User Modeling and User-Adapted Interaction **12:** 1–47, 2002.

Assessment of User Affective and Belief States for Interface Adaptation: Application to an Air Force Pilot Task

EVA HUDLICKA[1] and MICHAEL D. McNEESE[2]
[1]*Psychometrix Associates, Inc. Blacksburg, VA, USA*
[2]*The Pennsylvania State University, University Park, PA, USA*

(Received 15 July 2000; accepted in revised form 22 April 2001)

Abstract. We describe an Affect and Belief Adaptive Interface System (ABAIS) designed to compensate for performance biases caused by users' affective states and active beliefs. The ABAIS architecture implements an adaptive methodology consisting of four steps: sensing/inferring user affective state and performance-relevant beliefs; identifying their potential impact on performance; selecting a compensatory strategy; and implementing this strategy in terms of specific GUI adaptations. ABAIS provides a generic adaptive framework for integrating a variety of user assessment methods (e.g. knowledge-based, self-reports, diagnostic tasks, physiological sensing), and GUI adaptation strategies (e.g. content- and format-based). The ABAIS performance bias prediction is based on empirical findings from emotion research combined with detailed knowledge of the task context. The initial ABAIS prototype was demonstrated in the context of an Air Force combat task, used a knowledge-based approach to assess the pilot's anxiety level, and adapted to the pilot's anxiety and belief states by modifying selected cockpit instrument displays in response to detected changes in these states.

Keywords: adaptive interface, affect adaptation, affect assessment, affective computing, aviation, human–computer interaction, user modeling

1. Introduction

As computer systems requiring user adaptation and associated user interface (UI) technologies mature and proliferate into critical applications, and increasingly heterogeneous user populations, it becomes particularly important that they accommodate individual user characteristics. Particularly critical are dynamic characteristics that reflect the current affective and belief state of the user, since both these factors strongly influence performance. This requirement is necessary for a wide variety of systems, including decision support systems (particularly those that function in dynamic, stressful domains), instructional systems and virtual reality training (VR) environments, emerging VR treatment environments, and a variety of computer 'agents'. While some progress has been made in user-modeling and adaptive user interfaces, the majority of existing systems continue to assume normative performance, and fail to adapt to the individual characteristics of particular users, whether those that are relatively stable over time, or those that are susceptible to situational influences. This is particularly true for adaptation with respect of the user's current situation assessment (belief states) state and current emotion (affective states).[1]

This existing lack of detection, assessment, and modeling of belief and affective states on the one hand, and adaptation to these states on the other, in the majority of human–machine systems can lead to non-optimal behavior at best, and critical errors with disastrous consequences at worst. This is increasingly evidenced by a variety of accidents and incidents attributed to the broad area of 'human error' that exist in industrial settings, commercial and military aviation, and, increasingly, in health care.

Recent research provides increasing evidence that individual differences in general, and *affective states* in particular, have a major impact on performance (Williams et al., 1997; Eysenck, 1997; Mineka & Sutton, 1992; Isen, 1993; LeDoux, 1992; Deckert et al., 1994). Affective states influence a variety of perceptual, cognitive, and motor processes, both low-level processes such as attention and memory, and higher-level processes such as situation assessment, decision making, and judgement. Examples of these influences include:

- Altering the nature of attentional processing (e.g. change in focal area, increased/reduced size of focal area, biasing attention towards or away from particular stimuli, etc.);
- Helping to activate (or inhibit) particular perceptual and cognitive schemata that enhance (or limit) the perception or processing of specific stimuli;
- Promoting (or inhibiting) the selection of particular actions, and influencing the accuracy and speed of selected motor responses.

Similarly, experimental studies indicate that the user's current assessment of the situation, in other words, his/her *belief state*, plays a critical role in the decision making and, ultimately, response selection.

To address these influences we must develop user models that take into account the effects of affect and beliefs on performance, and develop strategies for adapting the machine aiding and user interface to these individual, possibly idiosyncratic, states. A number of issues arise in developing adaptive user interfaces capable of identifying the user's affective and belief state and compensating for the resulting biases in performance. The primary challenges are:

- Effective assessment of the user's current affective state.
- Prediction of its influences on performance, within the current task context.
- Identification of strategies that could compensate for the potential performance biases.

[1]We use the term 'emotion' and 'affective state' interchangeably, referring to transient states, with distinct triggers and individual decay functions, roughly at the level of basic emotions or Category 2 emotions (Panksepp, 1994).

- Generation of corresponding graphical user interface (GUI) and decision-aiding or training system adaptations.

To address these challenges we developed an Affect and Belief Adaptive Interface System (ABAIS). ABAIS implements an adaptive methodology framework capable of adapting the system interface format and content to the user's affective state, selected key personality traits, and to situation-specific beliefs that might influence performance (Hudlicka, 2000; Hudlicka & Billingsley, 1998). The ABAIS system was demonstrated in the context of an Air Force pilot task, which provided both a sufficiently constrained environment required for the application of the adaptive methodology, and an environment where a variety of affect and belief-induced performance biases were likely to occur.

This paper is organized as follows. First, we provide a review of existing empirical research on the effects of affect and belief states on performance, and a generic summary of affect assessment methods (Section 2.0), and briefly discuss specific existing work in affective assessment and adaptation (Section 3). Next, we describe the ABAIS adaptive methodology and the system architecture that implements this methodology (Section 4). We then briefly outline the task context: Air Force fighter pilot sweep task, to provide the necessary background for the concrete examples of system functionality (Section 5). We then outline an enhanced form of cognitive task analysis, which explicitly includes the possible effects of affect and personality traits on performance, and is therefore termed Cognitive Affective Personality Task Analysis (CAPTA) (Section 6). Next we describe the process of user affective and belief state assessment and behavior prediction (Section 7), and the compensatory strategy selection and specific GUI adaptation strategies (Section 8). We then illustrate the overall ABAIS prototype functionality via a brief description of system performance in the context of the demonstration task: Air Force fighter pilot sweep task (Section 9). The paper concludes with a summary, conclusions, and brief outline of future work and generalizability of the ABAIS methodology to other domains (Section 10).

2. Affective and Belief States: Effects on Performance and Assessment

This section provides background on existing research most relevant to our effort to develop an affect and belief adaptive system. Section 2.1 summarizes the effects of emotion on cognition and performance. Section 2.2 reviews generic methods for assessing affective states. Section 2.3 summarizes research on situation awareness and its relevance to assessing, and adapting to, the user's belief state.

2.1. Effects of affective states on performance

Although central to human development and functioning, emotions have, until recently, had a somewhat marginal status in both cognitive science and neuroscience.

Over the past 10 years, however, important discoveries in neuroscience and experimental psychology have contributed to an interest in the scientific study of emotion. A growing body of evidence from neuroscience research points to the existence of circuitry processing emotionally relevant stimuli (i.e. stimuli that threaten or benefit the survival of the organism or its species) (LeDoux, 1989). LeDoux and colleagues have studied fear conditioning in rats and identified a number of key results: (1) existence of dedicated circuitry processing stimuli that threaten or benefit organism or species survival; (2) evidence that emotional circuitry performs fast, less differentiated processing and behavior selection (e.g. freezing behavior in rats); (3) evidence that this processing is mediated by connections linking sensory organs directly to emotional circuitry in the brain, specifically, the amygdala (LeDoux, 1992). Cognitive psychologists have described a variety of appraisal processes involved in inducing a particular emotional state in response to a situation (Lazarus, 1991) and several models have been proposed (Ortony et al., 1988), some of which have been implemented in computational models (Scherer, 1993; Bates et al., 1992; Elliot, 1992). Damasio and colleagues have studied humans with brain lesions and identified the role of emotion in human information processing and decision-making (Damasio, 1994), suggesting that emotions 'prune' the search spaces generated through cognitive processing. Recent research thus provides evidence for the impact of emotion on cognitive processing and the central role of emotion in the control of behavior. The emerging findings also begin to blur the distinction between what has traditionally been thought of as the separate realms of cognition and emotion.

Of relevance to the ABAIS system are the consistent findings by cognitive and clinical psychologists regarding the differential impact of various emotional states on cognition. A number of affective states and personality traits have been studied extensively (e.g. anxiety, positive and negative affect, obsessiveness, extraversion, etc.). These factors influence perceptual and cognitive processes, including attention, perceptual categorization, memory, and general inferencing and judgment. Examples of specific findings are shown in Table 1. These findings provide an empirical basis for predicting the generic effects of emotional states and personality traits on performance. These generic effects can be used in the absence of task specific information, and also serve as guiding principles for the affective/cognitive task analysis required to identify specific performance effects in particular task contexts.

2.2. Assessment of affective states

Existing methods for affect assessment include psychological self report instruments, physiological sensing, facial expression recognition (Ekman & Davidson, 1994; Picard, 1997; Kaiser et al., 1998), speech analysis (Mozziconacci, 2001; Petrushin, 2000), diagnostic tasks, and expert observer evaluation (knowledge-based assessment). However, none of these methods alone provide the definitive solution.

Table 1: Effect of emotion and personality traits on cognition: examples of empirical findings

Anxiety and Attention (Williams et al., 1997; Mineka & Sutton, 1992).
Narrowing of attentional focus
Predisposing towards detection of threatening stimuli
Affective state and Memory (Bower, 1981; Blaney, 1986)
Mood-congruent memory phenomenon – positive or negative affective state induces recall of similarly valenced material
Obsessiveness and Performance (Persons & Foa, 1984; Sher et al., 1989)
Delayed decision-making
Reduced ability to recall recent activities
Reduced confidence in ability to distinguish among actual and imagined actions and events
Narrow conceptual categories
Affect and Judgment and Perception (Isen, 1993; Williams et al., 1997)
Depression lowers estimates of degree of control
Anxiety predisposes towards interpretation of ambiguous stimuli as threatening

Assessing affective states is an inherently difficult problem, in large part due to the variation in the expression of these states, both across and within individuals (Picard, 1997). Effective assessment of emotional states therefore requires a combined use of multiple methods. Below we provide brief background information about several methods and outline their relevance for ABAIS. Section 3 then describes examples of specific existing affective modeling and adaptation systems that implement these methods.

2.2.1. *Psychological Instruments/Self Reports*

Self-reports using standardized psychological instruments (i.e. 'pencil and paper' or computer-administered questionnaires) represent an established means of affect and personality trait assessment, in both clinical and experimental settings. Instruments exist for a broad range of affective states and personality traits (e.g. specific affective state and trait measures, specific personality trait instruments, social performance assessment instruments, workload and stress measures, etc.) (e.g. Minnesota Multiphasic Personality Inventory (MMPI) (Hathaway & McKinley, 1989); State-Trait Anxiety Scale; Anxiety Sensitivity Index (Peterson & Reiss, 1987); Positive and Negative Affect Scales – PANAS (Watson et al., 1988); Beck Depression Inventory, etc.). In addition, domain-specific instruments also exist (e.g. aviation-oriented Armstrong Laboratory Aviation Personality Survey (ALAPS) (Retzlaff et al., 1997).

There are several difficulties associated with the use of self-reports: (1) their use may be impractical in real-time environments (except to provide background information); and (2) inaccuracies due to the user's inability to recognize, or unwillingness to report, certain affective states, which may, nevertheless, influence performance.

In spite of these drawbacks, self-reports can be a valuable resource for affect assessment, provided the following conditions are met:

- The task environment provides opportunities for brief, simple self-assessment of specific affective states (e.g. a simple dialog box with a 'Are you now feeling anxious?' and a 'YES' 'NO' option).
- Users can be trained to accurately differentiate between the affective states of interest (e.g. high and a low-anxious state).
- Cooperation of users in providing accurate information can be assured.

Implications for ABAIS. Existing instruments can be used in two ways. *First*, during an off-line, initial assessment, to provide background information and suggest generic effects on performance. *Second*, during brief on-line assessment, where one or two items are presented to the user *during* task performance, to provide a specific, targeted assessment of their current affective state. This latter application of self-reports needs to be compatible with the task context and may not be appropriate in all situations.

2.2.2. *Physiological Sensing*

A large number of physiological assessment methods exist, varying in intrusiveness, reliability of the obtained data, and diagnosticity. A critical theoretical issue here is whether distinct emotions have distinct, recognizable physiological profiles. This is an area of active research and lively debate, with arguments on both sides (Ekman & Davidson, 1994; Cacioppo et al., 1993). A critical practical issue is the feasibility and reliability of implementing physiological sensing methods (e.g. large, bulky equipment for heart rate measures; uncomfortable, interfering electrodes for EEG and EMG, etc.).

Fortunately, however, there have been both theoretical and practical advances in recent years, to make selected physiological assessment feasible (Picard, 1997). *On the theoretical limitation side*, one approach is to limit the assessment to a differentiation between high and low arousal, and positive and negative valence, which is easier than accurate recognition of a large set of affective states[2]. *On the practical side*, the emerging technology of wearable computers promises to make fast, unobtrusive measurement of a variety of physiological signals feasible.

Implications for ABAIS. While a number of experimental methods are theoretically available, existing empirical results suggest that most reliably assessed affective measures are arousal and valence. The best *practical* signal for arousal detection is heart rate (Orr, 1998; Cacioppo et al., 1993). Other measures of arousal, such as galvanic skin response, pupil size, blood volume pressure, etc., either do not provide additional data and/or are not as readily assessed. While skin conductance

[2]Note, however, recent work by Picard and colleagues (Vyzas & Picard, 1998), who report increasing success in differentiating among several of the basic emotions using physiological data.

measures represent a better direct measure of anxiety, as opposed to arousal, the requirement of finger or palm sensors generally makes these impractical in computerized, automated environments[3]. The best means of assessing valence appears to be facial EMG, focusing on the corrugator and zygomatic muscle groups. The selection of specific methods and measures is thus highly task- and interface-dependent. Given the task considerations of the ABAIS prototype, the most appropriate physiological signal appears to be heart rate as a measure of anxiety level.

2.2.3. *Diagnostic Tasks*

Diagnostic tasks represent an additional means of assessing affective state in real time, using a variety of behavioral observations and performance metrics (e.g. accuracy, reaction time, type and timing of specific errors, etc.). Both can be assessed either via passive user monitoring or via the injection of specific diagnostic probes to collect measures of interest. A key advantage of diagnostic tasks is their ability to provide an individualized means of directly assessing actual performance biases in real time, rather than relying solely on indirect measures of anxiety/arousal. As with physiological sensing, while it would be unrealistic to use this method for differentiation among subtle affective states, it appears feasible to indirectly infer levels of anxiety or key personality traits (e.g. obsessiveness, aggressiveness, etc.).

Implications for ABAIS. This approach to affect assessment appears feasible, provided the following criteria are met:

- Domain-specific diagnostic tasks can be identified and customized to individual users and task context.
- Individual baseline performance data can be collected for comparison during real-time assessment.
- Implementation of a non-intrusive means of collecting the necessary data in real time is feasible.

2.2.4. *Expert Observer Evaluation – Knowledge-Based Assessment*

This approach in effect emulates an expert observer, familiar with the task and the user, who combines a variety of relevant data and determines the most likely user affective state. The knowledge-bases necessary to implement this approach contain mappings that combine both static and dynamic data (e.g. individual history, personality traits, task characteristics, skill level and current affective state, workload, physiological signals, task difficulty). These data are obtained from knowledge elicited from experts or technical literature, or derived from cognitive task analysis. A variety of inferencing mechanisms can then be used to derive the affective state from the dynamic data (e.g. rules, fuzzy sets, Bayesian belief nets, etc.). A key

[3]Note, however, rapidly emerging non-intrusive and wearable devices that may make complex physiological assessment more practical in the near future.

advantage of this approach is that it in effect allows the *simulated* implementation of a combination of multiple assessment methods.

In some sense, this approach is analogous to the cognitive appraisal theory of affect generation, which posits that affective states result from cognitive evaluations of the individual's goals and expectations, current situation, interpersonal environment, etc. A key distinction between the ABAIS knowledge-based approach and the cognitive appraisal process, other than the obvious difference between who is doing the assessment, is that the former draws on a broader variety of data (e.g. physiological data, diagnostic tasks, etc.)

Implications for ABAIS. The ability to combine a wide variety of data makes the knowledge-based approach an ideal candidate for an initial prototype implementation, designed to test the feasibility of integrating multiple assessment methods within a single inferencing formalism and architecture.

2.3. Effect of belief states on performance

Much recent research in decision making and skilled human performance, particularly in dynamic and real-time settings, has focused on the concept of situation assessment and situation awareness (Endsley, 1995). Briefly, situation awareness refers to the individual's ability to rapidly identify salient cues in the incoming data and map those cues onto a small set of relevant situations, which then guide further action selection. A series of extensive studies of situation assessment in the military and other real-time settings have been conducted by Klein and colleagues (1989). Klein has labeled this process *recognition-primed decision-making* (RPD), and identified RPD as a key element in tactical planning (Klein, 1997).

To the extent that affective state and personality traits influence attention, perception, and cognition, they also play a major role in influencing all aspects of situation assessment and belief formation, from cue identification and extraction, to situation classification, and finally decision-selection. An additional critical relevant area of study is the research in cognitive biases, resulting from the application of cognitive heuristics, many of which may be unconscious (Tversky & Kahneman, 1974). Specific biases identified include confirmation bias, primacy and recency effects, confirmation bias, overgeneralization, etc.).

Implications for ABAIS. The ABAIS belief assessment component corresponds to the situation assessment discussed above; the currently active beliefs correspond to knowledge schemata that influence all stages of the situation assessment process. The assessment of a user's belief state thus amounts to the identification of his/her set of knowledge schemata that guide situation assessment. The situation assessment literature helps identify both the distinct stages of situation assessment, and the role that specific knowledge plays in this process (Klein, 1997; Lipshitz & Ben Shaul, 1997). The emotion and cognitive bias literature then helps identify the set of specific performance errors that can result from perceptual and cognitive biases. Both sources provide a systematic basis for identifying possible belief states, for analyzing individual history information and applying it to dynamic belief assessment, and for identifying the relationships between specific affective states and cognitive biases.

3. Related Work in User Modeling and Adaptation

Two core functionalities must be addressed by effective user modeling and adaptation systems: assessment of the user's state (whether cognitive, physical, or personality and affective), and implementation of an appropriate adaptation strategy to provide information consistent with a particular state, compensate for performance degradation, enhance a particular state, or attempt to induce a particular state (again, cognitive, physical, or affective). User modeling and adaptation research has evolved rapidly over the past ten years and the number of systems, methods, and applications that attempt to solve these problems is too large to allow an exhaustive discussion of each potentially relevant system.

The traditional non-affective application domains include information filtering, document retrieval, web navigation (Pohl & Nick, 1999), tutoring, and personal assistants (Mitchell et al., 1994; Maes, 1994) in a variety of domains. The user states assessed typically consist of a variety of cognitive aspects of user knowledge, preferences, and performance (e.g. capabilities and limitations, interaction style preferences, goals and information needs, domain models, specific knowledge 'bugs', generic problem- solving knowledge, etc.) (Dieterich et al., 1993). The methods for obtaining the user knowledge include implicit inferencing (e.g. probabilistic information filtering and classification approaches, knowledge-based inferencing and statistical approaches to derive user model information, machine learning techniques to automatically construct a user model from identified patterns in collected behavioral data (Pohl & Nick, 1999)), and explicit queries of the user, with varying degrees of user involvement in the model construction and maintenance (Fleming & Cohen, 1999). The adaptations include modifying information retrieval criteria, changing tutoring strategies or material, and modifying user interfaces (e.g. Fijalkiewicz & DeJong, 1998).

Although the focus on affective assessment and adaptation in the broad user modeling area is relatively recent, much interesting and relevant work exists, systems are being developed and evaluated in applied settings, and basic research is being conducted on specific methods. In an attempt to reduce the complexity of this area it is helpful to focus on several key dimensions of user assessment and adaptation when making cross-system comparisons. In the *user assessment* area, these include:

- *which user characteristic* do they attempt to assess (e.g. cognitive aspects such as goals, intents, plans, preferences, beliefs, skill level; affective aspects such as current affective state or likely future affective state(s); or personality)

- *what data* are used to assess these characteristics (e.g. performance and behavior, physiological data, self reports, observations, etc.)
- *how* are the data manipulated and combined to perform the assessment (e.g. case-based reasoning, abductive reasoning, rule-based matching, pattern recognition algorithms, etc.).

In the *user adaptation* area these include:

- What *user characteristic is driving the adaptation* (e.g. affective state/change in affective state, personality, goal/change in goal; specific behavior, etc.)
- What is the *objective of the adaptation* (e.g. improve performance (time, accuracy), enhance subjective factors regarding the human–machine interaction, prevent disastrous consequences of errors, etc.)
- What are the *bases for selecting specific adaptation strategies* (e.g. personality, task context, performance, affective state, knowledge state, etc.)
- What *modalities and means are used to implement the adaptation strategy* (e.g. change tone/pace of interaction, introduce specific interaction designed to address a particular state, modify data type/frequency/presentation, etc.)

These dimensions are considered in the brief descriptions of relevant representative systems below. The selected systems include both those focusing on developing *tools* in particular application settings (e.g. tutoring (Elliot et al., 1999) and call monitoring (Petrushin, 2000)), and those focusing on exploratory development and assessment of particular *methods* (e.g. facial expression analysis (Kaiser et al., 1998; Bianchi & Lisetti, this issue), speech analysis (Petrushin, 2000; Mozziconacci, 2001), and physiological signal analysis (Healy & Picard, 2000)).

Elliot and colleagues have developed a pedagogical agent, based on the Affective Reasoner system (Elliot, 1992), which attempts to enhance its effectiveness through the assessment of the user's affective state (Elliot et al., 1999). The agent uses a type of cognitive appraisal process (Lazarus, 1991) to infer the affective state, implementing an enhancement of a cognitive appraisal model outlined by Ortony et al. (1988), and considers a variety of user characteristics (e.g. goals, principles that guide behavior, preferences, etc.). The assessment focus is on emotions such as hope and fear, and on the user's goals and goal characteristics (e.g. most critical goals, expectations regarding the achievement of this goal), in an attempt to capture the user's motivation. The data used include self-reports and behavior observations and the techniques include various AI inferencing approaches (e.g. case based abductive reasoning based on particular behavioral manifestations, recent individual history of the user (e.g. 'just failed on task' or 'just succeeded on task'). More recent efforts attempt to infer the user's affective state based on the agent's affective state, thereby attempting to implement a form of software empathy.

In an effort to enhance and enrich human-computer interaction in general, Breese and Ball (1998) have developed an affective adaptive architecture that assesses the user's affective state (in terms of the fundamental dimensions of valence and arousal), and personality (in terms of the dimensions of dominance and friendliness). The system uses dynamic Bayesian belief networks to combine a variety of observable data (e.g. speech rate, facial expressions, word choice)[4]. Once a state and personality trait are identified, the interaction agent generates a response whose affective and personality tone match those identified in the user.

With a similar objective in mind, Klein developed and evaluated an experimental system that assesses user's level of frustration using behavioral observations and self-reports, and implements an adaptation strategy that emulates human activities aimed at reducing negative affect (e.g. active listening, providing opportunity to vent, etc.) (Klein et al., 1999).

A number of recent efforts have attempted to assess user affective state via physiological sensing and a variety of prototype systems have been developed, primarily at the MIT Media Laboratory (/www-white.media.mit.edu/vismod/demos/affect/AC_research/recognizing.html). These approaches assume distinct sets of physiological correlates characterizing particular affective states, and use a variety of sensors and wearable computer devices for data collection, coupled with complex pattern recognition algorithms to identify the unique patterns characterizing a particular state. Examples of these projects include Healy's work in assessing user's stress level (Healy & Picard, 2000), which analyzes four physiological signals (EKG, EMG, respiration, and GSR), and the BlueEyes project at IBM (www.almaden.ibm.com/cs/blueeyes/) developing touch-sensitive input devices (e.g. Emotion mouse (www.almaden.ibm.com/cs/blueeyes/mouse.html)), by sensing and analyzing the user's pulse, temperature and GSR, to assess the user's level of anxiety, stress, and happiness and using this information to determine success of computer-generated behaviors in a variety of intelligent 'appliance' systems (e.g. intelligent TV channel selector, etc.)

The BlueEyes project also uses visual data based on observable behaviors (e.g. facial expression (focusing on eyebrows and corners of mouth), gaze tracking, and gesture observation) to assess the user's cognitive, physical, and affective states relevant to human-machine interaction (e.g. anxiety, happiness, dissatisfaction, etc.).

Extensive work in affective state assessment has been done by the Geneva Emotion Group (www.unige.ch/fapse/emotion/), as part of an extensive emotion research program. Particularly relevant to affect assessment is the in-depth work of Kaiser, Wehrle and colleagues, focusing on facial expression analysis (Kaiser et al., 1998). Their approach uses a complex coding scheme to code a variety of facial expression elements, including movements, to assess a variety of user states, including cognitive states (e.g. positive and negative emotions in general, distinguishing among several negative emotions such as fear, sadness, and anger, cognitive process engagement and complexity). An interesting outcome of this work is the finding that the most

[4]This work focuses more on the inferencing processes required to derive a particular state than on the data extraction itself.

extensively developed facial coding scheme to date (Ekman and Friesen's FACS coding system (1975)) may not be of general applicability.

Speech is another effective source of data for affect assessment. Petrushin (2000) used a variety of speech attributes (e.g. pitch, vocal energy, rate and pauses, etc.) to differentiate among five affective states (neutral, happy, sad, angry, and fearful), using several mathematical modeling approaches[5] to derive the final affective state. These methods have been applied to the analysis of telephone conversations in support call centers, to both prioritize messages and assign an appropriate human to handle particular calls. Mozziconacci (2001) provides an extensive discussion regarding the mapping of particular speech variables (e.g. pitch level, pitch range, and speech rate) onto particular emotions.

Within the pilot-vehicle context, several systems address the broad area of intelligent adaptive interfaces in the fighter-pilot domain (e.g, McNeese, 1986; Fraser et al., 1989). The early work in the pilot associate program focused on multi-level adaptation (Rouse, 1988). These early programs provided a much needed experimental context for today's successful Rotorcraft Pilot's Associate and more advanced envisioned worlds (Taylor, 2001). Examples of recent user assessment and adaptation efforts include a fighter-pilot adaptive interface that assesses the pilot's workload and implements content, format, and modality adaptations in the cockpit displays (Mulgund et al., 2001), and analogous work in the context of air traffic management (Harper et al., 2000).

4. ABAIS Adaptive Methodology and System Architecture

This section provides an overview of the ABAIS architecture and its constituent modules. The key components – assessment and adaptation – are described in detail in Sections 7 and 8, after the necessary domain background information is provided in Sections 5 and 6.

4.1. ABAIS ADAPTIVE METHODOLOGY

The ABAIS prototype implements a four step adaptive methodology consisting of: (1) sensing/inferring the individual's affective state and performance-relevant beliefs (e.g. high level of anxiety; aircraft is under attack); (2) identifying their potential impact on performance (e.g. focus on threatening stimuli, biasing perception towards identification of ambiguous stimuli as threats); (3) selecting a compensatory strategy (e.g. redirecting focus to other salient cues, presentation of additional information to reduce ambiguity); and (4) implementing this strategy in terms of specific GUI adaptations (e.g. highlighting relevant cues or displays); that is, presenting additional information, or presenting existing information in

[5] K-nearest neighbors and a variety of backpropagation neural network approaches.

a format that facilitates recognition and assimilation, thereby enhancing situation awareness (Endsley, 1995).

4.2. ABAIS SYSTEM ARCHITECTURE

The ABAIS system architecture (see Figure 1) implements the adaptive methodology described above and consists of four modules, each module implementing the corresponding step of the methodology:

- *User State Assessment,* which identifies the user's affective state and task-relevant beliefs;
- *Impact Prediction,* which identifies the effect user state on performance;
- *Strategy Selection*, which selects a compensatory strategy; and
- *GUI*/DSS *Adaptation*, which modifies the user interface content and format to improve detection, recognition, and assimilation of incoming data to enhance situation awareness.

Each of the modules is briefly described below in terms of its input/output behavior. Sections 7 and 8 then provide more detailed process description.

The *User State Assessment Module* receives a variety of data about the user and

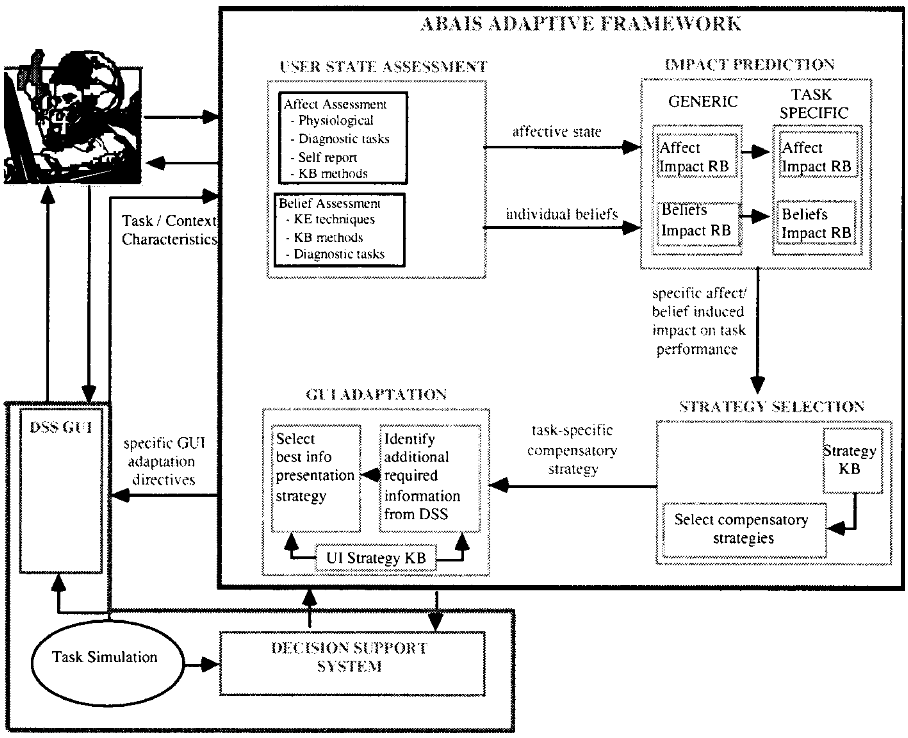

Figure 1. ABAIS system architecture.

the task context, and from these data identifies the user's predominant affective state (e.g. high level of anxiety) and situation-relevant beliefs (e.g. interpretation of ambiguous radar return as a threat). This is the most critical component of the ABAIS architecture and is described in detail in Section 7.

The *Impact Prediction Module* receives as input the identified affective states and associated task-relevant beliefs, and determines their most likely influence on task performance. The goal of the impact prediction module is to predict the influence of a particular affective state (e.g. high anxiety) or belief state (e.g. 'aircraft under attack', 'hostile aircraft approaching', etc.) on task performance. Impact prediction process uses rule-based reasoning (RBR) and takes place in two stages. First, the *generic effects* of the identified affective state are identified, using a knowledge-base that encodes empirical evidence about the influence of specific affective states on cognition and performance. Next, these generic effects are instantiated in the context of the current task to identify *task-specific effects*, in terms of relevant domain entities and procedures (e.g. task prioritization, threat assessment). The knowledge encoded in these rules is derived from a Cognitive Affective Personality Task Analysis (CAPTA), which predicts the effects of different affective and belief states on performance within the current task context. The separation of the generic and specific knowledge enhances modularity and simplifies knowledge-based adjustments.

The *Strategy Selection Module* receives as input the predicted effects of the affective and belief states, and selects a compensatory strategy to counteract resulting performance biases. Strategy selection is accomplished by rule-based reasoning, where the rules map specific performance biases identified by the Impact Prediction Module (e.g. task neglect, threat-estimation bias, failure-estimation bias, etc.) onto the associated compensatory strategies (e.g. present reminders of neglected tasks, present broader evidence to counteract threat-estimation bias, present contrary evidence to counteract failure-driven confirmation bias, etc.). As was the case with impact prediction, this module relies on a detailed analysis of the task context that identifies specific strategies available to counteract the possible biases. This analysis then allows the construction of the strategy selection knowledge bases.

The *GUI Adaptation Module* performs the final step of the adaptive methodology, by implementing the selected compensatory strategy in terms of specific GUI modifications. A rule-based approach is used to encode the knowledge required to map the specific compensatory strategies onto the necessary GUI/DSS (decision support system) adaptations. The specific GUI modifications take into consideration information about the individual pilot preferences for information presentation, encoded in customized user preference profiles. For example, different users may have varying preferences for highlighting critical information (e.g. blinking versus color change versus size change of the relevant display or icon).

4.2.1. *Ancillary Modules*

Several additional modules exist in the ABAIS prototype, enabling the simulation of the demonstration task, output of the simulation results on a simulated cockpit GUI (both adapted and non-adapted versions), and a series of displays and windows supporting the analyst-system interaction (e.g. entering user and task data, and monitoring system performance). These are briefly described below.

ABAIS Simulation Module. The core ABAIS framework is integrated within a dynamic flight simulation environment and supports two modes of system operation: (1) pilot-as-user mode, where the user actually flies the aircraft and interacts with a simulated environment consisting of other friendly aircraft, enemy aircraft, radars, and weapons; and (2) analyst-as-user, where the analyst watches a simulation of a scripted task and monitors the (scripted) pilot's performance, and the system run-time performance (i.e. details of the rule-based inferencing). Both modes include a pilot GUI consisting of key cockpit displays (see Figure 6 in Section 8 below).

Pilot's GUI. The pilot's GUI (see Figures 6, 7, and 8 in Sections 8 and 9 below) consists of four displays, corresponding to the *heads-up-display (HUD),* which combine a variety of navigation and sensor information (i.e. heading, airspeed, altitude, MACH speed, etc.) (upper portion of the display), two windows showing current incoming *communication* as text strings and an *alert notification* window (portion of the display), and the *radar and sensor display*, which combines information from a variety of aircraft instruments (e.g. active radar, IFF, NCTR, and RWR) as well as data from other friendly aircraft obtained via electronic datalink (bottom portion of display). (Refer to glossary in Appendix A.) The radar and sensor display symbology follows existing cockpit standards (see Appendix B).

Analyst's GUI. The analyst's GUI module serves three functions:

- It supports the specification of all ABAIS *system run-time parameters*, including task script editing and selection, adaptation thresholds, and execution monitoring windows.
- It supports the specification of all necessary *background pilot information*.
- It supports the display and monitoring of ABAIS *simulation and run-time* data.

Prior to a run, the necessary background information about the pilot must be provided. In the initial ABAIS prototype demonstration, these values were entered by the analyst. In a full-scope system, some of these parameters would be entered by the user (pilot) (e.g. self-reports and individual history information), gathered during training tasks (e.g. baseline physiological or diagnostic task data), or collected automatically during an actual system run (e.g. actual physiological signals or diagnostic task results). Different categories of information are specified, including personality, skill, individual history, and adaptation preferences.

5. ABAIS Demonstration Task: Fighter Pilot 'Sweep' Task

In this section we describe the essential details of the ABAIS demonstration task, to provide the necessary background for understanding the ABAIS rule-bases and inferencing described in Sections 7 and 8. While the initial prototype was implemented in the context of a fighter pilot task, the overall ABAIS methodology, and the implemented framework, provide a generic approach to affective adaptation and modeling (see discussion in Section 10.3).

5.1. Task context

The demonstration task simulates an Air Force fighter pilot sweep mission, where a group of friendly pilots attempts to clear the airspace of any enemy aircraft. The aircraft is assumed to be an F-15-like fighter aircraft. During the specific mission, two friendly aircraft ('lead' and 'wingman') are conducting a sweep mission over enemy territory, assisted by an AWACS aircraft providing additional information and command and control. Several unknown, presumed hostile aircraft, are approaching the friendly aircraft and the corresponding data (radar returns) are beginning to appear on the aircraft cockpit radar displays (refer to Figures 6–8 in Sections 8 and 9). Appendix A provides a glossary of scenario terms. Appendix B provides explanations of the cockpit display symbology.

5.2. Human context

The demonstration task focuses on the lead pilot as 'the user'. The lead pilot communicates with the wingman and with the AWACS aircraft operator, both via voice and via electronic datalinks, which display data directly on the lead's cockpit instruments (e.g. radar display, HUD).

The lead pilot's background information (user profile) is entered by the analyst prior to a run (e.g. personality traits, skill, individual history, physiological responsiveness, adaptation preferences).

5.3. Summary of demonstration task events

The lead and the wingman are conducting a sweep mission over enemy territory. Pilots are expecting strong enemy opposition. Friendly aircraft are likely to be in area, making fratricide a possibility. A high-anxious lead pilot misinterprets incoming unknown contact as hostile and prepares to fire by 'centering the dot' on his HUD. Table 2 summarizes the possible effects of affective and belief states on the lead pilot's performance. At the last minute, the wingman radios that a friendly identification has been obtained on this contact. In other words, that the approaching aircraft is in fact a friendly coalition aircraft. However, the lead pilot is busy targeting this aircraft and misses this transmission. Without adaptation, the lead would fire a missile and hit a friendly aircraft. With adaptation, the incoming

Table 2. Summary of possible affective and belief state influences on pilot behavior

Anxiety-Induced Narrowing of Attention
Lead focusing on 'centering the dot'
Misses 'friendly ID' voice communication from wingman
Misses results of NCTR (friendly ID) on radar display
Anxiety-Induced Perceptual Bias
Lead misinterprets ambiguous radar returns as threats

data (friendly ID) are enhanced and the pilot's attention is directed to this information, in an attempt to prevent the fratricide.

6. Cognitive, Affective, Personality Task Analysis (CAPTA)

Given the fact that a general model of human information processing is beyond the state of the art, any user modeling effort must focus itself on particular aspects of performance during a specific task of interest or an underlying mechanisms of interest. A systematic cognitive task analysis process is the foundation for the development of any such model. Since the focus of this effort is the influence of affect and belief states on performance, the cognitive task analysis focused not only the space of nominal and desirable behaviors and cognitive performance, but also the larger space of possible behavior variations due to the effects of these additional factors. We term this enhanced cognitive task analysis process Cognitive Affective Personality Task Analysis, or CAPTA for short. CAPTA formed the basis for developing the ABAIS system knowledge bases and adaptation strategies. In this section we briefly outline the CAPTA process and distinguish it from existing cognitive task analysis techniques (6.1), and indicate how it supports the ABAIS adaptive methodology and how it relates to the ABAIS architecture (6.2). A full description can be found in Hudlicka (2000a).

6.1. Description of the CAPTA process

The objective of cognitive task analysis (CTA) is to define the user's activities during a task at a sufficient level of detail to allow computational modeling, knowledge base definition, user interface requirements specification, or work analysis. In other words, to support the variety of tasks that comprise the definition, implementation, operation, and applications of user models.

A number of CTA techniques exist (Cooke, 1995; COADE) using a variety of methods and representational formalisms (e.g. rules, concept maps, frames and schemata, etc.). Their unifying objective is to define critical domain and user entities, their states, and their behaviors, including the user's actions.

CAPTA differs from the traditional CTA techniques by explicitly focusing on behavior variations due to the user's affective states, personality traits, and belief states. This has two advantages with respect to affective adaptation: (1) it makes

Table 3. Relationship of CAPTA to ABAIS architecture components

CAPTA information category	Relevance for ABAIS architecture	Pilot domain example
• Possible set of user's affective states • Possible set of user's belief states	• Basis for defining specific affective/belief state assessment strategies • Basis for predicting behavioral effects of specific states • Basis for identifying compensatory strategies associated with each state	• Pilot A can be calm or anxious • Pilot B can be calm or aggressive • Pilot can believe s/he is out of danger, about to be attacked, under attack • If a particular affective state (e.g. anxiety) reduces attentional capacity, modify display to reduce attentional demands
• Likely triggers of particular affective and belief states	• Defines knowledge-base within 'User Assessment' module, supporting the assessment of user's affective and belief state	• Pilot becomes anxious when large number of unknown radar contacts appear on the screen • Pilot assumes any unknown radar contacts are hostile
• User's likely response to a particular situation • User's likely behavior as a function of affective or belief state	• Defines knowledge-base within 'Impact Prediction' module, supporting the prediction of specific effects of user affective and belief states • Help define knowledge-base within 'GUI Adaptation' module and specific GUI adaptation strategies	• Pilot tends to delay weapon engagement • Pilot engages in excessive information gathering • Pilot detects alarms more rapidly when presented in auditory mode

Table 4. Examples of pilot cues, situations, and decisions

<table>
<tr><th>Cues (Incoming Stimuli)</th><th>Situations (Beliefs)</th><th>Decision (Behaviors)</th></tr>
<tr><td>Datalink – friendly | unknown | hostile</td><td>Hostile aircraft opening | closing</td><td>Fire weapon</td></tr>
<tr><td>IFF – friendly | unknown</td><td>Presumed hostile aircraft opening | closing</td><td>Initiate intercept</td></tr>
<tr><td>NCTR – <aircraft type></td><td>Unknown aircraft opening | closing</td><td>Initiate evasive action</td></tr>
<tr><td>RWR – no radar contact | hostile radar contact | friendly radar contact | SAM radar contact | unknown radar contact |</td><td>Cleared to fire w/positive EID</td><td>Communicate w/wingman</td></tr>
<tr><td>Active radar – friendly | unknown | hostile</td><td>Firing range for <weapon> maximum | beyond maximum</td><td>Communicate w/wingman</td></tr>
<tr><td>Targets – closing | opening</td><td>Attacking hostile aircraft</td><td>Communicate w/AWACS</td></tr>
<tr><td></td><td>Under attack from hostile aircraft</td><td>Focus on particular instrument</td></tr>
</table>

explicit the number and type of affective and belief states, and user behaviors associated with each; and (2) it produces a more complete and comprehensive description of the user's possible states and behaviors. Specifically, CAPTA addresses the following:

- What is the possible set of user's affective and belief states?
- What are the likely triggers of particular affective and belief states?
- How is the user likely to respond to a particular situation?
- How will this response vary depending on the user's affective or belief state?

Table 3 illustrates how these categories of information relate to the ABAIS architecture.

The CAPTA application within the current context assumes a naturalistic model decision making (Klein, 1997), where the primary skilled processing takes place at the perceptual – situation assessment side. Once the incoming cues are assembled into meaningful schemata and categorized into situations, there is a simpler mapping process between the situation and the selected action. This theoretical model underlies the three-stage task analysis approach implemented by CAPTA, which consists of the following steps:

- Constrain the possible user behaviors (i.e. decisions), situations (i.e. high-level cognitive and perceptual schemata), and stimuli (i.e. incoming sensory cues), within the context of the scenario and task domain.
- Define the mappings between the cues and the situations, and between the situations and the decisions.
- Map the user's possible affective and belief states, and their effect on behavior during each stage of perception and decision making, onto specific cue-situations and situations-actions mappings.

The last step distinguishes CAPTA from more traditional cognitive task analysis techniques. During this step, the cognitive engineer works closely with the subject matter expert and draws on the available empirical evidence about the effects of particular affect and belief states on perception, decision selection, and behavior. Thus the generic effects of the possible affective states identified from the empirical literature are instantiated within the specific task context. By combining the available empirical evidence with the practical knowledge of the domain expert, the cognitive engineer constructs a space of possible behaviors which takes into account not just the nominal path through the problem solving space, but also the variations resulting from different affective and belief states. For example, the empirical knowledge that anxiety biases attention and perception towards the detection of threatening stimuli, and the interpretation of ambiguous stimuli and situations as threatening, is combined with the expert's knowledge of the task at hand (e.g. air combat), to derive the alternative possible behaviors due to heightened state of anxiety (e.g. a pilot may interpret ambiguous radar returns as threats and fire prematurely at friendly or neutral aircraft which happens to be in the area).

6.2. Use of CAPTA to support the ABAIS architecture development

CAPTA thus produces a comprehensive description of the possible behaviors and behavior variations associated with particular user states, traits, and beliefs, thereby generating a more complete specification of the user-task problem space. Such problem space definition then becomes the basis for defining critical knowledge-bases of the ABAIS architecture modules (refer to Table 3). Below is a brief illustration of how the CAPTA process supports definition of the ABAIS architecture components, that is, the knowledge bases contained in the distinct modules.

6.2.1. *Defining User Behaviors, Situations, and Incoming Cues*

The CAPTA process must be grounded in a fixed set of possible actions, situations triggering those actions, and cues leading to the derivation of the situations. The first step of the process is therefore to define the limiting conditions – that is, the possible outputs (behaviors), key intermediate states leading to these actions (perceived situations), and incoming data or stimuli leading to the perception of the situations (cues). While the entities defining the end-points (i.e. cues and behaviors) of this process are fixed by the situation context and user capabilities (available displays and sensory channels on the input side, and possible behavioral outputs on the output side), the definition of the situation set is an art rather than a science. This process relies on the knowledge and cooperation of the subject matter expert, who must work closely with the cognitive engineer/model developer to select the most appropriate situations, at the correct level of abstraction, that provide coverage of the current task. Table 4 shows examples of cues, situations, and decisions in the current ABAIS fighter pilot task context.

6.2.2. *Defining Situation-Action and Cues-Situation Mappings*

Once the sets of possible behaviors, situations, and cues are defined, CAPTA defines the mappings linking cues and the situations, and situations and actions. In other words, based on the task knowledge elicited from the SME, the model developer specifies which cues trigger which situations, and which situations in turn trigger which behaviors. This knowledge then forms the basis for defining the rules in the ABAIS Impact Prediction Module knowledge-base.

To identify the situation-action mappings, we began with the possible sets of behaviors and identified the situations that triggered each behavior. For example, a pilot will fire if s/he sees a hostile target within range and is cleared to fire. By working backward from the possible behaviors we thus identified series of triggering situations for each behavior. These situation-actions mappings were then expanded to cover the different user profiles, and categorized into specific groups according to the affect and belief factors. Once the complete analysis was performed, the situation-action mappings were translated into the rule set in the ABAIS affect and belief Impact Prediction Module.

6.2.3. *Defining Cues-Situations Mappings*
To identify the cues-situation mappings, we began with the set of possible situations and identified the incoming cues that would indicate each situation (i.e. belief). For example, a 'hostile aircraft is closing' situation exists if there is a radar return representing a hostile aircraft, and the radar return indicates an approaching aircraft over time. Given the fact that CAPTA defines not only correct decision making but a variety of possible distortions (e.g. misinterpretation of cues; incorrect weighting of individual cues, etc.), as well as a number of perceptual variations, this process involved the construction of extensive cues-situations mappings that explicitly represented such distortions and variations. For example, while in general the presence of an unknown contact on the radar does not necessarily imply that the pilot is under attack, it is certainly a possibility that this contact may in fact represent a hostile aircraft. In the case of an anxious or aggressive pilot this possibility may then become the predominant belief guiding behavior. Thus the construction of these mappings involved the consideration of a large number of possible cues-situation mappings that might be used by various pilot types to conduct situation assessment and arrive at the resulting beliefs. These cues-situations mappings are the primary source for deriving the belief assessment rules within the ABAIS User Assessment module.

6.2.4. *Influences of Affect and Belief States*
Once the basic set of mappings was defined, it was expanded to account for the influences of the pilot's affect and belief states. This process combined existing empirical evidence with task-specific expertise. A systematic analysis of the possible pilot behavior and decision making during the course of the demonstration scenario yielded a set of possible perceptual and cognitive distortions, biases, and general variations resulting from the affect and belief states. The paragraph below describes the application of this process to the analysis of the effects of anxiety on behavior and provides examples of specific rules that result from this process.

The *generic effects of anxiety* on attention include narrowing of attentional focus, difficulty focusing attention (i.e. inability to select an action and consequent delayed reaction time), and increased attention to threatening stimuli. This narrowing of attention may also result in task neglect for other critical tasks, and a failure to detect other relevant cues.

Given this generic knowledge, the CAPTA process is then used to predict *task specific* situations where these biases may influence performance. In other words, to identify situations where ambiguous cues exist which can be misinterpreted as threatening, and to identify task segments where parallel signals may occur (e.g. two signals on radar from two different sources, radar and engine instruments, etc.) and identify points where parallel tasks take place. These then allow predictions as to which of these tasks is likely to be neglected during a state of increased anxiety (e.g. pilot is more likely to pay attention to radar signals than engine instruments or radio). Examples of *specific effects* of the generic anxiety-induced biases include:

- Focussing on target on radar display and failing to notice incoming communication from other sources (e.g. radio voice communication from wingman, AWACS, etc.) or other cockpit instruments (e.g. warnings of aircraft system malfunctions).
- Focussing on target information on HUD and failing to notice new information on radar.
- Interpreting ambiguous radar returns as threats.

Examples of specific rules constructed from this knowledge and used in the Impact Prediction module are shown in Table 5.

7. User State Assessment and Behavior Prediction

Having provided the necessary background information about the ABAIS adaptive framework and architecture, and the task domain, we now turn to the key aspect of affective adaptation: the assessment of the user's affective and belief states (Section 7.1) and the prediction of their likely effects on performance (Section 7.2).

7.1. User affect and belief state assessment

7.1.1. *Affect Assessment*

Due to the inherent uncertainty in the process, the key to successful affect assessment is the coordinated use of multiple methods. The User Assessment module provides facilities for the flexible integration of multiple methods (e.g. physiological sensing, diagnostic tasks, knowledge-based). The initial prototype described here implements the knowledge-based approach (refer to Section 2.2), and assesses the user's anxiety level. This approach was selected because it combines multiple sources of data and thus provides a means of essentially simulating the use of multiple methods. Anxiety was selected both because it is the most prevalent affect during crisis situations, and because its influence on cognition has been extensively studied and empirical data exist to support specific impact prediction and adaptation strategies.

Table 5. Example rules predicting impact of anxiety on performance

Anxiety-Induced Narrowing of Attention
IF (multiple targets on radar) THEN (focused on signals representing unknowns or threats)
IF (multiple unknown/threats targets on radar) THEN (focused on nearest/fastest-approaching targets)
IF (data arriving on multiple cockpit instrument) THEN (attention focused on radar or HUD)
IF (data arriving on HUD and radar) THEN (attention focused on HUD)
Anxiety-Induced Misinterpretation of Cues
IF (unknown or ambiguous targets on radar | NCTR exist) THEN (assume targets are hostile)
IF (unknown air-to-air radar lock on RWR) THEN (assume under attack)
IF (no reply from IFF) THEN (assume targets are hostile)

The knowledge-based assessment approach assumes the existence of multiple types of data (e.g. individual history, personality, task context, physiological signals), reflecting the multiple factors that influence the user's affective state (see Figure 2). The assessment process implements a fuzzy rule-based approach consisting of four stages (see Figure 3). First, a user profile is specified in terms of static and dynamic data, representing task-relevant user information. Second, the data in this profile are matched against the rules in the user assessment rule-base.

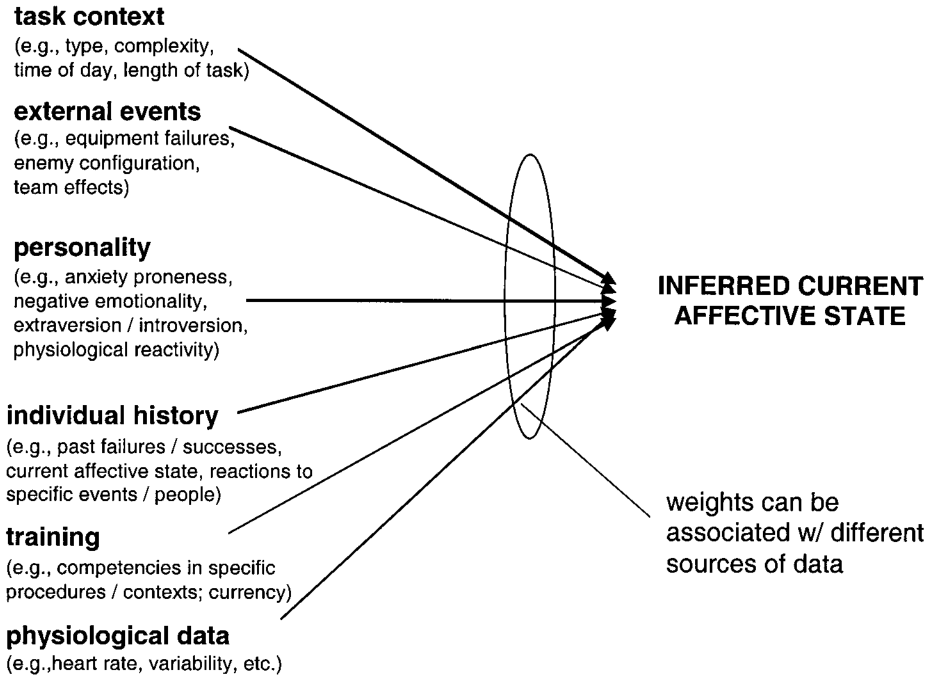

Figure 2. Sources of information for deriving pilot's affective state.

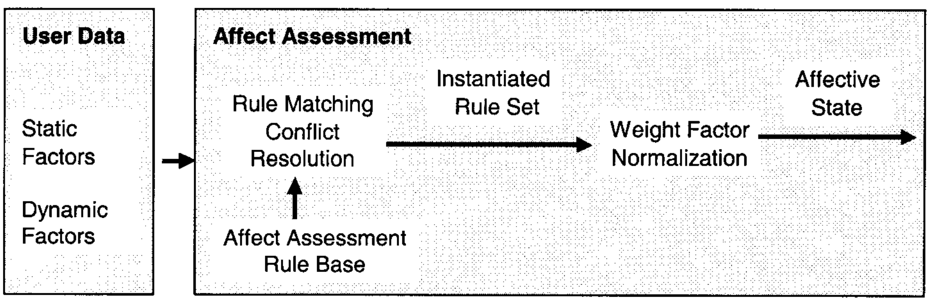

Figure 3. Rule-based approach to affect assessment.

Third, each relevant factor, represented by an instantiated rule, contributes a numerical weight component to the overall score of the corresponding affect. (This is the anxiety weight factor, or AWF, shown in the rules.) Individual factors or categories of factors may be weighted differently, to reflect their differential influence on the overall affective state (e.g. static task factors will typically have a lower weight than dynamic factors and real-time physiological signals). Finally, after all relevant rules are instantiated, the overall anxiety level is computed and the resulting value is mapped onto a three-valued qualitative variable (low, medium, or high). Examples of specific factors in each of the relevant categories are discussed below.

The factors contributing to the pilot's affective state fall into two broad categories: *static and dynamic*. The *static factors* represent influences that remain constant throughout the task (e.g. overall task difficulty, user's training and proficiency, and user's personality traits and individual history). The *dynamic factors* represent the changing external environment (e.g. incoming data from sensors such as radar contacts) as well as the changing state of the pilot (e.g. changes in physiological signals such as heart rate). These values are provided to the affective assessment rules throughout course of the simulation, allowing dynamic updating of the affect weight factor.

Static Factors. The static factor values are determined via a combination of knowledge elicitation from experts and users (e.g. task difficulty, level of training, personality) and off-line user assessment instruments (e.g. personality, skill level), and extensive interviews with users (e.g. individual history, personality). Examples of the *task context* and *individual history* static factors, and their possible values in the context of the demonstration task, are shown in Table 6.

Individual history factors represent a critical set of influences, and capture specific events from the user's history that may influence the current affective state. Given the importance of an individualized approach to affective and belief state assessment, these factors are among the most critical, particularly so since behavior prediction research indicates that the most reliable predictor of future behavior is past behavior. The individual history factors must obviously be tailored to the specific task context. Accordingly, the factors used in the initial ABAIS prototype represent the pilot's previous experience in combat tasks. These factors were obtained through direct knowledge elicitation interviews with domain experts. Examples of individual history factors, and their possible values in the context of the demonstration task, are shown in Table 6.

A critical set of static factors is the set of user's key *personality traits,* which represents a relatively stable set of characteristics that contributes to the user's affective state (e.g. emotional stability correlates with anxiety tolerance) and influences behavior in general (e.g. obsessiveness, aggressiveness). The selection of the specific personality factors below was guided by the following criteria:

Table 6. Examples of static factors used during user state assessment

<table>
<tr><th>Task Context</th><th>Individual History</th><th>Personality Traits</th></tr>
<tr><td>Task type 1:== {offensive | defensive}
Task type 2:== {air-to-air | air-to-grnd}</td><td>Successful situations in past:== { egress | enemy-radar-lock–hit | enemy-radar-lock–evasion | unknown-radar-lock–hit ...}</td><td>Emotional stability:== {1–10}
Impulsiveness:== {1–10}
Risk tolerance:== {1–10}</td></tr>
<tr><td>Phase:== {planning | detection | ...}</td><td>Failure situations in past:== {fratricide | repeat IFF interrogations – fratricide ...}</td><td>Aggressiveness:== {1–10}</td></tr>
<tr><td>Complexity:== {1 ... 10}</td><td>Affective reactions to individual/events:== {</td><td>Conscientiousness:== {1–10}</td></tr>
</table>

- Empirical evidence for existence of candidate factor as a distinct personality characteristic.
- Empirical evidence or knowledge elicitation data indicating specific effects of the personality factor on performance, particularly in the context of the task (e.g. aviation and air combat tasks).
- Likelihood of the personality factor playing a role in the selected demonstration task.

Specific personality factor selection is thus informed both by domain-independent personality theory and empirical data, and, to the extent possible, by studies performed in the specific domain of interest. In the case of the ABAIS prototype, some data were derived from studies assessing the pilot population in terms of a variety of standard psychological assessment instruments (e.g. NEO-PI-R, MMPI, etc.) (Callister et al., 1997), as well as instruments specialized for the fighter pilot population (e.g. ALAPS (Retzlaff et al., 1997)). However, little systematic empirical work has been done in the general area of linking personality factors to specific performance influences and biases, at a level of analysis that would provide the type of detail necessary for real-time adaptation. We therefore also relied on general personality research (e.g. 'Big 5', 'Giant 3' trait sets), and on knowledge elicited from domain experts (e.g. pilots or USAF psychologists and scientists). The objective was to capture personality traits that: (1) are likely to exist in the subject population (e.g. fighter pilots); and (2) exert a pronounced influence on behavior during the performance of the demonstration task. The selected personality factors, and their possible values in the context of the demonstration task, are shown in Table 6. Emotional stability was the primary factor of interest under the prototype development effort, since it is this factor that correlates with anxiety tolerance.

Dynamic Factors. The dynamic factor values represent factors that change during the course of the task. As such, their values must be determined in real-time as the task progresses, to track any dynamic task factors and internal changes in the user's state. An important set of dynamic factors are *external events*, which contribute to the task difficulty and, as such, influence the user's affective state. These include a variety of factors relating to the state of the environment and the task equipment that constitute the dynamic task characteristics (e.g. state of the aircraft, equipment failures, task specific factors such as the geometry of the intercept, any data appearing on the radar systems, team effects).

Another source of dynamic factors are *physiological data* collected from the user during the course of the task. Due to the high degree of individual variations in physiological signals, as well as within-individual variations over time and habituation, these measures must be normalized based on the user's baseline responsiveness measures, and baseline measures for the task and the current day. In the initial ABAIS prototype we focused on assessment of the user's anxiety level and thus considered physiological data that reflect anxiety. While a variety of measures are theoretically possible, (see discussion on physiological sensing in Section 2.2 and 3), the most reliable measures of state anxiety appear to be those related to arousal, that is: heart rate and skin conductance measures[6]. Although these measures reflect general arousal, rather than anxiety per se, it is assumed that during crisis situations in general, and during the demonstration scenario sweep task in particular, the arousal level would be a likely indication of anxiety. During the initial prototype we therefore focused on heart rate as the most reliable and practical measure of arousal, using estimates derived from existing empirical literature and interviews with fighter pilots.

Once the static factors and their values are specified, the user state assessment rules can be defined. These rules map the specific values of the static factors onto an affective state contribution weight. Once all relevant rules are instantiated, the individual contributing weights are combined to determine the final affective state (e.g. anxiety level). Examples of affect assessment rules using static factors are shown in Table 7.

7.1.2. *Belief Assessment*

For the discussion below, we assume a working definition of 'belief', where belief state represents the currently active or preferred set of knowledge constructs, schemata, or procedures guiding perception, influencing decision making, and determining the final behavioral outcome. In other words, the current belief state represents the currently active situation schemata and thus reflects the pilot's situation assessment and situation awareness. Which specific schemata are instantiated at any given time is a function of the user's training, individual history, personality and cognitive style differences, and affective state. Belief assessment in this context thus corresponds to what is generally referred to as situation assessment in the literature; that is, the identification of the most likely current interpretive schemata guiding situation interpretation, decision making, and subsequent action selection.

[6]GSR may not be a practical measure in the fighter pilot setting, both due to intrusive monitoring devices (i.e. finger sensors), and because the fighter pilot task environment may interfere with the data collection (i.e. finger sensors may obstruct other activities).

Table 7. Examples rules using static factors to derive user affective state

Task Context Factors Rules	
IF (phase = Planning | Detection | Commitment | Sorting | Engagement | Egress)	THEN (AWF = 1 | 3 | 5 | 7 | 10 | 3)
IF (task type_2 = offensive | defensive)	THEN (AWF = 5 | 10)
IF (task complexity = low | med | high)	THEN (AWF = 1/5/10)
IF (weather = clear | cloudy | fog | precipitation	THEN (AWF = 0 | 2 | 3 | 3)
IF (light conditions = light | dusk | dark)	THEN (AWF = 0 | 3 | 2)
Training and Proficiency Factor Rules	
IF (air combat hours = low | med | high)	THEN (AWF = 6 | 3 | 0)
IF (air combat exercises hours = low | med | high)	THEN (AWF = 7 | 4 | 0)
IF (training hours = low | med | high)	THEN (AWF = 4 | 2 | 0)
IF (recency of air combat hours = low | med | high)	THEN (AWF = 9 | 5 | 0)
Individual History Factor Rules	
IF (<current-situation> member-of <past-failures>)	THEN (AWF = 10) AND (mood factor = −5)
IF (<current-situation> member-of <past-successes>)	THEN (AWF = −5) AND (mood factor = +5)
IF (unknown type from NCTR)	THEN (AWF = 8)
IF (cleared to fire)	THEN (AWF = 8)
IF (confidence in wingman = poor/neutral/good)	THEN (AWF = 5/0/−5)

For example, in the aviation domain, a combination of pilot's training, recent events, and affective state might predispose him towards a particular interpretation of existing ambiguous data (e.g. unknown radar is hostile, approaching unknown aircraft are friendly, etc.), a pilot's training might predispose him/her toward a particular cockpit instrument scanning pattern, and individual experience might predispose him to a specific set of expectations regarding the outcome of a particular engagement.

Given this definition of beliefs, the following problems must be addressed to identify a belief state and its potential effects on performance. First, the possible set of beliefs relevant for a particular task context must be identified; in other words, the situation taxonomy for the task domain must be defined. Second, the factors contributing to the instantiation of a particular set of beliefs during situation assessment must be identified; these can then be used to dynamically assess the pilot's belief state. Finally, a dynamic assessment must be performed during task performance to determine the user's most likely set of active schemata, that is, the dominant belief state and corresponding situation assessment. These three problems, and the corresponding solutions implemented in the ABAIS prototype, are discussed below.

Identifying the Task Situation Taxonomy. The first problem requires a detailed ontological analysis of the task domain, identifying critical cues, a taxonomy of possible situations, and space of possible actions. This problem was addressed through the Cognitive Affective Personality Task Analysis process (CAPTA) described in Section 6 above and resulted in the set of cues, situations (beliefs), and possible actions described in Table 4.

Factors Contributing to a Particular Belief State. A variety of factors determine the final belief state, each contributing some piece of knowledge or evidence to establish, confirm, or refute a particular belief about the current situation (e.g. unknown target is friendly or hostile). The sum total of these influences then determines the pilot's overall assessment of the current situation. There is significant overlap in the knowledge and rules used to assess the affective state and those used to infer the belief state. A critical aspect of the belief state assessment is the inclusion of the pilot's presumed affective state. This in effect allows the implicit modeling of the influence of specific affective states on cognition and distinguishes the current approach to belief/situation assessment from existing situation assessment methods (e.g. SD_PVI of Zacharias, 1996; Pew & Mavor, 1998)).

Dynamic On-Line Belief Assessment. The process of dynamic belief assessment is the final step of user belief state assessment. During this phase the current knowledge factors contributing to the activation of particular beliefs are instantiated to derive the most likely set of activated schemata, that is the user's beliefs reflecting the current situation. This process essentially simulates, at the input-output level, the pilot's own situation assessment processes. In the context of the current demonstration scenario, the pilot's belief state is reflected in the pilot's assessment of the current situation from the available salient cues. While in theory an infinite number of situations are possible, in practice the set of situations for a particular task is generally limited (e.g. attacking versus being attacked, approaching aircraft are friendly or hostile, etc.). In fact, one of the conditions constraining the application of effective user modeling and adaptation is precisely the possibility of constraining the number of possible situations. In the context of the ABAIS demonstration scenario we therefore limit the possible situations to those identified through initial knowledge elicitation and cognitive task analysis (see Table 4).

For the initial ABAIS prototype, we selected the knowledge-based approach to implement the dynamic belief assessment. As with affect assessment described above, this approach in effect emulates an expert observer, familiar with both the task and the specific individual, and is implemented in terms of production rules. Again, as with the affective state assessment, it is important to keep in mind that the factors, their values, and the corresponding rules, are specified in the context of the current individual-task and can be changed as that context changes. In fact, such individualized tailoring of the ABAIS knowledge-bases is the key to its successful adaptation for a particular individual, or group of individuals in a team setting. The actual belief state was then derived from a combination of static, a priori information about the pilot and the task, and from dynamic data reflecting the changing task environment and pilot state, including the pilot's affective state.

The most critical categories of factors used were: (1) external events; (2) individual history; and (3) current affective state.

External events are described above. Here we briefly outline issues associated with the use of individual history and affective state for belief assessment.

Individual history combines the training and skill factors with specific experiences that influence the pilot's situation assessment and decision-making. In other words, specific successful or unsuccessful experiences that tend to predispose the pilot towards or against certain situations and maneuvers. For example, in the current demonstration scenario, occurrence of specific recent situations may bias the interpretation of current data; i.e. if the pilot has recently experienced a situation where a number of unsuccessful IFF interrogations were followed by a final identification of that aircraft as hostile, s/he may be predisposed to conclude that if an aircraft does not respond to IFF interrogations it is in fact hostile.

Current affective state. The pilot's affective state plays a critical role in his/her situation assessment. By taking into account the current affective state, the ABAIS User Assessment module in effect implicitly models the potential biasing influences of the different affective states and provides a structure which allows the explicit representation of the positive feedback between cognition and affect that is often seen in crisis situations. In other words, increased anxiety contributes to a particular situation assessment (e.g. aircraft is being attacked by hostile aircraft), which then narrows the attentional focus, limits processing of additional data that could give rise to alternative interpretations, and further increases the anxiety level. Belief assessment rules map the combinations of cues representing external events, individual history, and affective state onto the set of possible situations (see Figure 4).

7.2. AFFECT AND BELIEF STATE IMPACT PREDICTION

The goal of the impact prediction module is to predict the influence of a particular affective state (e.g. high anxiety) or belief state (e.g. 'aircraft under attack', 'hostile aircraft approaching', etc.) on task performance. Impact prediction thus represents an essential component of the overall adaptation strategy. Impact prediction process uses rule-based reasoning (RBR) and takes place in two stages. First, the *generic effects* of the identified affective state are identified, using a knowledge-base that encodes empirical evidence about the influence of specific affective states on cognition and performance. Next, these generic effects are instantiated in the context of the current task to identify *task-specific effects*, in terms of relevant domain entities and procedures (e.g. task prioritization, threat assessment). The effects of task-specific beliefs are defined at this point. The knowledge encoded in these rules is derived from CAPTA analysis process, which predicts the effects of different affective and belief states on performance within the current task context. This process is an essential component of building the impact prediction knowledge base, since the state-of-the-art of theoretical understanding and empirical research in per-

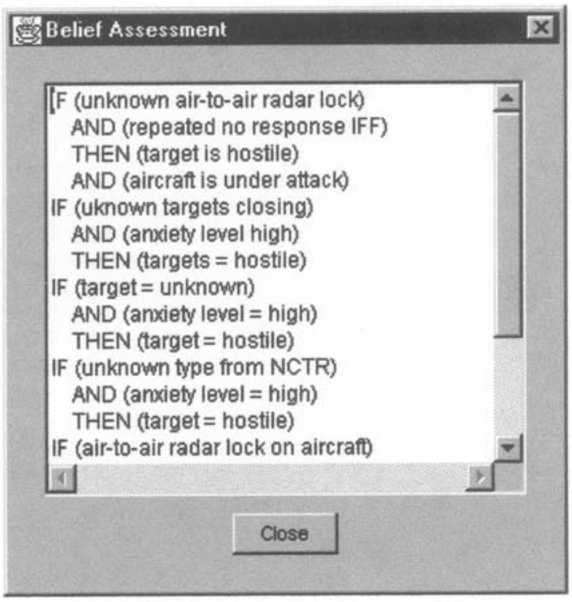

Figure 4. Examples of belief assessment rules from ABAIS rule base.

sonality and emotion do not allow accurate prediction of these influences in a generic, domain-independent manner.

8. Adaptation

Once the user affective and belief states are identified, and their likely impact is predicted, ABAIS identifies a compensatory strategy (Section 8.1) and selects a means of implementing this strategy in terms of specific user interface modifications (Section 8.2).

8.1. STRATEGY SELECTION

As was the case with impact prediction, the strategy selection module relies on a detailed CAPTA analysis to identify specific compensatory strategies to counteract the identified performance biases. This analysis serves as the basis for constructing the strategy selection knowledge bases, which map a specific behavioral bias (e.g. task neglect, threat-estimation bias, etc.) onto a particular compensatory adaptation strategy (e.g. present reminders of neglected tasks, present broader evidence to counteract threat-estimation bias, etc.)

Again, this process consists of two stages. First, generic strategy rules map the *generic* performance bias (e.g. task neglect) into a *generic* compensatory strategy (e.g. present reminders of neglected tasks). Next, the generic rules are instantiated in the task context, to determine the actual task-specific strategies. Examples of both generic and task-specific rules are shown in Table 8.

8.2. GUI ADAPTATION

Once the compensatory strategy has been identified, ABAIS performs the final step of implementing this strategy in terms of specific modifications to the user's interface. The GUI/DSS adaptation strategies are expressed in abstract terms, and are instantiated within the particular user-task context, taking into consideration the user preference profiles. In this final step of the user adaptation process, the ABAIS Adaptation Module performs three sequential functions:

- Identifies additional information required based on selected compensatory strategy.
- Selects best information presentation format.
- Applies individual information presentation preferences and capabilities (e.g. modality preference, color blindness, etc.).

Table 8. Examples of rules for compensatory strategies selection

Generic Rules	Task Domain Specific Rules
Anxiety	
IF (<task> importance = high) AND (pilot's assessment of <task> importance = low) THEN (present reminders for <task>) AND (direct attention to neglected instruments/data)	IF (recent change in radar target status) THEN (emphasize change in status of return)
IF (threat estimation bias = high) THEN (collect all evidence regarding radar signal identity)	IF (attention focus = HUD) AND (incoming radar data) THEN (redirect focus to radar)
IF (confirmation bias = high) THEN (collect any contradictory evidence) AND (enhance display of evidence)	IF (target = unknown) AND (target belief = hostile) THEN (emphasize unknown status) AND (collect more data)
Obsessiveness	
IF (obsessiveness = high) THEN (remind of consequences of delayed decisions) (remind that no data available to provide additional information) (remind of most recent tasks accomplished– present explicit checklists) (display task timeline and current position within timeline)	IF (likelihood of delayed attack = high) THEN (display all available info about enemy a/c) AND (display likelihood of attack by enemy a/c) AND (display envelope of vulnerability around own aircraft) AND (display reminders for attack tasks)

Examples of specific adaptation rules from the ABAIS prototype are shown in Figure 5.

Below, we discuss some general principles guiding the selection of specific GUI adaptation method and illustrate the different alternatives in the context of the ABAIS user interface.

In general, two broad categories of adaptation are possible:

- content-based, which *provide additional information,* and
- format-based, which *modify the format of existing information.*

Content-based adaptation involves the collection and display of additional data or knowledge to compensate for a particular performance bias. For example, providing additional disambiguating data about an ambiguous stimulus helps prevent an anxiety-induced bias to identify such stimuli as threats.

Format-based adaptation involves the presentation of existing data in an alternative format, to enhance visibility, to draw attention to neglected displays and, in general, to facilitate detection, recognition and assimilation of data. For example, modifying some attention-capture attribute of a display such as size, color, blink rate, etc. helps draw the user's attention to the display.

These types adaptations have been extensively evaluated in both laboratory and field settings, indicating that even small display changes can have major impact on attentional and cognitive processing (Wickens et al., 1983).

Level of Adaptation. Regardless of the method chosen, adaptation eventually results in a modification of specific user interface (UI) attributes. These include changes in

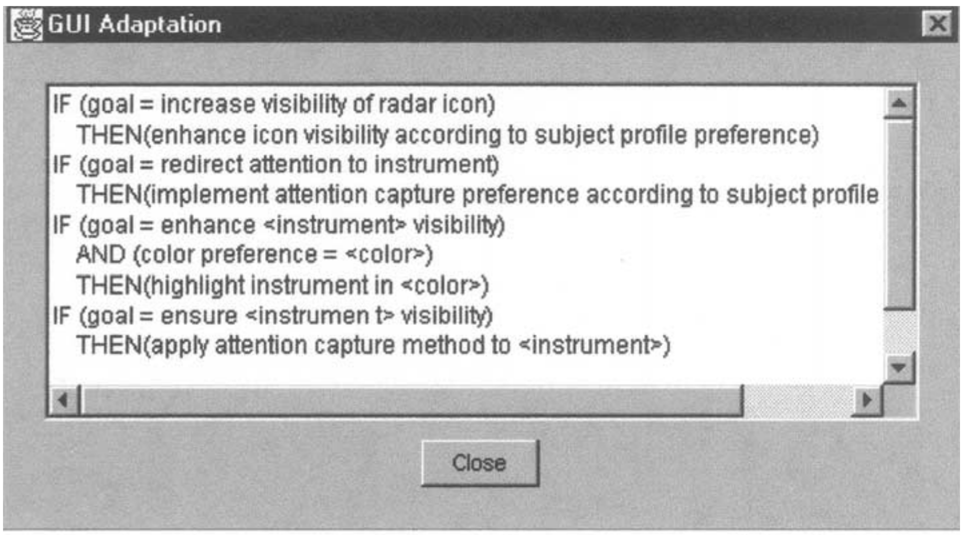

Figure 5. Examples of ABAIS GUI/DSS adaptation rules.

overall format, different choice of icons, or changes in UI elements, including color, location, size, orientation, modality, motion of stimulus, motion on periphery to re-direct attention by pre-attentive processes. Adaptation can thus take place at any of the four levels below:

- *Icon level.* Modify individual GUI icons by modifying one of the appearance attributes (e.g. highlighting, changing its location within a display, changing color or size, etc.) or modifying the icon appearance itself.
- *Display level.* Modify the display as a whole by changing its size or location (e.g. moving a critical display to a central location of the overall UI), changing its appearance (e.g. range setting on radar), or changing its contents (e.g. decluttering a display).
- *Notification level.* Augment interface by inserting new, or modifying existing, alarms and alert notifications. Examples of notification level adaptations include adding a notification string regarding desired focus of attention (see for example 'RADAR' on the HUD display or 'VULNERABLE' string on the radar display in Figure 6), or adding an icon to a display to represent new information (see triangle in Figure 6).
- *User Interface level.* Implement global changes to the user interface as a whole, or insert additional display elements designed to focus attention on particular areas of the overall UI. Examples of UI level adaptations include a reconfiguration of the entire set of instruments to reflect a different system mode, increasing the redundancy of warnings (e.g. adding an auditory warning

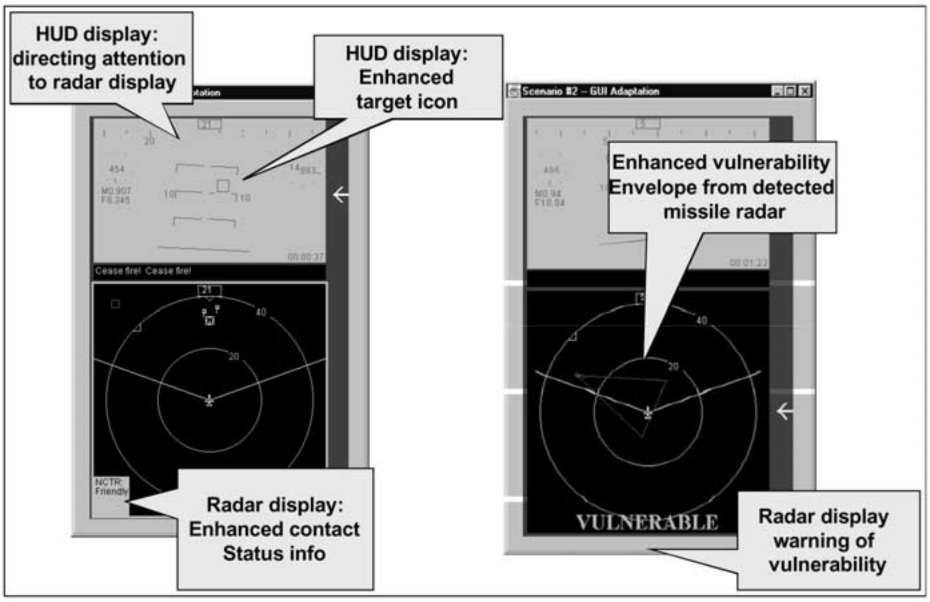

Figure 6. Summary of GUI/DSS adaptation strategies.

to a visual one, etc.), or insertion of attention-capturing and attention-directing elements designed to direct the user's attention to a particular icon or display.

Each of these levels affords different alternatives and is more or less suitable for a given situation, depending on the task, task context, and the individual. Figure 6 provides a summary of the adaptations implemented within the ABAIS prototype.

Individualized Adaptation. To be effective, the above strategies must be customized by taking into account the user's display and modality preferences (see Table 9). This is critical to any adaptive approach, due to the large individual differences that exist in human information processing and decision-making. ABAIS therefore allows the specification of multiple user display preference profiles (e.g. knowing that a particular user has a high-sensitivity to auditory signals, ABAIS suggests that auditory warnings be used to capture attention).

9. Demonstration of ABAIS System Performance

To demonstrate the ABAIS adaptive methodology and prototype performance, we defined several representative pilot profiles (high and low anxiety), varying in personality (obsessiveness, aggressiveness), training, individual history, and adaptation preferences. Their performance within scenario segments was simulated, generating varying levels of anxiety and alternative situation assessments at different points. Due to the precise timing required to demonstrate the adaptation GUI changes, the emphasis during this initial effort was on developing the analyst-as-user mode[7] and the associated script-based simulation, which allows precise control over the external task events necessary to demonstrate the real-time adaptation.

The pilot's anxiety levels were assessed and resulted in GUI/DSS adaptations. Specifically, ABAIS predicted that the heightened level of anxiety would cause

Table 9. Pilot information preference profile: categories of information and related GUI modification options

Information Category	Options
Preferred means of enhancing visibility	Color; Size; Blinking
Preferred color for alarms	Red solid; Red outline
Preferred alarm notification modality	Visual; Auditory
Preferred attention capture means	Movement at visual periphery; Shift display to foveal region; Enhance icon visibility; Display arrow pointing to desired icon; Superimpose blinking icon

[7]This is in contrast to the alternative user-as-pilot mode, where the user actually flies the simulated aircraft during the scenario.

narrowing of attention and interpretation bias towards threats, possibly causing the pilot to fail to notice a recent change in status of a radar contact from an 'unknown presumed hostile' to 'friendly'. ABAIS therefore suggested a compensatory strategy aimed at preventing possible fratricide by: (1) directing the pilot's attention to the display showing the recent status change; and (2) enhancing the relevant signals on the radar to improve detection (see Figures 7 and 8). Specifically, the blinking, enlarged, blue contact icon on the HUD display indicates a change in status. The blinking blue 'RADAR' string displayed on the HUD, the pilot's current focus, directs the pilot to look at the radar display, which shows an enhanced contact icon indicating a change in status, with details provided in the text box in lower left corner of the display.

Informal preliminary ABAIS evaluation by expert pilot indicated the following: (1) overall enthusiasm regarding the need for affective adaptation; (2) underscoring the importance of non-dramatic, 'benign' adaptations'; (3) general approval of the GUI adaptation strategies and modifications; (4) questions regarding the system's ability to perform *accurate* assessment in *real-time*; and (5) a degree of skepticism regarding the need for affective adaptive system in an *operational*, (vs training), fighter cockpit. A plan for extensive empirical evaluation to formally address these issues is outlined in Section 10.3.

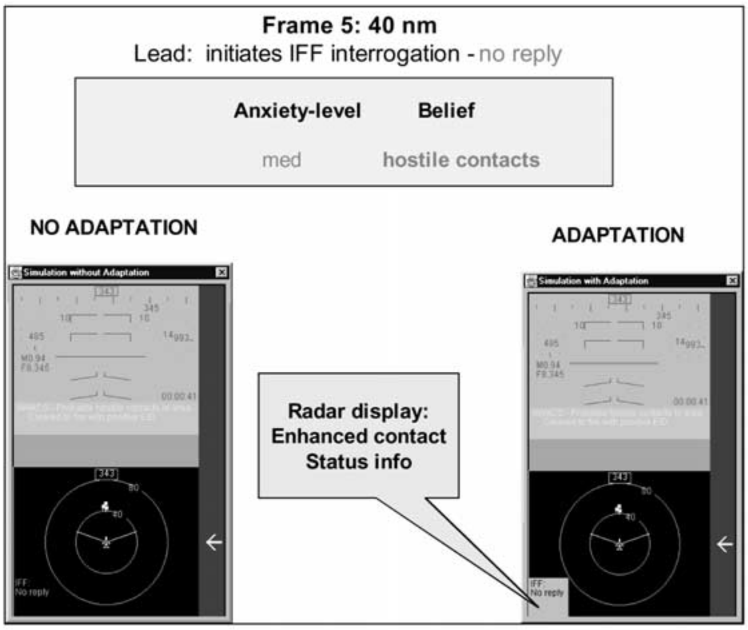

Figure 7. Frame 5 of the demonstration scenario: Adaptation occurs to enhance visibility and status of ambiguous radar returns.

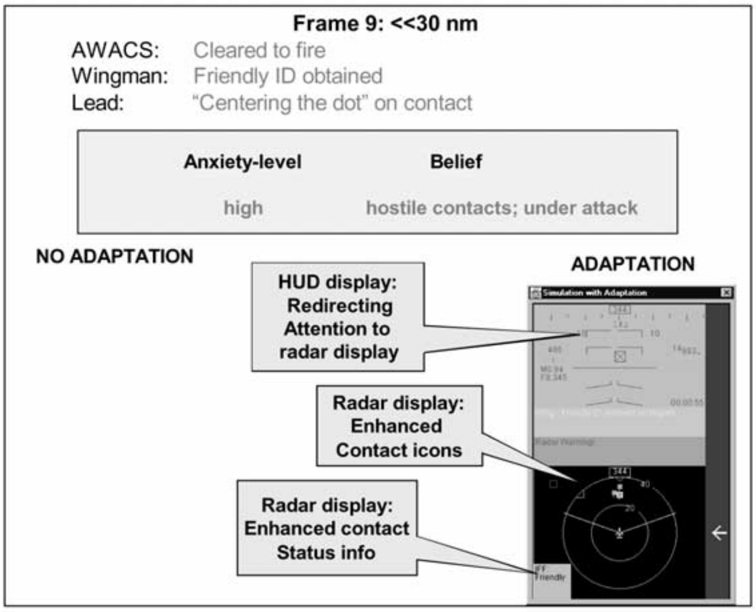

Figure 8. Frame 9 of the demonstration scenario: Adaptation occurs to redirect attention and enhance visibility of incoming data to prevent fratricide.

10. Summary, Conclusions, and Future Work

10.1. SUMMARY

The primary result of this effort was a proof-of-concept demonstration of an Affect and Belief Adaptive Interface System (ABAIS), designed to provide individualized GUI and decision support system (DSS) adaptations based on the user's affective and belief state. ABAIS implements a four-stage adaptive methodology for the assessment of, and adaptation to, the user's affective and belief states. The ABAIS adaptive methodology was implemented within a software prototype, and demonstrated in the context of an Air Force sweep mission task. Several representative pilot profiles were defined, varying in personality, physiological responsiveness, training, individual history, and adaptation preferences. Their performance within selected scenario segments was simulated, generating varying levels of anxiety and alternatives in situation assessments at different points during the scenario. The pilot's anxiety levels were assessed using the available data, resulting in GUI/DSS adaptations derived via the ABAIS adaptive methodology, using rule-bases in the four ABAIS modules. Specifically, ABAIS predicted that the heightened level of anxiety would cause narrowing of attention and interpretation bias towards threats, possibly causing the pilot to fail to notice a recent change in status of radar contact from 'unknown presumed hostile' to 'friendly'. ABAIS therefore suggested a compensatory strategy aimed at preventing possible fratricide by augmenting the existing cockpit GUI's to: (1) direct the pilot's attention to the display showing the recent status change; and (2) enhance the relevant signals on the radar to improve detection.

10.2. Conclusions

Development of the ABAIS proof-of-concept prototype demonstrated feasibility of the overall adaptive methodology and its implementation. ABAIS assessed the user anxiety level and belief states using a knowledge-based approach and information from a variety of sources (e.g. static task context, dynamic external events occurring during the scenario, individual history, personality, training, and simulated physiological data), predicted the effects of these states within the constrained context of the demonstration task, and suggested and implemented specific GUI adaptation strategies, taking into account the user's individual information presentation preferences (e.g. modified an icon or display to capture attention and enhance visibility). An empirical study with actual pilots flying the ABAIS simulation, and providing real-time assessment data, would be required to fully assess the actual effectiveness of the assessments and adaptations in an operational context.

Development of a remote heart rate monitor and its hookup with the ABAIS user interface successfully demonstrated the feasibility of non-intrusive heart rate monitoring, providing this information to the system, and making specific changes in the user interface as a result of detected heart rate changes. While the monitor was not integrated into the User Assessment module due to time constraints, these preliminary results indicate that such an integration is feasible.

The implementation of the ABAIS prototype demonstrated general feasibility of the adaptive methodology, and provided information about the specific requirements for a successful, operational affective adaptive graphical interface; namely:

- Limiting the number, type, and resolution of affective states (e.g. high versus low anxiety);
- Using multiple, complementary methods and multiple data sources for affective state assessment;
- Providing individualized user data, including details of past performance, individual history, personality traits, and physiological data;
- Constraining the overall situation in terms of situation assessment and behavioral possibilities;
- Providing a wide variety of task-specific data in an electronic format;
- Fine-tuning the rule-bases and inferencing to 'personalize' the system to the individual user-task context;
- Implementing 'benign' adaptations, that is, GUI/DSS modifications that at best enhance and at worst maintain current level of performance (e.g. adaptations should never limit access to existing information).

10.3. Future work

The objective of the initial ABAIS prototype was to implement a proof-of-concept demonstration of the ABAIS adaptive methodology within a adaptive system architecture. The existing prototype indicates that this represents a feasible approach to affective adaptation. However, much work remains to be done to demonstrate its effectiveness in an operational setting, to implement additional enhancements, and to generalize the ABAIS system to other domains where GUI adaptation is appropriate in response to different affective and belief states. Future work falls into four broad areas: Evaluation in an operational setting; Generalizability; Enhanced integrated affect assessment; and Real-time performance issues. These are briefly discussed below.

Evaluation.The most critical next step is an empirical study demonstrating improved human–machine performance with adaptation and providing feedback about the ABAIS methodology, architecture, and knowledge-base enhancements, shortcomings, and operating constraints.

A number of established methods and associated metrics exist for the evaluation of ‘cognitive’ adaptive systems. These include both qualitative and quantitative approaches; heuristic evaluation by a panel of experts and evaluations using real users as subjects; metrics focusing on outcome vs. process; and metrics using a variety of time- and accuracy-related variables (Woods, 1998; Nielsen, 1993; Bautsch et al., 1998). An interesting challenge in evaluating affective adaptive systems is the likely need for augmented evaluation procedures and additional metrics, to capture the often subtle *affective* effects induced by such systems, including overall reduction in baseline anxiety level; the pre-, post- and during-performance affective state changes induced by the adaptation, or even *prospect* of affective adaptation; the cumulative effects of the affective state (and possible reduction in negative states) on user ‘burn out’ rate; increase (or decrease?) in trust level; speed and efficiency of *user* adaptation to task changes; etc. A key question that arises in introducing affective adaptive systems is whether the adaptive component will be viewed as an intrusive ‘big brother’, as a backup expert available to provide assistance when necessary, or simply as an annoying paper clip?

The planned evaluation protocol is consistent with several previous approaches we have used to assess the performance of envisioned joint cognitive systems and combines a qualitative ‘cognitive walkthrough’ approach with a more traditional quantitative empirical evaluation. Each approach will test both novice and expert pilots, in both adapted and non-adapted conditions, across multiple scenarios (such as those already developed (see Section 9)). We briefly outline these approaches below.

Qualitative Evaluation. This method is based on a comprehensive cognitive systems engineering perspective (McNeese, 1996). The experimental protocol follows a standard 2×2 design (novices, experts; non-adapted; adapted scenarios).

Subjective User Data. First, a series of 'cognitive walkthroughs' and usability evaluations interviews are conducted, producing a series of concept maps, augmented with explicit representations of affective states, that capture the users' interactions with the system. (A concept map is a graph-based representation of the user's mental model in a specific field of practice (Zaff et al., 1993)). This technique would help identify the effects of adaptation on the concept map structure itself, on behavior during task performance, and ultimately on the task outcome. Comparisons between novice and expert users would provide further information about the effectiveness of different assessment methods and adaptation strategies, and will identify shortcoming and improvements in the ABAIS knowledge-bases (e.g. necessity for different types of impact prediction and strategy selection rules for different skill levels). Second, videotaped data of pilots performing the scenarios would be collected. These 'process tracings' (Woods, 1998) would then be analyzed using standard verbal protocol analysis techniques to identify the type and range of adaptation effects.

Heuristic Evaluation. Heuristic evaluation by a panel of experts from multiple disciplines will be conducted to obtain additional feedback regarding system usability and utility (Nielsen, 1993).

Quantitative Evaluation. The quantitative phase will implement a traditional human-in-the-loop, simulation-based evaluation protocol, with the ABAIS architecture embedded in an advanced fighter cockpit simulator. The resulting data, including the affective-adaptation specific metrics discussed above, would help determine where and how novices and experts need the most assistance in adapting to changing conditions in the mission context; where and how the ABAIS architecture is most effective in improving performance, and under what conditions an adaptive system might actually degrade performance.

In addition to evaluating the pilot performance, this phase would also collect physiological data and evaluate the effectiveness, benefits, and shortcomings of remote sensors and physiological assessment in general. We have conducted a similar study for a Maverick-launch mission where we compared a baseline cockpit system with a system that used real time information source updates (Bautsch et al., 1998) to compare the outcomes of human-in-the-loop with cognitive model simulations.

Collectively, the results from these evaluation experiments will provide information regarding specific performance enhancements, shortcomings, and constraints, to help define future improvements to the original ABAIS methodology, architecture design, and knowledge bases.

Generalizability. The next step is to demonstrate the generalizability of the ABAIS methodology and architecture across tasks and domains. ABAIS was designed to maximize generalizability in the broad area of GUI-based affect and belief adaptations. Specifically, the following elements apply across domains:

- ABAIS four-step adaptive methodology
- ABAIS architecture framework
- Assessment model integrating multiple factors
- Rules capturing generic effects of affective-state biases and generic compensatory strategies
- Integration of generic empirical data with task-specific domain data to identify possible effects of affective and belief states and possible compensatory strategies
- User interface modification framework (format/content levels of adaptation)

In addition, the CAPTA task analytic process underlying the development of the ABAIS architecture knowledge-bases is also domain independent.

However, to instantiate the ABAIS methodology and architecture in a different task domain, a number of system modifications must be implemented by the developers and knowledge engineers, to identify the task- and domain-specific data and background information about users, and encode these within the required ABAIS representational formalisms. Specifically, the following steps would be required:

- Systematic Cognitive Affective Personality Task Analysis (CAPTA) to identify domain and task specific effects of particular affective and belief states.
- Systematic CAPTA to identify domain and task specific compensatory strategies counter their effects.
- Construction of domain-specific components of the 'Impact Prediction' and 'Strategy Selection' knowledge bases.
- Specification of user background data (individual history, personality traits, training, etc.).
- Development of an appropriate task simulation module.
- Development of task- and domain-specific user interfaces.

Again, an empirical evaluation will be necessary to determine the exact level of effort required to perform such a translation, to quantify the benefits offered by the ABAIS architecture components, and to identify any constraints for such domain transitions (e.g. applicability of generic knowledge across domains, etc.).

Enhancement and Integration of Multiple Assessment Methods. The ABAIS architecture was designed to accommodate multiple methods of affect and belief assessment, with the initial prototype focusing on the knowledge-based approach. Future work in this area therefore includes the implementation and exploration of the integrated use of multiple, complementary methods; enhancing the types of data processed by these methods (e.g. user's goals, specific knowledge types); enhancing the inferencing algorithms used during the assessment process; enlarging the set of affective and belief states identified; and addressing a variety of issues such as the handling of contradictory data during assessment. Such integration will then allow the exploration and evaluation of the best 'mix' of these methods for particular task types, domain types, or task-domain-user combinations. We would also like to explore a variety of second-order effects to enhance the reliability of affect assessment (i.e. explicit representation and analysis of the interaction among distinct affective states and among multiple factors influencing a particular affective state).

Real Time Performance. The spectrum of systems where affective assessment and adaptation are relevant ranges from the 'slow off-line' applications such as off-line assessment of the affective reactions to a particular system feature (e.g. tutoring or training system), designed to elicit functionality requirements and usability improvements; through 'slow real-time' applications such as some types of process control; to 'fast real-time' applications such as the current fighter pilot context. The last case representing the most challenging end of this spectrum, requiring instantaneous assessment and adaptation. Much additional work is necessary to develop effective guidelines about the best means of affect and belief assessment and adaptation as a function of the task real-time requirements. Tradeoffs among methods must be analyzed to determine the best mix of multiple methods. For example, self-reports are slower than wearables but may be faster than diagnostic tasks; on the other hand, the reliability and completeness of these methods varies by user, domain, and task.

The field of affective computing is in its infancy. The confluence of technologies that facilitate affective assessment and adaptation on the one hand, and the increasing need and desire for such functionalities, provide a rich environment within which to investigate a number of fundamental issues about the role of emotion in human-human and human-computer performance and interaction. Key questions include issues such as: to what extent are existing user modeling and adaptation methods applicable to affective adaptation; what emotions *should* and *can* be recognized, modeled, and adapted to in human-machine interfaces; when should an agent attempt to enhance the user's affective state, when should it adapt to the user's affective state, and when should it attempt to counteract it. In addition to these research and technical issues, a number of ethical questions emerge once affect enters the stage. Canamero offers an excellent summary of some of the affect-related issues that must be addressed by the user modeling community (Canamero, 1998).

We conclude with a quote from a virtual agent of yore: 'This fills my head with ideas, only I don't exactly know what they are.' (Carroll, 1941).

Acknowledgements

This work was supported in part by USAF contract number F41624-98-C5032. The authors wish to thank the following individuals who contributed to this effort. Mr. John Billingsley of Psychometrix Associates was the software developer for the ABAIS prototype, responsible for the software system design and implementation. Mr. Bob Shaw of FCI Associates developed the demonstration scenario and served as the primary SME. Major Ray King, Major Joseph Callister, LTC Tim Sowin, and LTC Royland Marsh provided information about personality assessments within USAF. Major Daniel Callan and LTC Vincent Caterina provided useful suggestions and feedback regarding the task scenario selections. Dr. Thomas von Wiegand of MIT developed the heart monitor. Drs. Scott Orr of Harvard University and Stefan Hofmann of the Boston University Anxiety Center provided information about physiological sensing. Dr. Greg Zacharias provided helpful discussions about the Charles River Analytics SD_PVI system. Dr. Rosalind Picard of MIT Media Lab provided information about wearable computing, and background information on physiological sensing and facial recognition.

Appendix A: Glossary of Task-Relevant Terms

HUD	Head Up Display
EID	Electronic Identification
IFF	Interrogation Friend/Foe
NCTR	Non-Cooperative Target Recognition; provides aircraft type identification based on visual form of aircraft
RWR	Radar Warning receiver
TWS	Track while scan radar (air to air radar system)

Appendix B: Description of Task Display Symbology

The own aircraft is shown in the center, with the concentric rings indicating range in miles, using standard radar symbology. The contacts are displayed as filled circles when data are arriving from on-board sensors, and as hollow circles when data are arriving via datalink. The heading of the individual contacts is indicated by the associated lines, with the line lengths corresponding to the contact speed. The sensor display can also show radar locks, both those originating from the friendly aircraft, and those originating from hostile or unknown radars, and appear on the radar as inward-pointing triangles shown on the outer circle of the display. Ground-based radar emitters are shown as rectangles on the outside of the radar display. Specific contact symbology is depicted as follows: rectangular ship icon means unknown/enemy; circular ship icon means friendly; green ship icon means friendly, red ship icon mean enemy, yellow ship icon means unknown; white box around ship icon indicates that user is targeting that ship. Friendly missiles are represented by white dots, with a radar-lock line pointing from the missile icon to its target.

References

Bates, J., Loyall, A. B. and Reilly, W. S.: 1992, Integrating Reactivity, Goals, and Emotion in a Broad Agent. In: *Proceedings of the 14th Meeting of the Cognitive Science Society*.

Bautsch, H. S., Narayanan, S. and McNeese, M. D.: 1998, Development and evaluation of a cognitive model of human performance in fighter aircraft. In: *Proceedings of the IEEE Systems, Man, Cybernetics International Conference*. Los Alamitos, CA: IEEE Computer Science Society, 1032–1036.

Bianchi-Berthouze, N. and Lisetti, C. L.: 2002, Modeling multimodal expression of user's affective subjective experience. *User Modeling and User-Adapted Interaction* **12**(1), 49–84 (this issue).

Blaney, P. H.: 1986, Affect and Memory. *Psychological Bulletin* **99**(2), 229–246.

Bower, G. H.: 1981, Mood and Memory. *American Psychologist* **36**, 129–148.

Breese, J. and Ball, G.: 1998, Bayesian Networks for Modeling Emotional State and Personality. In: *Proceedings of Emotional and Intelligent: The Tangled Knot of Cognition*. AAAI Fall Symposium Series, TR FS-98-03, Menlo Park, CA: AAAI Press, 37–42.

Cacioppo, J. T., Klein, D. J., Bernston, G. G. and Hatfield, E.: 1993, The Psychophysiology of Emotion. In: M. Lewis and J. Haviland (eds.): *Handbook of Emotions*. New York: Guilford, 119–142.

Callister, J. D., King, R. E., Retzlaff, P. D. and Marsh, R. W.: 1997*, Using the NEO-PI-R to Assess the Personality of US Air Force Pilots*. AL/AO-TR-1997-0097. Brooks AFB, TX: Aerospace Medicine.

Canamero, D.: 1998, Issues in the Design of Emotional Agents. In: *Proceedings of Emotional and Intelligent: The Tangled Knot of Cognition*. AAAI Fall Symposium, TR FS-98-03, Menlo Park, CA: AAAI Press, 49–54.

Carroll, L.: 1941, *Alice in Wonderland*. NY: Heritage Press.

COADE: A Framework for Cognitive Analysis, Design, and Evaluation. Final Report, Panel 8 on the Defense Applications of Human and Bio-Medical Sciences RSG.19 on Decision Aids in Command and Control NATO Defense Research Group. Tech Report AC/243 (Panel 8) TR/17.

Cooke, N. M.: 1995, Varieties of Knowledge Elicitation Techniques. *Intl. Jnl. of Human–Computer Studies* **41**(6), 801–849.

Damasio, A. R.: 1994, *Descartes' Error: Emotion, Reason, and the Human Brain*. NY: G. P. Putnam's Sons.

Deckert, J. C., Entin, E. B., Entin, E. E., MacMillan, J. and Serfaty, D.: 1994, *Military Command Decisionmaking Expertise* (Report 631). Burlington, MA: Alphatech, Inc.

Dieterich, H., Malinowski, U., Kuhme, T. and Schneider-Hufschmidt, M.: 1993, State of the Art in Adaptive Interfaces. In: M. Schneider-Hufschmidt, T. Kuhme and U. Malinowski (eds.): *Adaptive User Interfaces*. NY: Elsevier, 13–48.

Ekman, P. and Davidson, R. J.: 1994, *The Nature of Emotion: Fundamental Questions*. New York: Oxford.

Ekman, P. and Friesen, W. V.: 1975, *Unmasking the Face*. Englewood Cliffs, NJ: Prentice Hall.

Elliot, C., Lester, J. and Rickel, J.: 1999, Lifelike pedagogical agents and affective computing: An exploratory synthesis. In: M. Wooldridge and M. Veloso (eds.), *AI Today*. Lecture Notes in AI. NY: Springer-Verlag.

Elliot, C.: 1992, The Affective Reasoner, The Affective Reasoner: A process model of emotions in a multi-agent system. Institute for the Learning Sciences Tech. Report #32. Evanston, IL: Northwestern University.

Endsley, M. R.: 1995, Measurement of Situation Awareness in Dynamic Systems. *Human Factors* **37**(1), 65–84.

Eysenck, M. W.: 1997, *Anxiety and Cognition: A Unified Theory*. Hove, East Sussex: Psychology Press.

Fijalkiewicz, P. and DeJong, G.: 1998, CHESHIRE: An Intelligent Adaptive User Interface. In: *Proceedings of Second Annual Symposium on Advanced Displays.* College Park, MD: University of Maryland.

Fleming, M. and Cohen, R.: 1999, User Modeling in the Design of Interactive Interface Agents. In: J. Kay (ed.): *User Modeling: Proceedings of the Seventh International Conference UM99*. NY: Springer, 67–76.

Fraser, N. M., Hipel, K. W., Kilgore, D. M., McNeese, M. D. and Snyder, D. E.: 1989, An architecture for integrating expert systems. *Decision Support Systems* **5**, 263–276.

Harper, K., Guarino, S. and Zacharias, G.: 2000, Adaptive Human–Machine Interface for Advanced Air Traffic Management. In: *Proceedings of 2000 AIAA, Navigation and Control Conference*, 134–142.

Hathaway, S. R. and McKinley, J. C.: 1989, MMPI-2: Minnesota Multiphasic Personality Inventory – 2. Minneapolis, MN: The University of Minnesota Press.

Healy, J. and Picard, R.: 2000, SmartCar:Detecting Driver Stress. In: *Proceedings of the 15th International Conference on Pattern Recognition,* Barcelona, Spain. (Also MIT Media Lab TR #525)

Hudlicka, E.: 2000a, *Cognitive Affective Personality Task Analysis*. Psychometrix Report #0104. Blacksburg, VA: Psychometrix Associates, Inc.

Hudlicka, E.: 2000, Increasing SIA Architecture Realism by Modeling and Adapting to Affect and Personality. In: *Proceedings of the AAAI Fall Symposium*. Falmouth, MA. TR FS-00-04, Menlo Park: AAAI Press, 65–70.

Hudlicka, E. and Billingsley, J.: 1998*, ABAIS: Affect and Belief Adaptive Interface System. Report 9814.* Lincoln, MA: Psychometrix Associates, Inc. (Also AFRL-HE-WP-TR-1999-0169. Wright-Patterson AFB, OH).

Isen, A. M.: 1993, Positive Affect and Decision Making. In: J. M. Haviland and M. Lewis, (eds.): *Handbook of Emotion*s. New York, NY: The Guilford Press, 261–277.

Kaiser, S.,Wehrle, T. and Schmidt, S.: 1998, Emotional episodes, facial expressions, and reported feelings in human–computer interaction. In: *Proceedings of the Xth Conference of the International Society for Research on Emotions*. Wursburg: ISRE Publications.

Klein, G. A.: 1997, The recognition-primed decision (RPD) model: Looking back, looking forward. In: C. Zsambok and G. Klein (eds.): *Naturlistic decision making*. Mahwah, NJ: Erlbaum, 285–292.

Klein, G. A.: 1989, Recognition-Primed Decisions. *Advances in Man-Machine Systems Research* **5**, 47–92.

Klein, J., Moon, Y and Picard, R. W.: 1999, This Computer Responds to User Frustration. *CHI 99 Short Papers*, Pittsburgh, PA.

Lazarus, R. S.: 1991, *Emotion and Adaptation*. New York, NY: Oxford University Press.

LeDoux, J. E.: 1992, Brain Mechanisms of Emotion and Emotional Learning. *Current Opinion in Neurobiology* **2**(2), 191–197.

LeDoux, J. E.: 1989, Cognitive-Emotional Interactions in the Brain. *Cognition and Emotion* **3**(4), 267–289.

Lipshitz, R. and Ben Shaul, O.: 1997, Schemata and mental models in recognition-primed decision making. In: C. Zsambok and G. Klein (eds.): *Naturlistic decision making*. Mahwah, NJ: Erlbaum, 293–303.

Maes, P.: 1994, Agents that reduce work and information overload. *Communications of the ACM* **37**(7), 30–40.

McNeese, M. D.: 1996, A comprehensive cognitive engineering process for human-information systems. In: *Proceedings of the 3rd Annual Symposium on Human Interaction with Complex Systems, 1,* Los Alamitos, CA: IEEE Computer Science Society, 260–267.

McNeese, M. D.: 1986, Humane intelligence: A human factors perspective for developing intelligent cockpits. *IEEE Aerospace and Electronic Systems* **1**(9), 6–12.

Mineka, S. and Sutton, S. K.: 1992, Cognitive Biases and the Emotional Disorders. *Psychological Science* **3**(1), 65–69.

Mitchell, T., Caurana, R. Freitag, D., McDermott, J. and Zabowski, D.: 1994, Experience with a learning personal assistant. *Communications of the ACM* **37**(7), 80–91.

Mozziconacci, S. J. L.: 2001, Modeling emotion and attitude in speech by means of perceptually based parameter values. *User Modeling and User-Adapted Interaction* **11**(4), 297–326.

Mulgund, S., Rinkus, G. and Zacharias, G.: 2001, Adaptive Pilot/Vehicle Interfaces for the Tactical Air Environment. In: *Psychological Issues in the Design and Use of Virtual Adaptive Environments*. Mahwah: LEA (in press).

Nielsen, J.: 1993, *Usability Engineering*. Boston, MA: Academic Press.

Orr, S. P.: 1998, Personal communication.

Ortony, A., Clore, G. L. and Collins, A.: 1988, *The Cognitive Structure of Emotions*. NY: Cambridge University Press.

Panksepp, J.: 1994, The Basics of Basic Emotion. In: P. Ekman and R. J. Davidson (eds.): *The Nature of Emotion*. NY: Oxford, 20–24.

Persons, J. B. and Foa, E. B.: 1984, Processing of fearful and neutral information by obsessive-compulsives. *Behavior Res. Ther.* **22**, 260–265.

Peterson, R. A. and Reiss, S.: 1987, *Test Manual for the Anxiety Sensitivity Index*. Orlando Park, IL: International Diagnostic Systems.

Petrushin, V. A.: 2000, Emotion Recognition Agents in Real World. In: *Proceedings of the AAAI Fall Symposium*. Falmouth, MA. TR FS-00-04, Menlo Park: AAAI Press, 136–138.

Pew, R. W. and Mavor, A. S.: 1998, *Representing Human Behavior in Military Simulations.* Washington, DC. National Academy Press.

Picard, R.: 1997, *Affective Computing*. Cambridge: MIT Press.

Pohl, W. and Nick, A.: 1999, Machine learning and knowledge representation in the LabUR approach to user modeling. In: J. Kay (ed.): *User Modeling: Proceedings of the Seventh International Conference UM99*. NY: Springer, 179–188.

Retzlaff, P. D., Callister, J. D. and King, R. E.: 1997, *The Armstrong Laboratory Aviation Personality Survey (ALAPS): Norming and Cross-Validation*. AL/AO-TR-1997-0099. Brooks AFB, TX: Aerospace Medicine Directorate.

Rouse, W. B.: 1988, Adaptive aiding for human/computer control. *Human Factors* **30**(40), 431–443.

Scherer, K.: 1993, Studying the Emotion-antecedent appraisal process: The expert system Approach. *Cognition and Emotion* **7**, 325–355.

Sher, K. J., Frost, R. O., Kushner, M., Crews, T. M. and Alexander, J. E.: 1989, Memory deficits in compulsive checkers. *Behavior Res. Ther.* **27**, 65–69.

Taylor, R. M., Bonner, M. C., Dickson, B., Howells, H., Miller, C., Milton, N., Pleydell-Pearce, K., Shadbolt, N., Tennison, J. and Whitecross, S.: 2001, Cognitive cockpit engineering: Coupling functional state assessment, task knowledge management, and decision support for context sensitive aiding. In: M. D. McNeese and M. A. Vidulich (eds.): *Cognitive systems engineering in military aviation domains: Avoiding cogminutia fragmentosa!* Wright-Patterson AFB, OH: Human Information Analysis Center. (in press)

Tversky, B. and Kahneman, D.: 1974, Judgements under Uncertainty: heuristics and biases. *Science* **185**, 1124–1131.

Vyzas, E. and Picard, R.: 1998, In: *Proceedings of Emotional and Intelligent: The Tangled Knot of Cognition*. AAAI Fall Symposium Series, TR FS-98-03, Menlo Park, CA: AAAI Press, 176–182.

Watson, D., Clark, L. A. and Tellegen, A.: 1988, Development and validation of brief measues of positive and negative affect: The PANAS Scales. *Journal of Personality and Social Psychology* **54**, 1063–1070.

Wickens, C. D., Sandry, D. and Vidulich, M.: 1983, Compatibility and resource competition between modalities of input, output, and central processing. *Human Factors* **25**, 227–248.

Williams, J. M. G., Watts, F. N., MacLeod, C. and Mathews, A.: 1997, *Cognitive Psychology and Emotional Disorders*. NY: John Wiley.

Woods, D. D.: 1998, Designs are hypotheses about how artifacts shape cognition and collaboration. *Ergonomics* **41**(2), 168–173.

Zacharias, G. L.: 1996, SAMPLE: Situation Awareness Model for Pilot-in-the-Loop Evaluation. Final Report R95192. Cambridge, MA: Charles River Analytics.

Zaff, B. S., McNeese, M. D. and Snyder, D. E.: 1993, Capturing multiple perspectives: A user-centered approach to knowledge acquisition. *Knowledge Acquisition* **5**(1), 79–116.

Authors' Vitae

Dr Eva Hudlicka is a Principal Scientist and President of Psychometrix Associates. She received her B.S. in Biochemistry from Virginia Tech, her M.S. in Computer Science from The Ohio State University, and her Ph.D. in Computer Science from the University of Massachusetts-Amherst. Dr Hudlicka's primary research interest lies at the intersection of affective computing and cognitive modeling, with emphasis on modeling the interaction between affective states and cognitive processes. Dr Hudlicka currently directs a number of projects whose focus is the representation, analysis, or modeling of the effects of emotions and personality traits on cognition and performance, and the development of decision-support systems and associated adaptive user interfaces and visualizations. Prior to founding Psychometrix Associates in 1995, Dr Hudlicka was a Senior Scientist at Bolt Beranek and Newman, Cambridge, MA, where she directed or provided technical leadership in the areas of cognitive modeling, decision-support systems, user interface design, and knowledge elicitation. She also held positions as a Visiting Assistant Professor at University of Massachusetts-Amherst, Adjunct Associate Professor at Worcester Polytechnic Institute, and a Senior Research Associate at the Boston Institute for Psychotherapy. Dr Hudlicka has authored over 60 technical papers.

Dr Michael D. McNeese is an Associate Professor of Information Sciences and Technology, and Psychology at The Pennsylvania State University, University Park, PA. At Penn State he is the Head of the Laboratory for MINDS (Multidisciplinary Initiatives in Networked Decision Supports), is a Fellow at the IST Solutions Institute, and is Co-Director of the Human Computer Interaction Institute. Dr McNeese received a B.A. (cum laude) from The University of Dayton in

Psychology, an M.A. in Experimental-Cognitive Psychology from the University of Dayton and an Interdisciplinary Ph.D. in Cognitive Science from Vanderbilt University. Prior to coming to Penn State last year, Dr McNeese was a Senior Scientist at the United States Air Force Research Laboratory, Wright-Patterson Air Force Base, OH, where he was the Director of the Collaborative Systems Technology Laboratory. Dr McNeese has worked on various aspects of advanced human–computer interfaces including affective computing and belief systems, computer-supported cooperative work, cognitive systems engineering, and pursues several theoretical research interests in the cognitive and learning sciences, including perceptual learning and the socio-cognitive factors underlying the acquisition and transfer of knowledge. He has authored over a hundred technical papers and currently has two books in press.