Affect-awareness Framework
for Intelligent Tutoring Systems

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Abstract. **The paper proposes a framework for construction of Intelligent Tutoring Systems (ITS), that take into consideration student emotional states and make affective interventions. The paper provides definitions of 'affect-aware systems' and 'affective interventions' and describes the concept of the affect-awareness framework. The proposed framework separates emotion recognition from its definition, processing and making decisions on interventions. The components of the proposed framework were described, including trustworthiness model and affect-aware control mechanisms, and a case study of the proposed framework implementation in GERDA Intelligent Tutoring System was also presented. Presented evidence allows to state, that affect-awareness framework allows to reduce the risk of unnecessary and disturbing application intervention and improves application adaptability and trustworthiness.**

Keywords: **affective computing, affect-awareness, Intelligent Tutoring Systems.**

I. INTRODUCTION

THERE is lots of evidence, that some emotional states support learning processes and other suppress them [1][2]. In traditional classroom affective issues such as fatigue, deconcentration, low motivation or boredom are addressed by teachers and their actions may include long-term actions, but sometimes simple words of encouragements or appraisal work as well. In asynchronous e-learning environments, a learner is often left alone with educational resources and underlying software. In such case one may fail to deal with fluctuation in motivation, concentration or feelings of boredom, frustration and stuck (and more). As a result effectiveness of a learning process may be reduced or learning process may be paused or even abandoned. Some virtual universities reported large problem of resignation rate before course completion (up to 70% of courses were paused or abandoned) and the problems were addressed by human mentoring on-line [3]. Human mentors devote at least as much time and attention to emotional goals in tutoring as they do to the achievement of cognitive goals [4]. At the same time, ITS and other e-learning environments almost always address only the cognitive goals [4]. Nobody denies, that interest, active participation and motivation are important factors in the learning process and therefore enhancement of ITS with affect recognition and intervention mechanisms is so important. In 2004 a group of affective computing researchers defined the following gaps in affective learning to be addressed: the extension of cognitive theory to explain and exploit the role of affect in learning, incompatibility of emotion theories with computer-based processing, reliable measurements of emotional states symptoms and objective interpretation, embodied agent influence on user affect [4]. In 2013, nine years later, most of the problems identified remain open and research reveals sometimes more questions than answers.

II. RESEARCH OBJECTIVES

An **affect-aware system** can be defined as a software program of any main functionality, that additionally recognizes emotional state of a user and has control mechanisms and application logic able to handle the information on affect. The systems could and should make an intervention, when certain objectives (f.e. task effectiveness) are not met. Moreover, the system should not make an intervention, while it would disturb the user to do appropriate tasks. The main question addressed by the research described in this paper is: how to reduce risk of unnecessary and disturbing intervention of intelligent applications that deal with user emotional states? The research was confined to Intelligent Tutoring Systems (ITS) design, however the results can be applied in multiple disciplines. In this paper an **affect-awareness of ITS** is defined as: the system being aware of the emotional state of a learner and being able to make intervention, when learning process is endangered (and only then). In Intelligent Tutoring Systems user emotion recognition has the overall purpose of recognizing emotional states, that support or disturb learning processes. The mechanism provided for ITS emotion recognition must deal with uncertainty and fuzzy nature of emotion and the information on uncertainty must be taken into consideration in control mechanisms. In this research an **affect-awareness framework** is proposed – a design model for affect-aware intelligent software, that comprises: user emotional state elicitation (recognition), user affect interpretation and analysis, affect-aware intervention and control. In this framework emotional state elicitation and interpretation can be considered as testing a hypothesis: 'user emotional state requires intervention' against null hypothesis: 'user emotional state does not require intervention'. In that context type I error indicates that a system recognizes non-existent emotional state and makes unnecessary intervention, while type II error means

that counterproductive emotional state was not recognized and the systems fails to make intervention when required. Although both errors should be minimized, it is sometimes impossible minimize both at the same time and in that case the choice of the optimization purpose must be based on the real-life consequences of an error. In Intelligent Tutoring Systems it would be better when a system sometimes not makes required intervention than when it makes them unnecessarily and perhaps instantly, which would be very disturbing.

Therefore a research hypothesis addressed by this paper would be given as follows: *construction of ITS based on consistent emotional state representation and control including uncertainty model (affect-awareness framework) allows to reduce the risk of unnecessary and disturbing application intervention*. The proposed framework is not a complete affect-processing engine, but intends to be an extendable, modular and maintainable structure to be applied in many affect-aware systems.

III. RELATED WORK

Works that are mostly related to this research fall into three categories: (I) studies on emotional states in learning processes, (II) research on affective computing methods, including emotion recognition, processing and expression by intelligent software, (III) research on affective learning supported with technologies and implementations of ITS.

There are some studies on how emotional states influence learning processes, however they were rather conducted by psychologists. The unquestionable achievements of affective computing is research on the states of frustration and flow and on emotional states in different types of educational tasks [5]. However, the research usually focuses on one perspective or one emotional state only, for example only on frustration or only on boredom [6][7]. Some educational tasks are also better investigated than others [8]. Findings on emotional states in educational processes may be applied in affect-awareness framework to define emotional states that support and suppress learning.

Second group of related work includes numerous emotion recognition algorithms, that differ on information input: video, voice, text or physiological measurements [12-15]. Although there are so many algorithms, they have two major drawbacks. Firstly, they are based on different emotional state representation models, making their outputs incomparable with other algorithm findings and their combination and application difficult. Secondly, most of them lack of expression of uncertainty of the final emotional state recognized.

There are also some research and examples of tutoring systems that address the issue of student emotional states recognition and elicitation [9][15]. Woolf et al proposed a set of useful cognitive-affective terms scales for emotion labeling dedicated to learning processes. The states were additionally assigned with numeric representation of desirability in educational processes (for example concentration was rated 2- 'highly desirable', while boredom was rated 0 – 'not desirable') [9]. A very

interesting affective tutor Eve is equipped with emotion recognition based on multimodal input, which shows, that combination of different features extracted from multiple channels is a promising approach [13]. Research on interest classification based on selected 11 features from 4 channels were also an inspiration to research described in this paper. Multimodal features combination using Gaussian Processes and SVM showed an accuracy of 86% and the significant problem of missing or noisy channels was also recognized [14]. Sarrafzadeh et all [13] proposed a term of Affective Tutoring Systems, which may be considered as synonymous with affect-aware ITS.

IV. CONCEPT OF AFFECT-AWARENESS FRAMEWORK

The concept of the affect-awareness framework is based on decomposition, which is one of the most powerful principles for complex problem solving and system design. Three major components of affect-awareness were distinguished: affect recognition, interpretation and affect-aware reaction (intervention) and they were then decomposed to more specialized components, as shown in Figure 1. For each component a group of processes and supporting models or libraries were distinguished to illustrate the design of affect-aware ITS:

- user emotional state **representation model**,
- **emotion recognition** algorithms (one or multiple, perhaps multimodal),
- **trustworthiness model** that deals with uncertainty and fuzziness of emotion recognition,
- user **emotional state elicitation** algorithm (from multimodal hypothesis provided by the recognition algorithms),
- **patterns of emotion** and **emotional state classification** (emotion labeling),
- **emotional stereotyping** (interpretation of the state) and **user affect modeling**,
- **affect-aware control** mechanism based on system **affective intervention model** (definition of emotional states, that require intervention),
- **multimodal response** based on system **behavior library** (intervention scenarios).

The proposed framework separates emotion recognition from its processing and making decisions on interventions. Most important foundations of the framework include choosing one emotion representation model consistent within all the affect processing mechanisms and dealing with emotion uncertainty on each stage of the process. Most of the ITS address the issue of emotion fuzziness and algorithm imperfection at the recognition phase and forget it in interpretation and control mechanisms.

In affect-awareness framework the process starts with multiple emotion recognition algorithms based on multimodal inputs – each of those may provide a hypothesis on user affective state expressed with different representation model.
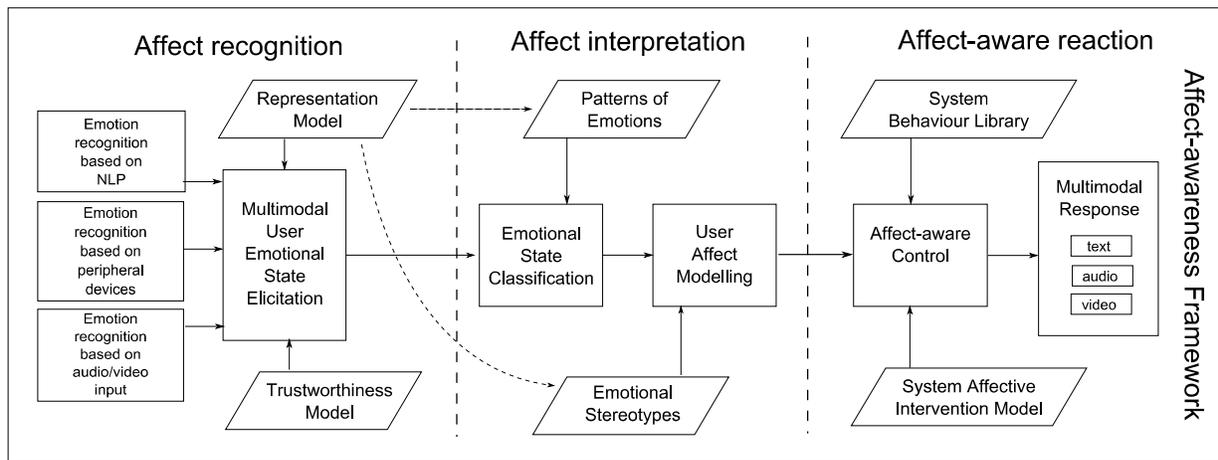
Fig. 1. Components of affect-awareness framework for Intelligent Tutoring Systems. For major components of affect recognition, interpretation and reaction the processes (rectangles) were shown, supplemented with the models or libraries (parallelograms) they use.

User emotion elicitation process adjusts the outputs from emotion recognition algorithms to elaborate a trustworthy hypothesis compliant with the chosen representation model. The elicitation process must deal with noisy or missing input channels, hypothesis contradiction and representation model incompatibility.

A trustworthy hypothesis on user emotional state is then matched to patterns of emotions. Classification process must deal with fuzziness of labeling and overriding classes. Patterns of emotions should be independent on the application domain, however some differences may arise due to limitations of chosen representation model. Affective stereotypes are specific for the intelligent system application domain and perhaps even for specific tasks (f.e. at this stage of the task majority of students feel frustration). Student affective model process tracks changing student emotional state and its fit to stereotypes. If emotional state is atypical or counterproductive, affect-aware control process decides whether to make an intervention. The decision should be based on: current hypothesis on emotional state, the certainty of this hypothesis, emotional stereotype and available intervention models (available system behaviors).

The proposed framework and its components must also comply with several quality requirements, including adaptability and trustworthiness. Adaptability is ability to conform to changing circumstances, without external interventions. Trustworthiness is a way of dealing with uncertainty by eliminating it or addressing in response and control mechanisms.

V. COMPONENTS OF THE AFFECT-AWARENESS FRAMEWORK

A. Emotional state representation model

Choosing emotional state representation model is a fundamental decision in affect-aware ITS design as it influences affective states interpretation, the selection of recognition algorithms, emotional patterns and stereotypes definition as well as system affective intervention model.

There are three major model types of emotional state representation: discrete, dimensional and componential. Discrete models distinguish a set of basic emotions and describe each affective state as a combination of the basic ones. The most important model in this category is Ekman six basic emotion model including: joy, sadness, fear, surprise, anger and disgust with emotional state expressed as a combination of these [16]. Some emotional states are hard to represent in that model, for example boredom. Dimensional models use two- or three- dimensional space for emotional states representation. Two-dimensional scale known as Whissel wheel includes valence (positive-negative attitude) and arousal (high or low stimulation) [17]. Third dimension proposed by Russell and Mehrabian – dominance represents 'fight or escape' reaction to stimuli resulting in PAD (positiveness- arousal-dominance) emotional space [18]. Emotional states at Whissel wheel or PAD scale are usually represented as points. An example of componential model is OCC, that is used for modelling, how human emotions are evoked [19]. Some other representation models are also based on labels (words) but they are strongly discouraged due to fuzziness of linking concepts with words and problem of semantic disambiguation.

Dimensional models are the most convenient for computing purposes and therefore they are most commonly used in affective computing and PAD space is a recommend representation model for affect-aware Intelligent Tutoring Systems. One may choose different representation model, however restriction must be made to use this model consequently in affect recognition, interpretation and control processes.

B. Emotion recognition algorithms

For affect-awareness mechanisms any emotion recognition algorithm can be selected as long as the following conditions are fulfilled: its input is collectable in the application environment, its output matches or can be transformed into chosen representation model, it provides information on certainty of the result.

Although many algorithms for emotion recognition are

known (based on single or combined modalities), most of them were never applied in e-learning environments and their accuracy was not verified in the learning context. Some were tested only with intentionally expressed emotions and not in real situations, when symptoms may be more modest and contradictory. For many of those emotion recognition methods only their authors verified the accuracy of the algorithms. Therefore the proposed framework is designed for the ease of recognition algorithms detach, exchange and optimization.

C. Trustworthiness model and affective state elicitation process

Affect recognition must deal with uncertainty, which has at least four sources: fuzzy nature of emotions, insufficient accuracy of emotion recognition algorithms, unstable nature of emotion (frequent changes in time) and limitations of representation model. The uncertainty of emotion recognition process cannot be fully eliminated and must be properly addressed.

The affect-awareness framework proposes an approach based on certainty factors and trustworthiness model. All of the affect recognition algorithms must be assigned with a representation of uncertainty information. **Certainty factor** is a quantified attribute assigned to a hypothesis provided by algorithm, that expresses algorithm belief on the quality of the provided result. Hypothesis from different modules may then be combined based on their similarity and certainty. The combination method is not trivial, as the hypothesis may be contradictory and have different levels of certainty. The proposed trustworthiness model addresses the uncertainty in hypothesis combination. There are different frameworks of dealing with uncertainty, including probability, theory of evidence, fuzzy set theory, possibilities theory, interval analysis and rough sets theory [20].

Addressing uncertainty is a new approach in affect recognition and was not proposed before. The trustworthiness model may be considered as the most original and significant contribution of the proposed framework.

D. Patterns of emotions and emotional state classification

Not all emotional states can be detected based on limited set of knowledge sources in e-learning environment. Moreover not all emotional states must be recognized and distinguished to provide proper interventions of Intelligent Tutoring Systems. A minimal set of distinguishable emotional states must be defined, including at least two subsets of states: the ones, that require intervention and the ones that do not. The psychological research on affect that facilitates learning can be summarized with the following findings [12-16]:

- extreme emotional states suppress learning (both negative and positive),
- best for learning are: engagement, concentration and flow,
- different emotional states facilitate different cognitive tasks,

- slightly negative states are better than slightly positive, as they foster critical thinking,
- active emotional states are better than passive (and on dominance scale anger is better than fear).

An assumption was made, that there exists an optimal learning area within PAD space, that includes most of neutral emotional states and some others that support the learning process. Recognizing a student's emotional state within that area does not require any affect-aware intervention form ITS and the essential lesson scenario may be continued. Student's emotional states that require ITS intervention include all the other emotional states, especially feelings of anger, frustration, boredom, weariness and deconcentration. Such emotional states as disgust or fear are rare in e-learning environment, however they may be included for model completeness.

Classification process must deal with emotional states fuzziness, overriding patterns or incomplete models. In affect-awareness framework it is proposed to separate definitions of emotions and their application in classification, as definitions depend on representation model and can be adjusted to fit the purpose of ITS.

E. Student affect modeling and emotional stereotypes

Student affect modeling includes tracking individual emotional reactions to stimuli and emotional state fluctuation in time. Differences in emotional reaction patterns may be caused by different root causes, including: previous experience, type of the task assigned, individual differences of neural system (high or low reactivity).

The data on the recognized emotional states and assigned tasks may be stored and may be the subject of different analysis, including pattern recognition and timeline trend analysis. As a result, emotional reaction patterns to different stimuli and different learning tasks could be recognized and described. Moreover, timeline analysis would allow to recognize the pattern of emotion burn-down curve, which is expected to vary on the initial value of valence and arousal.

In the long-time perspective sufficient amount of the data may be gathered and by the means of classification and clustering techniques student or task stereotypes may be identified.

F. System affective intervention model and affect-aware control

Affective intervention model is a definition of emotional states that require an intervention and the ones, that do not. An **affective intervention** is a modification of standard control flow or standard interaction path, that addresses counterproductive emotional state. The intervention can be thematic (change of task assigned, modification of planned learning path) or off-topic (learning companion telling a joke or virtual teacher expressing encouragement). The most important claim of affect-aware framework is that the control mechanism should make decisions on interventions taking into account not only hypothesis on emotional state of a user, but also certainty of that hypothesis to reduce a risk of unrequired and disturbing intervention.

G. System behavior library and multimodal response

Decision on intervention must be followed by performing it using available means of expression, that may include: text, audio or video response. An intervention scenario is a pair: emotional state plus system reaction design expressed in terms of multimodal response. If ITS is equipped with virtual learning companion or mentor, naturally, its reactions should be expected in intervention scenario. For video-based or text-based environments it is also necessary to provide more than one possible reaction of each type to avoid repeatability as it would be unnatural.

VI. CASE STUDY OF GERDA INTELLIGENT TUTORING SYSTEM

Gerda bot is a prototype of conversational Intelligent Tutoring System developed during preceding research of the paper author and it questions students on operating systems. Gerda uses a metaphor of conversation with virtual teacher and question-answer dialog is performed using keyboard input (voice channel is not used). Gerda was alfa-tested with a group of students in December 2011 and at the moment of the experiment Gerda has not included any affect-awareness mechanisms. The students rated topic-based Gerda reactions as satisfactory, while off-topic response completely missed their expectations. The main surprise during that experiment, was the engagement of the randomly chosen student group in interaction with Gerda (students were not assigned any additional bonus for the participation). Their commitment and trials of getting into her (including attempts to make a date) took much longer than it was planned (the expected interaction time of 15 minutes was in practice doubled and some students were explicitly told to stop). Although Gerda reactions were evaluated as unsatisfactory, the experiment led to several important conclusions: off-topic reactions are as much important (or maybe more) as topic-based ones for student satisfaction and questionnaire is not enough for determining how a user feels – engagement was not expressed at all, although three independent observers of the experiment considered that to be strong.

In 2012 an affect-awareness mechanisms was build into GERDA using the framework proposed in this paper. Design decisions and affect-related component details are described in the following subsections.

A. Representation model

PAD representation model was chosen for Gerda ITS and it was consequently used in emotion recognition, interpretation and control. From the three emotion recognition algorithms implemented in Gerda two used PAD as their output, while one provided a hypothesis with Ekman six. An additional wrapper module was implemented that transformed the output to a PAD point, however inaccuracy of the result might be also affected by the transformation imperfection. The emotion patterns were described as fuzzy segments of PAD scale.

B. Emotion recognition algorithms

Gerda is a conversational ITS and emotional state recognition was based on lexical analysis of user inputs. There were three independent modules that performed recognition algorithms based on keyword spotting and some additional heuristics (use of smileys, punctuation, letter capitalisation). The algorithms were implemented taking inspiration from Synesketch project [21] and they were similar, but based on different keyword lexicons: Synesketch lexicon [21], ANEW [22] extension with WordNet and ANEW extension with ConceptNet. The three algorithms are referenced as Syn, ANEW-WN and ANEW-CN hereinafter. The algorithms provide affective state hypothesis (sometimes contradictory) depending on input word presence in lexicons. An extension of emotion recognition with algorithms based on keystroke dynamics analysis and biomeasurements is planned in Gerda application in the future [23][24].

C. Trustworthiness model

The affective state recognition algorithms were extended with the definition and calculation of certainty factor based on available keyword count, standard deviation of affective value assigned to word and some heuristics. The hypothesis on user emotional state provided by different algorithms were then combined using fuzzy set theory. The certainty factor was used in order to eliminate contradictory hypothesis. As a result a final hypothesis on user emotional state was provided, followed by its certainty factor. The certainty factor of the final hypothesis on user emotional state was calculated using the information on preliminary hypothesis contradiction and their certainty. The proposed approach was inspired by the Dempster-Shafer theory of evidence [20].

D. Patterns of emotions and emotion classification

Emotion recognition and elicitation process delivers a hypothesis on emotional state of a learner represented with a PAD space point. The state must be interpreted and in Gerda the state was classified into one of the following emotional states: anger, boredom, frustration, hilarity, neutral and other. The first four states were assigned with affective interventions, while neutral and other emotional states were considered as not requiring system intervention. Other emotional states than distinguished were rare (human expert rated only 5% of student statements as falling into other category). During conversation most (81,8%) of the emotional states of a learner were considered neutral (as expected). Emotion classification into the distinguished classes was carried by naïve algorithm based on minimal distance to the middle of emotion pattern segment.

E. Emotional stereotypes and student affect modeling

Model of student affect was updated after each input – a value of emotional state hypothesis was stored, followed by its interpretation. Task or user stereotypes were not identified due to insufficient amount of data.

F. System behavior library and multimodal response

Gerda is a conversation-based software and the interface consists of text communication widget and avatar visualisation widget. Visual Gerda reactions are adjusted to

conversation status and are implemented with a set of actor-based films sequenced on the run. Films last for less than a minute and actor performs different body and facial reactions, also affective ones such as smile or disapproval. Also textual responses are defined providing multiple options to choose from. Separation of behavior library from intervention definition allows to randomize system response within reaction category in order to avoid repeatability.

The textual and visual affective behaviour is synchronized (not lip movements, but emotional expression) to assure consistent and effective intervention.

G. System affective intervention model and affect-aware control

For each emotion pattern recognized there were several scenarios proposed, depending on the emotion gradation and certainty of the hypothesis on affective state of a learner. A list of Gerda ITS affective scenarios is provided in table 1.

TABLE 1: SCENARIOS OF AFFECTIVE INTERVENTION IN GERDA ITS.

Scenario	Emotion	Certainty
Anger1	Moderate Anger	Low to medium
Anger2	Strong Anger	Low to medium
Anger3	Strong Anger	High
Frustration 1	Moderate frustration	Low to medium
Frustration 2	Moderate frustration	High
Frustration 3	Strong frustration	Low to high
Boredom 1	Moderate boredom	Low to high
Boredom 2	Strong boredom	Low to medium
Boredom 3	Strong boredom	High
Hilarity	Strong hilarity	High
Idleness	not applicable	not applicable

There were three scenarios for frustration, boredom and anger as these emotional states were considered as the most counterproductive. For low certainty scenarios were started with questions (for example: *Are you bored? Maybe next task?*). Some scenarios were just simple statements or encouragements (usually with moderate emotion graduation or low certainty). For hilarity (student joking and distracted), the intervention was undertaken only if it was strong hilarity with high certainty. Additional scenario was proposed for idleness, when a learner seems inactive for a predefined amount of time.

Affect-awareness framework implementation in Gerda was supported with control mechanism that took information on affect as one of the inputs. The affect-aware control algorithm is shown in figure 2.

For each conversation turn observable data was gathered including text and peripherals use, however the second information was not used in recognition process. Idleness time was also counted. Emotional state recognition modules provided their hypothesis and they were then combined to provide one of a higher certainty. The final hypothesis was used to update student model and to make decisions on affective interventions. If an intervention was not required – Gerda continued lesson scenario: student input substantive assessment, cognitive interventions (hinting, prompting) and another conversation turn was started. If intervention was required, text response and Gerda visualization was randomly chosen from the provided set that fitted the scenario. After the intervention was performed (including perhaps more than one conversation turn), the next turn was initiated according to lesson scenario. Detail on Gerda affect-aware intervention model are described in technical report [25].
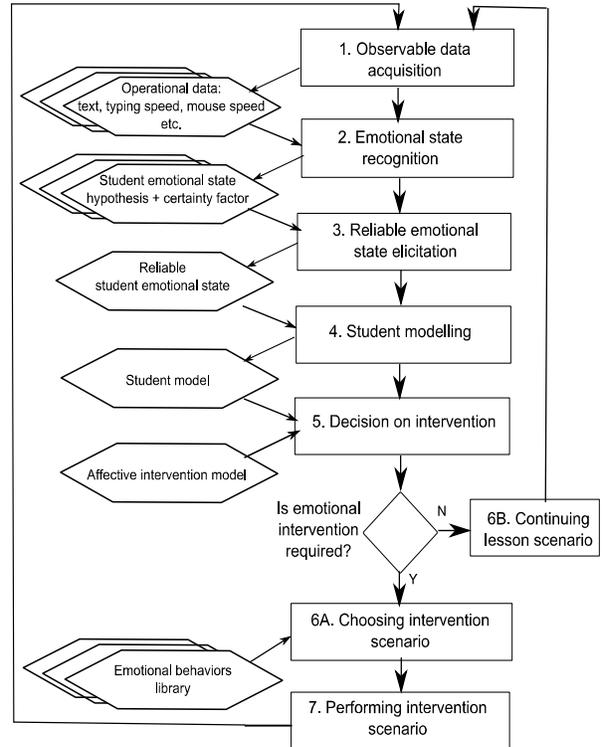

Fig. 2. Gerda Intelligent Tutoring System control algorithm based on affect-awareness framework.

H. Architectural pattern

Affect-awareness framework was in Gerda design supported with *Scoreboard* architectural pattern [26]. The pattern uses inversion of control and dependency injection in order to provide maintainability of the application system. The pattern is based on one *Blackboard* container that is accessible by all of the modules, providing, that it is the only way of communication and message passing. Moreover, a *Scoreboard* container was added, that allows to evaluate modules and algorithms on the run. The Scoreboard design pattern is dedicated to non-deterministic problem solving and experimental software [26]. In Gerda the pattern allows to reduce component coupling and increase cohesion, which is one of the system decomposition principles.

VII. CASE STUDY EVALUATION

An evaluation of affect-awareness framework in prototype tutoring system GERDA is conducted using

Goal-Question-Metric method, as it allows to focus analysis on key quality factors. The goal of the analysis is defined as *"Analyze implementation of affect-awareness framework from the perspective of its applicability in intelligent systems"*. The following questions were identified: *Does the method allow to minimize unrequired intervention (error I type as defined in section 2)? Is the solution trustworthy? Is the solution adaptable?*

There were two stages of evaluation process performed. Both stages were conducted using real conversations of students with Gerda application. In the first stage all student entries from experiments were analyzed (434 entries) automatically. For the second stage only selected entries (95) were additionally evaluated in detail by human experts (5 experienced teachers). Selection of the entries was performed differentiating topical and off-topic student responses. Off-topic entries were manually selected and a random group of topical responses was also added. Human experts used the same emotional state set described with labels, as affective patterns used in Gerda prototype. Proposed metrics, their values and evaluation are described in the following subsections.

A. Minimization of type I error evaluation

The first stage of automatic analysis of student entries revealed emotional states that did not required affective intervention in 85,3% cases – entries were evaluated as neutral (81,8%) or other than defined in intervention scenarios (3,5%). Hypothesis on positive emotional states that may require intervention (hilarity) were encountered in 7,37% of entries, while negative emotional state hypothesis (anger, frustration, boredom) were estimated in 3,0%, 2,8% and 1,6% cases respectively. This means, that a little less than 15% entries were evaluated as requiring intervention (about every sixth student input). Detailed analysis of selected discourses led to conclusion, that student were challenging Gerda in several ways with frequent off-topic entries, including even swears. However, affective intervention after every 6th student input seems too often.

Comparison of evaluated emotional states with human expert opinions in second stage of evaluation process shown, that almost 50% of interventions identified only on emotional state hypothesis would be unnecessary (13 out of 27). Further reduction of unnecessary interventions was based on certainty of emotional state hypothesis. Required level of certainty required for intervention and number of unnecessary intervention (percentage in parenthesis) are provided in table 2.

TABLE 2: NUMBER OF UNNECESARY INTERVENTIONS DEPENDENCY ON HYPOTHESIS CERTAINTY FACTOR.

Certainty factor	Number of unnecessary interventions - type I error (percent of interventions)
not used	13 (48%)
>0.6	11 (41%)
>0,7	10 (37%)
>0,8	6 (22%)
>0.9	3 (11%)

Detailed analysis of intervention performed by Gerda showed, that for acceptable level of type I error and type II error certainty factor limit should be set to 75% for negative states and 90% for positive states. Therefore intervention decision in Gerda was based not only on emotional state, but also on its certainty. It can be concluded, that construction of ITS based on control mechanism including uncertainty model allows to reduce the risk of unnecessary and disturbing application intervention.

B. Trustworthiness evaluation

The proposed framework addresses uncertainty of emotion recognition in processes of emotion elicitation and interpretation as well as in control mechanisms.

Certainty factor was assigned values ranging from 0 to 1, but in practice minimum value assigned was about 0,2 and maximum 1. Number of results falling into five distinguished certainty factor ranges for each of the algorithms and final hypothesis is provided in Table 3 (with share in total results below).

TABLE 3: RANGES OF CERTAINTY FACTOR

Certainty factor range	0-0,2	0,2-0,4	0,4-0,6	0,6-0,8	0,8-1
Algorithm Syn hypothesis	212 48%	24 5%	60 13%	48 11%	90 21%
Algorithm ANEW-WN hypothesis	149 34%	24 6%	55 13%	73 17%	133 30%
Algorithm ANEW-CN hypothesis	94 22%	18 4%	47 11%	69 16%	206 47%
Final hypothesis	0 0%	1 0% (0,2%)	105 24%	131 30%	197 45%

Based on the results provided in Table 3 it is easy to spot a weakest algorithm in this comparison (algorithm based on the smallest dictionary Synesketch, denoted as Syn). Final hypothesis certainty average (0,69) is about the same as for algorithm ANEW-CN (0,71), however, it was possible to reduce the number of hypothesis with the lowest certainty results by the means of hypothesis combination (if there are three hypothesis of low certainty spotting at the similar emotional state, the resulting certainty is higher).

Certainty factor was also a good predictor of algorithm accuracy and it is possible to evaluate algorithms on the basis on certainty factor values they provide.

C. Adaptability evaluation

As stated before, adaptability is ability to conform to changing circumstances without external interventions. One of the problems addressed by the affect-awareness framework is missing or noisy channels in emotion elicitation process. In real-life situations it may happen, that some input channels for emotion recognition will be unavailable (for example lightning at student home desk may be insufficient for emotion recognition based on face analysis). In the framework a hypothesis on emotional state

is combined from multiple modules and in the case of missing channel a module may provide no hypothesis or may reduce its certainty to fit the level of channel noise. The affect-awareness mechanism will handle the problem of reduced certainty in emotion elicitation and in control structures. Moreover, affect-awareness framework allows to combine tens of emotion recognition algorithms and to treat them as complementary source of knowledge in case of missing channels.

D. Validity of case study results

Main threats to validity of this case study include: subjectivity of evaluation process and limited representativeness of Gerda Intelligent Tutoring System. Subjectivity of evaluation process was partially eliminated by the GQM distinction of quality attributes and by the second stage of evaluation process involving independent human experts.

With only one case study performed, this paper must be considered as reporting preliminary results for most of the affect-awareness framework components. Although Gerda is a typical conversation-based ITS, more robust conclusions could be drawn when framework would be applied to at least two comparable intelligent systems. The framework however was proven implementable and extendable as some of the components were already exchanged with little effort, but high optimization result. The proposed trustworthiness model allows to reduce uncertainty in emotion recognition, reduces the risk of unnecessary intervention and positively influences adaptability in the case of missing or noisy channels.

VIII. CONCLUSION

The proposed affect-awareness framework is comprehensive and therefore complex, but its implementation scope can be restrained to fit the purpose of affect-aware system. Due to decomposition, however, it is possible to start with very simple models and algorithms for each of the predefined processes and then to adjust and advance mechanisms to optimize system effectiveness.

The framework is dedicated to Intelligent Tutoring Systems, however may be adopted in different affect-aware software of any main functionality and domain of application.

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