity of the biocybernetic loop is engineered to prevent over-corrective activation and interventions are made according to a conservative regime. In other words, the user should be allowed to experience a negative emotional state before the system responds. This is necessary for the system to demonstrate face validity, but not to constrain users' self-regulation of behaviour and mood to an excessive degree.

2.5.2. Positive vs. negative control dynamics

The biocybernetic loop may work according to two inherent dynamics—negative or positive feedback control (Carver and Scheier, 2000; Rouse, 1977; Wiener, 1948). The decision of which dynamic to employ is important for the design of physiological computing systems. Negative control loops create behavioural stability by reducing the discrepancy between the input signal (real-time psychophysiological measure of engagement) and a desired standard (the desired level of engagement). Negative feedback control is perfect for adaptive systems that are designed to keep the user within a 'safe' or 'comfort' zone (Hancock and Warm, 1989). By contrast, positive feedback control is designed to amplify the discrepancy between the input signal and the desired standard in an exponential fashion. Positive feedback control leads to performance instability (Freeman et al., 1999); a biocybernetic system working on this basis may adjust the desired standard of engagement upwards as the person became more engrossed with the task. In the case of safety systems, it is desirable to use a negative control dynamic to keep the operator within a stable zone of performance effectiveness. However, this kind of stability is an anathema to a learner or computer gamer (Ryan et al., 2006) whose performance and pleasure may benefit from the propulsive momentum of a positive control dynamic. Alternatively, the biocybernetic loop may switch between positive and negative control dynamics. Toggling control dynamics would intersperse unstable episodes of skill acquisition courtesy of a positive control dynamic with periods of performance stability and skill consolidation achieved under a negative control. In this way, the user is 'stretched' and subsequently granted the opportunity to consolidate new skills, i.e., moved from zone *b* to zone *d* in Fig. 1. This strategy also represents a tacit attempt to simultaneously fulfill meta-goals that are mutually exclusive, i.e., to use positive control to provoke intense engagement and negative control to assuage any resulting accumulation of stress and/or fatigue.

The biocybernetic loop encapsulates the values of the system and embodies a dynamic that promotes stable or unstable task performance. The dynamics of the control loop may be alternated for certain application to avoid the placement of excessive constraints on user behaviour.

2.6. Ethical issues

There are a number of ethical issues associated with the design and use of physiological computing systems. This technology is designed to tap private psychophysiological events and use these data as the operational fulcrum for a dynamic HCI. The ethical intention and values of the system designer are expressed by the meta-goals that control the biocybernetic loop (see previous section), but regardless of good intentions, the design of any technology may be subverted to undesirable ends and physiological computing systems offer a number of possibilities for abuse (Reynolds and Picard, 2005b).

2.6.1. Privacy

Invasion of privacy is one area of crucial concern for users of physiological computing systems. Ironically, a technology designed to promote symmetrical communication between user and system creates significant potential for asymmetry with respect to data protection, i.e., the system may not tell the user where his or her data are stored and who has access to these data. If data protection rights are honored by the physiological computing system, it follows that ownership of psychophysiological data should be retained formally and legally by the individual (Hancock and Szalma, 2003). In addition, these data are potentially very sensitive and access to other parties and outside agencies should be subject to formal consent from the user. It should be noted that certain categories of psychophysiological data may also be used to detect medical conditions (e.g., cardiac arrhythmias, hypertension, epilepsy) of which the individual may be unaware. The introduction of physiological computing should not provide a covert means of monitoring individuals for routine health problems without consent. In a similar vein, Picard and Klein (2002) argued that control of the monitoring function used by an affective computing system should always lie with the user. This is laudable but impractical for the user who wishes to benefit from physiological computing technology whilst enjoying private data collection. However, granting the user full control over the mechanics of the data collection process is an important facility and a means of reinforcing trust in the system.

Kelly (2006) proposed four criteria for information exchange between surveillance systems and their users that are relevant here:

1. The user knows exactly what information is being collected, why it is being collected, where these data are stored and who has access to these data.
2. The user has provided explicit or implicit consent for data collection and can demonstrate full knowledge of data collection.
3. The user has access to these data, the user may edit these data or use these data himself or herself.
4. Users receive some benefit for allowing the system to collect these data (e.g., recommendations, filtering).

This 'open source' relationship between user and technology is called reciprocal accountability (Brin, 1999). This relationship may be acceptable for users of physiological computing systems provided the apparent transparency of the process does not mask crucial inequalities, i.e., vague formulations of data rights by private companies or governments. The provision of written consent to specify this relationship should allay users' concerns and there is evidence to support this position (Reynolds and Picard, 2005a).

A second threat to privacy concerns how psychophysiological data recorded in real-time may be expressed at the interface, i.e., explicit feedback from the interface may be perceived by colleagues or other persons when the computer is situated in a public space. The provision of explicit verbal messages or discrete text/symbolic messages in response to the detection of frustration or boredom are potentially embarrassing for the user in the presence of others. The fact that computer systems are used in public spaces constitutes a call for discretion on the part of the interface design, particularly with respect to the use of auditory feedback. It is also essential to include a facility that enables users to disable those messages or modes of feedback that make them susceptible to 'eavesdropping' by others.

2.6.2. The autonomy of the user

Physiological computing systems are designed to 'manipulate' the state of the user in a benign direction via the positive meta-goals of the biocybernetic loop. But how do users feel about being manipulated by autonomous technology (Picard and Klein, 2002; Reynolds and Picard, 2005a)? The verb 'manipulate' is a loaded term in this context as people manipulate their psychological state routinely via psychoactive agents (e.g., caffeine, nicotine, alcohol), leisure activities (e.g., exercise, playing computer games) and aesthetic pastimes (e.g., listening to music, watching a TV show or movie) (Picard and Klein, 2002). The issue here is not the manipulation of psychological state per se but rather who retains control over the process of manipulation. When a person exercises or listens to music, they have full control over the duration or intensity of the experience, and many may balk at the prospect of ceding any degree of control to autonomous technology. These concerns reinforce arguments that reciprocal accountability and granting the individual full control over the system are essential strategies to reassure and protect the user. In addition, users need to understand how the system works so they are able understand the range of manipulations they may be subjected to, i.e., an analytic method for tuning trust in an automated system (Parasuraman and Miller, 2004). Picard and Klein (2002) argued that affective computing systems should support self-management of emotions rather than treating the user as a passive recipient. This is an important point, particularly when considering the effects of explicit and implicit system adaptation on the user, i.e., implicit adaptation does not provide overt cues to support the self-management of user state (Section 2.4).

The strategy employed by physiological computing technology has been described as 'wiretapping' (Wolpaw et al., 2000). This description draws attention to the fact that both neurological processes of self-awareness and the biocybernetic loop draw from a common source of physiological data (see Section 2.4). The user perceives feeling and emotions based partly on interoceptive cues and somatic markers from the body (Damasio, 1999). The system provides explicit feedback of psychological state in real-time, which may reinforce or contradict the users' self-appraisal. It has been argued that sustained use of this technology may effectively fracture the unitary experience of the self as the user is exposed to parallel representations of motivations/feelings/emotions (Hancock and Szalma, 2003). At the very least, use of a physiological computing system may blur the perception of self or act as an unwanted source of interference on self-perception. This 'splitting' of self-perception is certainly plausible but difficult to evaluate or address at the current time. We need to understand how long-term exposure to a physiological computing system may influence self-perception (e.g., to sharpen or blunt this process, to render self-perception reliant on the presence of technology) or impact on mental health (e.g., to induce dissociative states).

To summarise, physiological computing systems have the potential to be subverted to achieve undesirable outcomes such as invasion of privacy and tacit manipulation of the user. It is impossible to safeguard any new technology in this respect but provision of full transparency and reciprocal accountability drastically reduces the potential for abuse. It is important that the user of a physiological computing system remains in full control of the process of data collection (Picard and Klein, 2002) as this category of autonomous technology must be designed to empower the user at every opportunity (Hancock, 1996; Norman, 2007).

3. Conclusions

This review has argued that physiological computing has the potential to provide a new paradigm for HCI by allowing a computer system to develop and access a dynamic representation of the cognitions, emotions and motivation of the user. Enabling machines to extend awareness of the user is crucial for the development of 'smart' technology where human-computer symbiosis is adaptive and collaborative (Hancock, 1997; Norman, 2007). The same facility allows the user to communicate with the computer subconsciously and unintentionally (Hettinger et al., 2003). The biocybernetic loop is the cornerstone of the physiological computing system and is designed to serve a particular purpose with explicit reference to goal states, e.g., to maximise pleasure, avoid stress and fatigue. These meta-goals represent a fledgling version of machine values and intentionality (Hancock, 1997), albeit one tied to the dynamic behaviour of the human user. If this type of physiological computing can be effectively realised, the communication dynamic of HCI will shift from an asymmetrical dyad of two monologues to a symmetrical dialogue (Norman, 2007).

Physiological computing has huge potential for innovation but the development of this technology faces a number of obstacles. Understanding the complexity of the psychophysiological inference (Section 2.1) is fundamental to the successful operation of a physiological computing system. If researchers and designers do not pay sufficient attention to this issue, the performance of prototype systems will be erratic and unreliable, which runs the risk of premature abandonment. It is also important for the designer to carefully specify the required fidelity of psychophysiological diagnosis required for system operation as a first step in the development process. The number of classes on a psychological continuum or discrete categories of emotion is the starting point for system specification; this characteristic sets the standards for the sensitivity, diagnosticity and reliability (Section 2.1) of the psychophysiological inference. At this early stage of development, it is important to export psychophysiological methods from the laboratory to a realistic field environment. These measures must be tested with a full range of the target population in the field, hence the requirement to establish psychophysiological validity (Section 2.2). If the designer does not have complete confidence in the psychophysiological inference at the heart of the biocybernetic loop, an accurate evaluation of system performance is impossible.

The designer of the physiological computing system must be creative with respect to the use of psychophysiology to represent the state of the user. Operationalising the user state requires an awareness of the intricacies of psychophysiological measurement as well as sensitivity to human factors design and the experience of the user. In principle, an accurate and dynamic representation of user state should increase the 'intelligence' of an adaptive computing system, i.e., adaptive responses from the system should appear both intuitive and timely from the users' perspective. Part of this intelligence is derived from the timeliness of system intervention, which is determined by the sensitivity and diagnosticity of the psychophysiological response (Section 2.1). A second aspect is related to the range and complexity of adaptive strategies exhibited by the system, i.e., an extensive repertoire of adaptive responses or graded versions of the same adaptive response both increase the potential precision of system adaptation. It has been argued that the 'intelligence' exhibited by a physiological computing system is directly related to how the representation of the user is translated into an adaptive output (Section 2.3). The dynamic model of the user generated by psychophysiology may be relatively crude or finely graded, i.e., mental workload could be categorised as acceptable vs. overload or classified into four grades such as low/medium/high/overload (Wilson and Russell, 2007). Representations of the user may also vary with respect to complexity, being unidimensional (i.e., mental workload) or multidimensional (Fig. 1). With respect to this point, it has been argued that the fidelity and complexity of the user representation determines the adaptive vocabulary of the system. However, the required range of adaptive response must be determined by the context of the task and crude/simplistic user representations may have inherent advantages over more complex ones, particularly at this early stage of technological development.

There may be another advantage in limiting the adaptive range of the system; (Karwowski, 2000) has argued that increased system complexity often limits the maximum level of compatibility between user and system, i.e., due to increased functionality, reduced feedback at the interface. In line with this argument, one challenge for physiological computing is how to design systems that respond proactively and intelligently without exposing the user to high levels of uncertainty. We should recognise that potential exists to obscure the benefits of physiological computing by the presence of unexpected drawbacks, and in this respect, designers should heed those issues that arose from the introduction of system automation (Parasuraman and Riley, 1997).

There is a second strand to the argument that multidimensional psychophysiological assessment is required to inform a complex representation of the user. Researchers who have combined psychophysiology with other behavioural markers, e.g., Kapoor et al. (2007), have demonstrated the potential of this approach. The use of multimodal data capture to index user state promises to be an effective technique to establish concurrent validity in real-time (Section 2.2). The complexity of the psychophysiological inference (Section 2.1) may be clarified by combining physiology with overt markers of behaviour and/or objective measures of task performance (Section 2.3). The same advantage may be gained from combining real-time psychophysiology with a representation of the task in order to give context to the former, e.g., task phase or task activity. The provision of task context provides one easily available means of extending and prescribing the adaptive repertoire of the system, i.e., the detection of frustration during task *x* prompts one type of help information whereas frustration during task *y* leads to a completely different category of assistance.

Multidimensional measures of psychophysiology also provide the means by which to capture user state with respect to cognition, emotion and motivation. HCI researchers are often interested in negative user states that encompass all three aspects, e.g., a frustrated user may feel anger, be easily distracted and disinclined to continue with the task (Burleson and Picard, 2004). These complex, cognitive-energetical states (Hancock and Desmond, 2001; Hockey, 1997) are challenging to capture but offer greater verisimilitude as the experience of cognition and emotion are highly interconnected (Picard et al., 2004; Stemmler et al., 2001). It is argued that future research should focus on cognitive-energetical states that are relevant to user experience with respect to specific applications, e.g., states of 'stuck' (Burleson and Picard, 2004) or challenge (Mandryk and Atkins, 2007), as opposed to capturing generic categories of emotional experiences, which may be a red herring in any case (Feldman Barrett, 2006).

The evaluation of physiological computing systems will not be a straightforward exercise. The perception of system error rests on a fuzzy neurological process of self-perception and the presence of explicit feedback at the interface (Section 2.4). The introduction of both self-perception and explicit feedback may render users' perceptions of system accuracy unpredictable, regardless of the validity of the psychophysiological inference underlying the system. There is also some uncertainty surrounding the choice of criterion for successful system performance. Some may argue that a successful system will exhibit high face validity, i.e., high correspondence between the diagnosis produced by the system and users' self-perception. Others may claim that a successful system should demonstrate objective improvements in performance effectiveness. Both aspects are important and relative weighting of each will depend on the type of application under evaluation; the assessment of safety–critical systems will emphasise performance effectiveness whilst subjective perceptions of enjoyment and fun are central to the evaluation of computer games (Yannakakis et al., 2007). In methodological terms, important methodological lessons for system evaluation have emerged from research on adaptive automation (Prinzel et al., 2003; Wilson and Russell, 2007). These researchers emphasised the importance of (a) yoked groups in order to disentangle the influence of adaptation on performance per se from the temporal qualities of adaptation, (b) comparing the diagnosis produced by simple vs. complex categorisation of user states, and (c) tailoring the trigger criteria for adaptation to the individual person.

Physiological computing has the potential to render human–machine dialogue as dynamic, collaborative, spontaneous and effortless. This capabilities will only be realised by close attention to fundamental methodological issues and creative interface design; this is a multidisciplinary challenge for psychophysiologists, human factors professionals and computer scientists.

4. Executive summary

4.1. Introduction

Physiological computing uses real-time psychophysiology to represent the internal state of the user (e.g., cognitions, motivation, emotion), which is used as the basis for real-time system adaptation. Psychophysiology represents an implicit form of user monitoring that places no additional requirement on the user and can deliver continuous data, even in the absence of any overt behavioural response. This approach may be used to extend the communication bandwidth within HCI and to enable symmetrical communication between user and system. Physiological computing also has the potential to tailor each interaction to the specific responses from the individual user. This approach has been suggested as a means of controlling adaptive automation and enabling affective computing, e.g., the detection of frustration as a cue to provide help information.

4.2. Fundamental issues

A review and synthesis of the existing literature is used to presents a series of basic challenges to the design and implementation of physiological computing systems.

4.2.1. Psychophysiological inference

The relationship between physiology and psychology is complex and contains overlapping causal pathways. When designing a physiological computing system, psychophysiological variables should be selected on the basis of diagnosticity (ability of variable to index target psychological state and remained unaffected by related states), sensitivity (ability of variable to respond rapidly to changes in psychological state) and reliability (consistency of the psychophysiological inference across different individuals and environments).

4.2.2. Psychophysiological validity

The relationship between selected psychophysiological variables and target states must be validated with respect to both independent variables (task manipulations) or dependent variables (subjective measures and/or behavioural indicators of target states). Psychophysiological validity should be established under operational conditions and with the target user population.

4.2.3. Representation of the user

Psychophysiology may be used to represent the user in a simplistic unidimensional way (e.g., low vs. high frustration) or in a multidimensional framework (e.g., valence vs. activation). A number of methods for representing user state are considered, including multimodal representations, i.e., combining psychophysiological data with other data sources such as user behaviour. It is argued that the complexity of user representation determines the range and specificity of adaptive responses from the system.

4.2.4. Awareness and interaction design

Physiological computing systems are capable of delivering explicit or implicit interventions at the interface. The former provide an overt signal to the user that a particular state has been detected whereas the latter may occur without awareness. Explicit intervention may be a more potent influence on user behaviour compared to implicit adaptation, but carry the disadvantage of providing feedback of system error (e.g., false alarms) by presenting a mismatch with users' perceptions of their own psychological state. The implications of both type of intervention are discussed with reference to users' assessment of accuracy and trust in the technology.

4.2.5. Dynamics of the biocybernetic loop

The biocybernetic loop translates psychophysiological data into computer control of system adaptation. This loop is the crux of the physiological computing system, representing both the rules of the system as well as the quantitative trigger points for system adaptation (e.g., IF heart rate >20% THEN offer help). This section considers the design of loop and the implications of biocybernetic control for user autonomy. The dynamic of the loop may be positive (discrepancy-enlarging, leading to instability) or negative (discrepancy-reducing, leading to stability) and the implications of both dynamics for the design of the system are discussed.

4.2.6. Ethical implications

Physiological computing involves the operationalisation of the personal and private experience of the user. In some cases, this measurement or representation may be presented explicitly at the interface. This section considers the consequences of privacy and data protection for user acceptance of this technology. There are also questions regarding the manipulation of user state (particularly by implicit system adaptations) and the effects of this technology on self-perception that have ethical implications.

4.3. Conclusions

The huge potential of physiological computing to innovate contemporary HCI will not be realised unless these fundamental issues are addressed by current research in this area.

Acknowledgement

The author would like to thank Dr. Jen Allanson for her helpful input to an earlier draft of this paper and the comments of two anonymous referees.

References

Aarts, E., 2004. Ambient intelligence. A multimedia perspective. IEEE Multimedia 11 (1), 12–19.

Ahn, H., Teeters, A., Wang, A., Breazeal, C., Picard, R.W. (2007). Stoop to conquer: Posture and affect interact to influence computer users' persistence. Paper presented at the Second International Conference on Affective Computing and Intelligent Interaction, Lisbon, Portugal.

Allanson, J., 2002. Electrophysiologically interactive computer systems. IEEE Magazine 35 (3), 60–65.

Allanson, J., Fairclough, S.H., 2004. A research agenda for physiological computing. Interacting With Computers 16, 857–878.

Anttonen, J., Surakka, V. (2005). Emotions and heart rate while sitting on a chair. Paper presented at the CHI, Portland, Oregon, USA.

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

Bongard, S., Al'Absi, M., 2005. Domain-specific anger expression and blood pressure in an occupational setting. Journal of Psychosomatic Research 58, 43–49.

Brin, D., 1999. The transparent society: will technology force us to choose between privacy and freedom. Perseus Books.

Burleson, W., Picard, R.W. (2004). Affective agents: sustaining motivation to learn through failure and a state of "stuck". Paper presented at the Workshop on Social and Emotional Intelligence in Learning Environments.

Byrne, E., Parasuraman, R., 1996. Psychophysiology and adaptive automation. Biological Psychology (42), 249–268.

Cacioppo, J.T., Gardner, W.L., 1999. Emotion. Annual Review of Psychology 50, 191–214.

Cacioppo, J.T., Klein, D.J., Berntson, G.G., Hatfield, E., 1993. The psychophysiology of emotion. In: Lewis, M., Haviland, J.M. (Eds.), Handbook of Emotions. Guilford Press, New York, pp. 119–142.

Cacioppo, J.T., Tassinary, L.G., 1990. Inferring psychological significance from physiological signals. American Psychologist 45 (1), 16–28.

Cacioppo, J.T., Tassinary, L.G., Berntson, G.G., 2000. Psychophysiological science. In: Cacioppo, J.T., Tassinary, L.G., Berntson, G.G. (Eds.), Handbook of Psychophysiology. Cambridge University Press, Cambridge UK, pp. 3–26.

Cameron, O.G., 2001. Interoception: the inside story—a model for psychosomatic processes. Psychosomatic Medicine 63, 697–710.

Carver, C.S., Scheier, M.F., 2000. On the structure of behavioural self-regulation. In: Boekaerts, M., Pintrich, P.R., Zeidner, M. (Eds.), Handbook of Self-regulation. Academic Press, San Diego, pp. 41–84.

Churchland, P.S., 2002. Self-representation in nervous systems. Science 296, 308–310.

Craig, A.D., 2004. Human feelings: Why are some more aware than others? Trends in Cognitive Sciences 8 (6), 239–241.

Critchley, H.D., 2004. The human cortex responds to an interoceptive challenge. Proceedings of the National Academy of Science 101 (17), 6333–6334.

Csikszentmihalyi, M., 1990. Flow: the Psychology of Optimal Experience. Harper Perennials, New York.

Critchley, H.D., Wiens, S., Rotshtein, P., Ohman, A., Dolan, R.J., 2004. Neural systems supporting interoceptive awareness. Nature Neuroscience 7, 189–195.

Damasio, A.R., 1999. The Feeling of What Happens: Body and Emotion in the Making of Consciousness. Harcourt Brace, New York.

Dekker, A., Champion, E. (2007). Please biofeed the zombies: enhancing the gameplay and display of a horror game using biofeedback. Paper presented at the DiGRA.

Dennerlein, J., Becker, T., Johnson, P., Reynolds, C., Picard, R.W. (2003). Frustrating computer users increases exposure to physical factors. Paper presented at the Proceedings of the IEA, Seoul, Korea.

Dolan, R.J., 2002. Emotion, cognition and behaviour. Science 298, 1191–1194.

Etzel, J.A., Johnsen, E.L., Dickerson, J., Tranel, D., Adolphs, R., 2006. Cardiovascular and respiratory responses during musical mood induction. International Journal of Psychophysiology 61, 57–69.

Fairclough, S.H. (2007). Psychophysiological inference and physiological computer games. Paper presented at the ACE Workshop—Brainplay'07: Brain-Computer Interfaces and Games.

Fairclough, S.H., Venables, L., 2004. Psychophysiological candidates for biocybernetic control of adaptive automation. In: de Waard, D., Brookhuis, K.A., Weikert, C.M. (Eds.), Human Factors in design. Maastricht, The Netherlands: Shaker, pp. 177–189.

Fairclough, S.H., Venables, L., 2006. Prediction of subjective states from psychophysiology: a multivariate approach. Biological Psychology 71, 100–110.

Fairclough, S.H., Venables, L., Tattersall, A., 2005. The influence of task demand and learning on the psychophysiological response. International Journal of Psychophysiology 56, 171–184.

Fairclough, S.H., Venables, L., Tattersall, A., 2006. The use of autonomic measures for biocybernetic adaptation. Psychophysiology 42 (S1), S25.

Feldman Barrett, L., 2006. Are emotions natural kinds? Perspectives on Psychological Science 1 (1), 28–58.

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

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

Gendolla, G.H.E., Richter, M., 2006. Cardiovascular reactivity during performance under social observation: the moderating role of task difficulty. International Journal of Psychophysiology 62, 185–192.

Gevins, A., Smith, M.E., Leong, H., McEvoy, L., Whitfield, S., Du, R., et al., 1998. Monitoring working memory load during computer-based tasks with eeg pattern recognition models. Human Factors 40 (1), 79–91.

Gilleade, K.M., Dix, A. (2004). Using frustration in the design of adaptive videogame. Paper presented at the Advances in Computer Entertainment Technology.

Gilleade, K.M., Dix, A., Allanson, J. (2005). Affective videogames and modes of affective gaming: assist me, challenge me, emote me. Paper presented at the Proceedings of DiGRA 2005.

Haag, A., Goronzy, S., Schaich, P., Williams, J. (2004). Emotion recognition using bio-sensors: first steps towards an automatic system. Paper presented at the Proceedings of LNCS.

Hancock, P.A., 1996. Teleology for technology. In: Parasuraman, R., Mouloua, M. (Eds.), Automation and Human Performance. Erlbaum, Hillsdale, NJ, pp. 461–497.

Hancock, P.A., 1997. Essays on the Future of Human-Machine systems. BANTA, Eden Prairie, MN.

Hancock, P.A., Caird, J.K., 1993. Experimental evaluation of a model of mental workload. Human Factors 35 (3), 413–429.

Hancock, P.A., Desmond, P.A., 2001. Stress, Workload, and Fatigue. Erlbaum, Mahwah, NJ.

Hancock, P.A., Pepe, A.A., Murphy, L.L., 2005. Hedonomics: the power of positive and pleasurable ergonomics. Ergonomics in Design 13 (1), 8–14.

Hancock, P.A., Szalma, J.L., 2003. The future of neuroergonomics. Theoretical Issues in Ergonomic Science 44 (1–2), 238–249.

Hancock, P.A., Warm, J.S., 1989. A dynamic model of stress and sustained attention. Human Factors 31 (5), 519–537.

Healey, J., Picard, R.W. (1997). Digital processing of affective signals. Paper presented at the Proceedings of ICASSP, Seattle, WA.

Helander, M.G., Tham, M.P., 2003. Hedonomics—affective human factors design. Ergonomics 46 (13/14), 1269–1272.

Hettinger, L.J., Branco, P., Encarnaco, L.M., Bonato, P., 2003. Neuroadaptive technologies: Applying neuroergonomics to the design of advanced interfaces. Theoretical Issues in Ergonomic Science 4 (1–2), 220–237.

Hockey, G.R.J., 1997. Compensatory control in the regulation of human performance under stress and high workload: a cognitive-energetical framework. Biological Psychology 45, 73–93.

Ju, W., Leifer, L., 2008. The design of implicit interactions: making interactive systems less obnoxious. Design Issues 24 (3), 72–84.

Kapoor, A., Burleson, W., Picard, R.W., 2007. Automatic prediction of frustration. International Journal of Human-Computer Studies 65, 724–736.

Karwowski, W., 2000. Symvatology: the science of artifact-human compatibility. Theoretical Issues in Ergonomic Science 1 (1), 76–91.

Kelly, K. (2006). Symmetrical and asymmetrical technologies. Available from: http://www.kk.org/thetechnium/archives/2006/02/symmetrical_and.php.

Kiecolt-Glaser, J.K., McGuire, L., Robles, T.F., Glaser, R., 2002. Emotions, morbidity and mortality: new perspectives from psychoneuroimmunology. Annual Review of Psychology 53, 83–107.

Klein, G., Woods, D.D., Bradshaw, J.M., Hoffman, R.R., Feltovich, P.J., 2004. Ten challenges for making automation a "team player" in joint human-agent activity. IEEE Intelligent Systems 19 (6), 91–95.

Klein, J., Moon, Y., Picard, R.W., 2002. This computer responds to user frustration: theory, design and results. Interacting with Computers 14, 119–140.

Kulic, D., Croft, E. (2005). Anxiety detection during human–robot interaction. Paper presented at the Conference on Intelligent Robots and Systems, Edmonton, Canada.

Kulic, D., Croft, E. (2006). Estimating robot induced affective state using hidden markov models. Paper presented at the IEEE International Symposium on Robot and Human Interactive Communication.

Laine, T.I., Bauer, K.W., Lanning, J.W., Russell, C.A., Wilson, G.F., 2002. Selection of input features across subjects for classifying crewmember workload using artificial neural networks.. IEEE Transactions on Systems, Man and Cybernetics A Systems and Humans 32 (6), 691–704.

Lang, P.J., Bradley, M.M., Cuthbert, B.N. (2005). The International Affective Picture System (IAPS). University of Florida.

Larsen, J.T., Norris, C.J., Cacioppo, J.T., 2003. Effects of positive and negative affect on electromyographic activity over the zygomaticus major and corrugator supercilii. Psychophysiology 40, 776–785.

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

Lisetti, C.L., LeRouge, C. (2004). Affective computing in tele-home health. Paper presented at the 37th Hawaii International Conference on System Sciences.

Lisetti, C.L., Nasoz, F., 2004. Using noninvasive wearable computers to recognize human emotions from physiological signals. EURASIP Journal on Applied Signal Processing 11, 1672–1687.

Lisetti, C.L., Nasoz, F., LeRouge, C., Ozyer, O., Alvarez, K., 2003. Developing multimodal intelligent affective interfaces for tele-home health care. International Journal of Human-Computer Studies 59, 245–255.

Liu, C., Rani, P., Sarkar, N. (2005). An empirical study of machine learning techniques for affect recognition in human-robot interaction. Paper presented at the IEEE Conference on Intelligent Robots and Systems.

Mandryk, R.L., Atkins, M.S., 2007. A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies. International Journal of Human-Computer Studies 65, 329–347.
Mandryk, R.L., Inkpen, K.M., Calvert, T.W., 2006. Using psychophysiological techniques to measure user experience with entertainment technologies. Behaviour and Information Technology 25 (2), 141–158.
Matthews, G., Campbell, S.E., Falconer, S., Joyner, L.A., Huggins, J., Gilliland, K., et al., 2002. Fundamental dimensions of subjective state in performance settings: task engagement, distress and worry. Emotion 2 (4), 315–340.
Mota, S., Picard, R.W. (2003). Automated posture analysis for detecting learner's interest level. Paper presented at the Workshop on Computer Vision and Pattern Recognition for Human–Computer Interaction.
Muir, B., Moray, N., 1996. Trust in automation. Part ii. Experimental studies of trust and human intervention in a process control simulation. Ergonomics 39 (3), 429–460.
Nisbett, R.E., Wilson, T.D., 1977. Telling more than we can know: verbal reports on mental processes. Psychological Review 84 (3), 231–259.
Norman, D.A., 2007. The Design of Future Things. Basic Books, New York.
ODonnell, R.D., Eggemeier, F.T., 1986. Workload assessment methodology. In: Boff, K., Kaufman, L., Thomas, J. (Eds.), Handbook of Human Perception and Performance, vol. 2. Wiley, New York, pp. 42.41–42.49.
Pantic, M., Pentland, A., Nijholt, A., Huang, T., 2007. Human computing and machine understanding of human behaviour: a survey. In: Huang, T., Nijholt, A., Pantic, M., Pentland, A. (Eds.), Artificial Intelligence for Human Computing. Springer, pp. 47–71.
Parasuraman, R., Hancock, P.A., 1999. Using signal detection theory and bayesian analysis to design parameters for automated warning systems. In: Scerbo, M.W., Mouloua, M. (Eds.), Automation, Technology and Human Performance. Erlbaum, Mahwah, NJ, pp. 63–67.
Parasuraman, R., Miller, C.A., 2004. Trust and etiquette in high-criticality automated systems. Communications of the ACM 47 (4), 51–55.
Parasuraman, R., Riley, V., 1997. Humans and automation: use, misuse, disuse, abuse. Human Factors 39, 230–253.
Partala, T., Surrakka, V., 2004. The effects of affective interventions in human–computer interaction. Interacting With Computers 16, 295–309.
Picard, R.W., 1997. Affective computing. MIT Press, Cambridge, Mass.
Picard, R.W., 2003. Affective computing: challanges. Interacting With Computers 59, 55–64.
Picard, R.W., Klein, J., 2002. Computers that recognise and respond to user emotion: theoretical and practical implications. Interacting with Computers 14, 141–169.
Picard, R.W., Vyzas, E., Healey, J., 2001. Towards machine emotional intelligence: analysis of affective physiological state. IEEE Transactions on Pattern Analysis and Machine Intelligence 23 (10), 1175–1191.
Picard, R.W., Papert, S., Bender, W., Blumberg, B., Breazeal, C., Cavallo, D., et al., 2004. Affective learning—a manifesto. BT Technology Journal 22 (4), 253–269.
Pope, A.T., Bogart, E.H., Bartolome, D.S., 1995. Biocybernetic system evaluates indices of operator engagement in automated task. Biological Psychology 40, 187–195.
Pope, A.T., Palsson, OS. (2001, 26–27th October). Helping video games "rewire our minds". Paper presented at the Playing by the Rules: the Cultural Challenges of Video Games, Chicago.
Prendinger, H., Mori, J., Ishizuka, M., 2005. Using human physiology to evaluate subtle expressivity of a virtual quizmaster in a mathematical game. International Journal of Human-Computer Studies 62, 231–245.
Prinzel, L.J., 2002. Research on hazardous states of awareness and physiological factors in aerospace operations (No. NASA/TM-2002-211444). NASA, Hampton, Virginia.
Prinzel, L.J., Freeman, F.G., Scerbo, M.W., Mikulka, P.J., Pope, A.T., 2000. A closed-loop system for examining psychophysiological measures for adaptive task allocation. The International Journal of Aviation Psychology 10 (4), 393–410.
Prinzel, L.J., Freeman, F.G., Scerbo, M.W., Mikulka, P.J., Pope, A.T., 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, L.J., Scerbo, M.W., Freeman, F.G., Mikulka, P.J (1995). A bio-cybernetic system for adaptive automation. Paper presented at the Human Factors and Ergonomics Society 39th Annual Meeting.
Rani, P., Sarkar, N., Liu, C. (2005). Maintaining optimal challenge in computer games through real-time physiological feedback. Paper presented at the 11th Human–Computer Interaction International, Las Vegas, USA.
Rani, P., Sarkar, N., Smith, C.A., Adams, J.A. (2003). Affective communication for implicit human–machine interaction. Paper presented at the 2003 IEEE International Conference on Systems, Man and Cybernetics, Washington, DC.
Rani, P., Sims, J., Brackin, R., Sarkar, N., 2002. Online stress detection using psychophysiological signal for implicit human–robot cooperation. Robotica 20 (6), 673–686.
Reynolds, C., Picard, R.W. (2005a). Affective sensors, privacy and ethical contracts. Paper presented at the CHI'2005, Vienna, Austria.
Reynolds, C., Picard, R.W. (2005b). Evaluation of affective computing systems from a dimensional metaethical position. Paper presented at the First Augmented Cognition Conference, Las Vegas, Nevada.
Richter, P., Gendolla, G.H.E., 2006. Incentive effects on cardiovascular reactivity in active coping with unclear task difficulty. International Journal of Psychophysiology 61, 216–225.
Rouse, W.B., 1977. Estimation and control theory: application to modeling human behaviour. Human Factors 19 (4), 315–329.
Ryan, R.M., Rigby, C.S., Przybylski, A., 2006. The motivational pull of video games: a self-determination approach. Motivation and Emotion 30, 347–363.
Scerbo, M.W., Freeman, F.G., Mikulka, P.J., 2003. A brain-based system for adaptive automation. Theoretical Issues in Ergonomic Science 4 (1–2), 200–219.
Scheirer, J., Fernandez, R., Klein, J., Picard, R.W., 2002. Frustrating the user on purpose: a step toward building an affective computer. Interacting With Computers 14, 93–188.
Smith, M.E., Gevins, A., Brown, H., Karnik, A., Du, R., 2001. Monitoring task loading with multivariate eeg measures during complex forms of human–computer interaction. Human Factors 43 (3), 366–380.
Stemmler, G., Heldmann, M., Pauls, C.A., Scherer, T., 2001. Constraints for emotion specificity in fear and anger; the context counts. Psychophysiology 38, 275–291.
Strauss, M., Reynolds, C., Hughes, S., Park, K., McDarby, G., Picard, R.W. (2005). The handwave bluetooth skin conductance sensor. Paper presented at the ACM II.
van Reekum, C.M., Johnstone, T., Banse, R., Etter, A., Wehrle, T., Scherer, K.R., 2004. Psychophysiological responses to appraisal dimensions in a computer game. Cognition and Emotion 18 (5), 663–688.
Villon, O., Lisetti, C.L. (2006). A user-modeling approach to build user's psychophysiological maps of emotions using bio-sensors. Paper presented at the 15th IEEE International Symposium on Robot and Human Interactive Communication, Hatfield, UK.
Ward, R.D., Marsden, P.H., 2003. Physiological response to different web page designs. International Journal of Human-Computer Studies 59, 199–212.
Weiser, M., Brown, J.S., 1997. Designing calm technology. In: Denning, P.J., Metcalfe, R.M. (Eds.), Beyond Calculation: the Next fifty Years of Computing. Springer-Verlag, New York.
Wiener, N., 1948. Cybernetics: Control and Communication in the Animal and the Machine, second ed. MIT Press, Cambridge, Mass.
Wilhelm, F.H. (2002). Continuous electronic data capture of cardiopulmonary physiology, motor behaviour, and subjective experience with lifeshirt: towards a comprehensive monitoring of affective states in real life. Available from: <www.vivometrics.com/docs/Ab and posters/2002 White Paper Continuous electronic data capture of cardiopulmonary physiology, posture, and subjective experience with t.pdf>.
Wilson, G.F., 2003. Pilot workload, operator functional state and adaptive aiding. In: Hockey, G.R.J., Gaillard, A.W.K., Burov, O. (Eds.), Operator Functional State: the Assessment and Prediction of Human Performance Degradation in Complex Tasks. ISO Press, Amsterdam, pp. 194–203.
Wilson, G.F., Lambert, J.D., Russell, C.A. (2007). Performance enhancement with real-time physiologically controlled adaptive aiding. Paper presented at the Human Factors and Ergonomics Society Annual Meeting, Baltimore, Maryland.
Wilson, G.F., Russell, C.A., 2003. Operator functional state classification using multiple psychophysiological features in an air traffic control task. Human Factors 45 (3), 381–389.
Wilson, G.F., Russell, C.A., 2007. Performance enhancement in an uninhabited air vehicle task using psychophysiologically determined adaptive aiding. Human Factors 49 (6), 1005–1018.
Wolpaw, J.R., Birbaumer, N., Heetderks, W.J., McFarland, D.J., Peckham, P.H., Schalk, G., et al., 2000. Brain–computer interface technology: a review of the first international meeting. IEEE Transactions on Rehabilitation Engineering 8, 164–173.
Yamada, F., 1998. Frontal midline theta rhythm and eyeblinking activity during a vdt task and a video game: useful tools for psychophysiology in ergonomics. Ergonomics 41 (5), 678–688.
Yannakakis, G.N., Hallam, J., Hautop Lund, H., 2007. Entertainment capture through heart rate activity on physical interactive playgrounds. User Modeling and User-Adapted Interaction 18, 207–243.