Inferring a Learner´s Cognitive, Motivational and Emotional State in a Digital Educational Game

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Abstract: Digital educational games (DEGs) possess the potential of providing an appealing and intrinsically motivating learning context. Usually this potential is either taken for granted or examined through questionnaires or interviews in the course of evaluation studies. However, an *adaptive* game would increase the probability of a DEG being actually motivating and emotionally appealing. In order to adapt the game to the learner´s motivational and emotional state *while* engaged with a particular game scenario, an ongoing assessment of these states is required. An explicit assessment, e.g. by questionnaires occurring repeatedly in short time intervals on the screen would probably destroy the learner´s flow experience. Thus, it is necessary to apply an approach that assesses the learner´s current states in a non-invasive way. In the course of this paper we describe such a non-invasive, implicit assessment procedure which is based on the interpretation of *behavioral indicators*. A set of behavioral indicators has been elaborated whereby some of them are derived from the theory of *information foraging* (Pirolli and Card, 1999). Values for each behavioral indicator (e.g. amount, frequency, seconds, etc.) are gathered after equally long lasting *time slices*. After each time slice, these values serve as weighted predictors to multiple regression equations for the dimensions of a motivation model, an emotion model and a construct called clearness. The motivation model is based on the two dimensions of *approach* and *avoidance motivation*. The emotion model encompasses the dimensions *valence* and *activation.* Clearness is defined as appropriate problem representation. A comparison of the resulting values on these dimensions between the current and previous time slices covers fluctuations of the learner`s states over time. The assessment of such changes forms the prerequisite for providing in-game adaptations which aim to enhance the learner`s state, targeting towards a full exploitation of DEGs' pedagogical potential.

Keywords: digital educational games, motivation, emotion, problem representation, non-invasive assessment.

1 Background

Advantages offered by modern information and communication technologies, such as rapid information access, flexibility regarding time and location, as well as the possibility to apply constructivist learning approaches have been exploited (Chang, Gütl, Kopeinik and Williams, 2009). Nowadays, Technology-enhanced learning (TEL) applications are broadly used in the field of distance and blended education. One of such TEL applications has been developed in the course of the European research project TARGET (http://www.reachyourtarget.org), funded by the European Commission (7th Framework Programme).

The TARGET project aims to reduce the *time-to-competence* of knowledge workers in the domains of project management, innovation management and global sustainable manufacturing. TARGET´s main focus is on the intersection between these three learning domains. This intersection represents basically a set of social interaction skills, usually known as *soft skills*, which are highly associated to the *competence to communicate* (Greene and Burleson, 2003). One example in the context of TARGET is the competence to negotiate with different stakeholders. In order to reach TARGET´s ambitious aims, a new kind of TEL-platform will be provided. The TARGET platform consists of several tools and software components, designated to support self-directed learning (Schunk and Zimmermann, 2008), critical reflection on the learner´s own results by means of open student modelling (e.g. Bull, 2004), collaborative learning and most important, life-like learning experiences. The very heart of the TARGET platform is a *digital educational game* (DEG) presented within a 3D virtual environment. This DEG consists of a set of game scenarios, which address critical incidents of the knowledge domains. The theoretical foundation of the scenarios design and their narrative structures is primarily founded on competence-based learning (Cheetham and Chivers, 1999) and problem-based learning approaches (Barrows and Tamblyn, 1980).

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2 TARGET´s Digital Educational Game

When entering the DEG of the TARGET platform, the learner is first provided with a description of the game scenario´s background, the description of the aims to achieve and the role descriptions of other game characters, so called *non-playable characters* (NPCs). The 3D virtual environment consists of an office building and various outdoor locations. In order to finish a game scenario successfully, the learner needs to interact with artefacts and to communicate or negotiate with different NPCs to gather valuable pieces of information. For this, the learner has the opportunity to use several tools, for example a *chat tool* to communicate with the NPCs, a *teleport tool* to switch between different locations, an *emotion tool* enabling to express nonverbal communication (which might influence the NPCs' behaviour and in consequence, increase or reduce the learner´s probability of success), or a *face cam* that shows the own avatar`s face to evaluate whether the emotions are expressed as intended by the learner. Figure 1 shows a screen of the 3D virtual environment, an NPC, and some of the tools just mentioned.

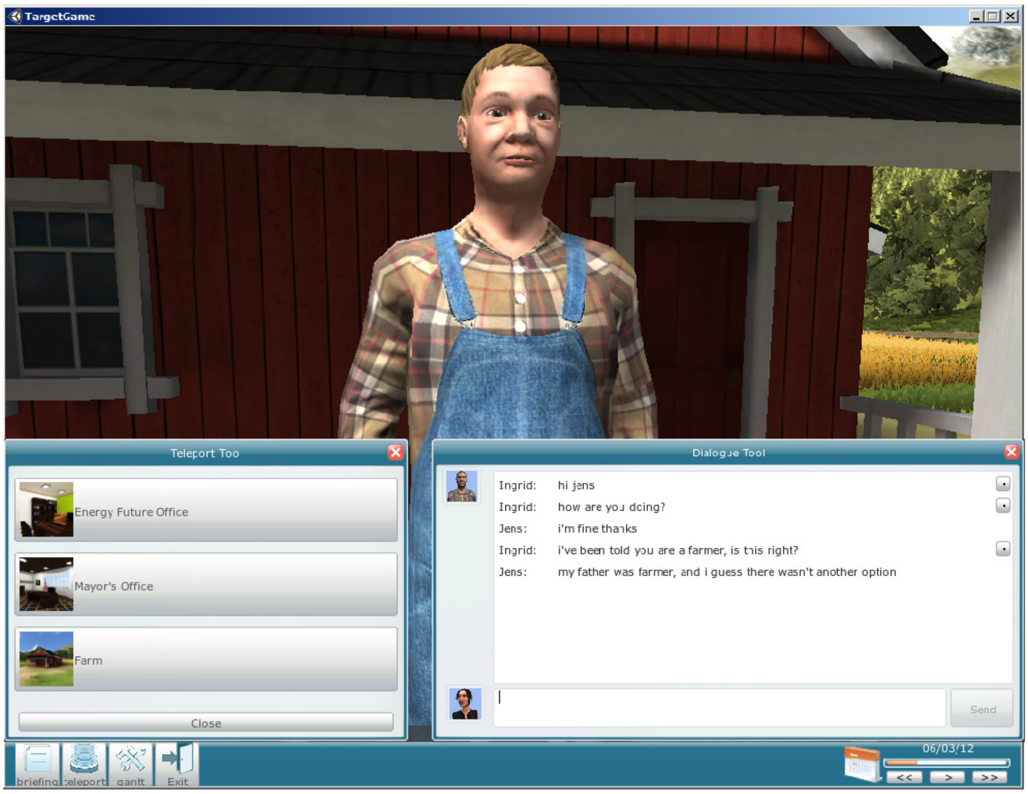

Figure 1: Screen of TARGET´s DEG

In general, TARGET´s game scenarios offer a large set of possible actions to be carried out by the learner and a high amount of alternatives to be chosen from. Speaking in terms of *problem solving* (Sternberg, 1994), this leads to an extensive problem space, i.e. a large set of *problem states* or game situations constituting a complex and ill-defined problem. On the one hand, such an extensive problem space has the potential of providing an appealing learning context which is intrinsically motivating and challenging to engage with. It provides life-like learning experiences. On the other hand, it also inherits the risk of overburden the learner. This might particularly happen when an extensive problem space is coupled with a lack of clear guidance and instruction (Kirschner, Sweller and Clark, 2006). A suitable balance between guidance and degrees of freedom (i.e. a medium level of complexity and challenge) is known to be an important factor for motivating games and favours the occurrence of flow experiences (Csikszentmihalyi, 1990).

2.1 Adaptive Digital Educational Games

In most cases, the presence of the motivational potential of DEGs is either taken for granted or examined by means of questionnaires, interviews or behavioural observations in the course of evaluation studies. As indicated in the previous section, a medium complex game scenario - or in other words: A game scenario which causes a medium level of *arousal* - is expected to be most promising for being motivating and emotionally appealing. Thus, a game should adapt to the learner`s current competence, motivational or emotional state if necessary. The principles and phases of an adaptive approach are shown in Figure 2.

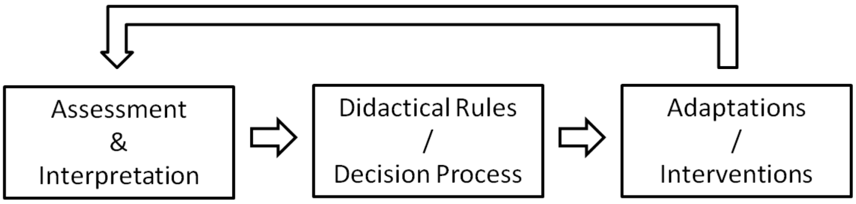

Figure 2: Principles and phases of an adaptive approach

The first step in providing appropriate adaptations is the valid assessment of the learner`s current state. The assessment results have to be interpreted in terms of “sufficient” or “insufficient” states. Didactical rules or a predefined decision process determine the kind of adaptations or interventions to be provided, taking psycho-pedagogical and situational considerations (e.g. current restrictions on the game side) into account. Since the effect of the adaptation on the learner should be evaluated, the described principles can be considered as an iterative process.

Since the duration of game scenarios may range from a couple of minutes to several hours, the distinction between *macro*- and *micro-adaptivity* has been suggested (Kickmeier-Rust, Hockemeyer, Albert and Augustin, 2008). Macro-adaptivity refers to adaptations of the next game scenario to be played (based on the learner´s performance in the previous one), i.e. macro-adaptive principles are applied between two consecutive game scenarios. Micro-adaptivity refers to adaptations within a single game scenario. An explicit assessment by means of a short questionnaire or ratings via slider scales might be less disturbing when appearing between two game scenarios (i.e. in the context of macro-adaptivity) but it would most likely destroy the learner`s flow experience when appearing in regular time intervals while playing the game scenario (i.e. in the context of micro-adaptivity). Thus, when aiming for applying micro-adaptive principles it is necessary to assess the learner´s state by applying an implicit or *non-invasive assessment technique*.

2.2 Non-invasive Assessment

The micro-adaptivity approach has been established in the European research project ELEKTRA (http://www.elektra-project.org/). In ELEKTRA, the assessment of the learner`s competence state has been continuously updated based on the interpretation of the learner`s actions and behavioural patterns within game scenarios in terms of underlying competences (Kickmeier-Rust, Hockemeyer, Albert and Augustin, 2008). As an example for a micro-adaptive intervention, an NPC could provide a hint to the learner on how to solve a particular problem within the scenario (Kickmeier-Rust and Albert, 2010). In TARGET, we extend the micro-adaptivity approach by aiming also for the non-invasive assessment of the learner’s *motivational* and *emotional* state; in addition to a problem-solving related construct which we call *clearness*. These constructs are considered as important parts of a holistic view on the individual`s learning process.

The inference of these constructs from the observation of the learner´s actions and behavioural patterns (called *Behavioural Indicators* in the following) during game-play and the interpretation of the assessment is the main focus of this paper. However, we will also provide a brief overview on applied didactical rules and exemplify one intervention at the end of the paper to cover all three phases of the (micro-) adaptivity approach shown in Figure 2. In the following section, we describe the constructs in more detail and outline their underlying theories, models and dimensions.

3 The constructs of the extended micro-adaptivity approach

3.1 Motivation

In the context of TARGET the emphasis is on *achievement motivation* as described by McClelland, Atkinson and colleagues (e.g. Atkinson, 1957; McClelland, Atkinson, Clark and Lowell, 1953). According to Elliot and Dweck (2005) achievement motivation should be considered in terms of competences. It can be distinguished between two forms of achievement motivation (e.g. Elliot and Covington, 2001): *Approach motivation* and *avoidance motivation*. Approach motivation is defined as the learner's motivation to learn in order to become competent and to do justice to her or his own performance standard (e.g. the learner is engaged in a learning activity because she or he is interested in the topic or domain and enjoys the learning material). Avoidance motivation is defined as the motivation to *avoid incompetence*, or the foreseen consequences of incompetence. For example: A student learns because she or he wants to avoid a bad grade. According to Covington and Omelich (1991), approach and avoidance motivation are two independent dimensions, resulting in a quadripolar model of achievement motivation.

The model assumes that both, high approach and avoidance motivation, respectively, are associated with a similar observable behaviour: The learner will learn (i.e. he or she will *approach* the situation or the stimuli). To the opposite, the absence of approach motivation and avoidance motivation, respectively, will most likely lead to a *withdrawal* from the situation or the stimuli.

3.2 Emotion

We follow the approach of Peter and Herbon (2006) and Cai and Lin (2011). According to this approach, emotions are represented by the circumplex model of emotion (e.g. Russell, 1980; Larsen and Diener, 1992). The circumplex model consists of the two continuous dimensions of pleasantness and activation. Pleasantness, also called *valence*, is considered as a bipolar dimension with the two poles pleasantness and unpleasantness. *Activation*, also called arousal, is considered as a unipolar dimension with the poles of low and high activation (e.g. Harcourt and Lang, 1995). Each emotional or affective state can be described in terms of these two independent dimensions. For example, the emotional state excitement could be characterized as highly activated and pleasant (Larsen and Diener, 1992). Studies on the effect of emotional states on learning outcomes and efficiency (in particular with respect to valence) have yielded ambiguous results (Bower, 1992). However, with respect to activation, research indicates unambiguously that a medium level of activation leads to a superior learning process in terms of efficiency and sustainability in comparison too high or too low activation levels (Revelle and Loftus, 1992).

3.3 Clearness

In the context of this paper the construct *clearness* refers to the learner´s *appropriate problem representation*, i.e. the awareness of the current problem state and the knowledge about the steps to undertake to approach the goal state (or sub-goal states) of the scenario. Problem representation is the mental organization of the known information about a problem. It consists of i) a description of the initial problem state, ii) a description of the problem`s solution state, iii) knowledge on the operators able to manipulate the current problem state in order to get closer to the solution state and iv) knowledge on possible constraints (Ellis and Siegler, 1994).

It is assumed that the absence of clearness leads to the learner being stuck within a scenario not being able to progress. This situation cannot be attributed to missing competences, lack of achievement motivation or to an unfavourable emotional state. In the context of TARGET´s DEG, the construct clearness is considered particularly relevant as the story structure provides a high degree of freedom to the learner. The TARGET game scenarios can be considered as complex and ill-defined problems. Ill-defined problems are characterized by ambiguous goals (solution state) and different possible solution paths, where the obstacles to the solution state have to be overcome by the problem solver (Pretz, Naples and Sternberg, 2003). They can hardly be solved by applying a constrained set of rules.

3.4 Interrelations between the constructs

The underlying models and dimensions of motivation, emotion and clearness suggest that they are not independent from each other but rather highly interrelated. For example, achievement motivation in general is probably related to high activation, whereby such a relation shouldn`t be misinterpreted as a causal statement. Approach motivation is associated with a pleasant emotional state and avoidance motivation is associated with an unpleasant emotional state (Elliot and Covington, 2001). In addition to that, it seems feasible to assume that the absence of clearness for a longer period of time may cause frustration, which is perceived as a highly activated and unpleasant emotional state.

Due to the interrelations between the constructs and their constituting dimensions, it is reasonable to assume that also some of the observable behavioural indicators (BIs) to assess the constructs are interrelated or even similar. Consequently, it is neither possible nor useful or necessary to identify and define BIs that are solely related to a single construct, because a particular indicator may be valid to assess more than one construct or dimension. A suitable framework for elaborating BIs in the context of ill-defined and complex problems in which the problem solver (i.e. the learner) has to gather pieces of information from different sources (e.g. the NPCs and artefacts) is the theory of *Information Foraging* by Pirolli and Card (1999). In the next section we briefly outline this theory and its most important concepts before describing the set of BIs in more detail.

4 The Theory of Information Foraging

The *theory of information foraging* (Pirolli & Card, 1999) aims at describing and understanding the strategies that people employ in order to seek for, gather and consume information, for instance during the task of finding relevant information on the Web. Human search behaviour is regarded as adaptive to our environment in order to extract or gain information from external sources *effectively* and *efficiently*. External sources are called *patches*, for example communication partners or on-line documents. Especially in the context of ill-defined problems (e.g. acquiring appropriate knowledge for writing a scientific paper) an ideal information forager maximizes the rate of gaining valuable information by seeking for a balanced ratio of *explorative* and *exploitative search behaviour*. In order to acquire knowledge efficiently, available time has to be divided into the search for new sources bearing valuable information (e.g. journal papers) as well as into the elaborate processing of these items to extract relevant information (e.g. at least reading through the abstract, introduction, and discussion). While the time spent on exploration is called *Between-Patch* processing, the time spent on exploitation is called *Within-Patch processing*. By solely concentrating on one single patch (e.g. a single paper) valuable information of external resources won't become available. To the contrary, an excess of exploration (e.g. searching the Web) will lead to ignorance of important details.

The costs and the utility of pieces of information are concretized by the dimension of time within the theory of information foraging. Information that helps to reduce the time to achieve a target is valuable (high utility). If it takes long to gather some kind of information, the costs of the underlying *information seeking actions* (during within and between patch processing) will be regarded as high. Fu and Gray (2006) propose a U-shaped curve for the relationship between time savings and information foraging actions: A moderate number of information seeking actions will be associated with the most optimal performance. Too much as well as too little information seeking will diminish performance. Even if the theory of information foraging has been initially developed in the context of navigation on the Web, within this research we go a step further and apply the principles by adapting some of the indicators to the area of DEGs because:

i) The learner has to search for and to communicate with several NPCs in order to collect all information necessary to master the game scenarios;
ii) It is assumed that a successful information forager experiences a state of clearness and a positive emotional state more often than an unsuccessful one;
iii) The trade-off between costs and benefits of information-seeking "*may not be fully under the person's cognitive control*" (Fu and Gray, 2006: 196). We assume that indicators capturing automatic aspects of a learner's behaviour (in contrast to controlled cognition) positively contribute to a reliable measurement technique. Behaviour driven by automatic and unconscious cognition is biased by situative factors to a lesser extent and therefore, allows for reliable inferences about a learner´s states, and
iv) Information foraging is built upon the rational analysis of human memory (e.g. Anderson, 1990) that is supposed to adapt to the cost and information structure of the environment and hence, to function rationally.

In the context of information foraging *rationality* stands for the adoption of an appropriate, i.e. moderate, number of information seeking actions. In order to prevent abstraction from human rationality, proponents of information foraging suggest building upon the concept of *bounded rationality*, meaning that adaptive behaviour proceeds within the "*bounds of limited time, knowledge, and computational power*" (Fu and Gray, 2006: 199). Therefore, we assume that a learner's information seeking during a DEG will reveal her or his cognitive bounds, such as the ability to represent goal states. A learner, who balances well between efficient exploration and exploitation, thereby increasing the rate of information gained, is assumed to be both, aware of a current problem state and motivated to solve the problem. In the next section it is explained how the concepts of Between- and Within-Patch processing can be applied to the characterization of search behaviour in a DEG

5 Assessment Procedure

In this section the non-invasive assessment procedure for the constructs, respectively their dimensions, *clearness*, *approach*- and *avoidance* motivation, *activation* and *valence* is described. The dimensions are assessed by BIs, which are gathered continuously throughout the game-play. For the ongoing assessment, the overall game-play is divided into consecutive, equally long lasting periods of time, so called *time slices*. As a starting point (obtained during pilot studies), we set the length of the time slices to 30 seconds. The behavioural indicators' "raw values" are calculated at the end of each time slice, i.e. they should be considered as *values per time slice* (i.e. units or frequencies).

We start with the operationalization of the BIs which are considered as the main "building blocks" of the assessment. Then we will exemplify a subset of them, which are based on the principles of the theory of information foraging. The section closes with a description of how to combine the indicators' raw values to obtain a single value for each dimension.

5.1 Operationalization of Behavioural Indicators

Table 1 lists a set of developed BIs, whereby indicator 1 and indicators 5 to 9 have already been proposed by Linek, Öttl and Albert (2010). The indicators 1 and 2 have been suggested to measure aspects of activation. The indicators 3 to 9 are quite focused on TARGET´s DEG features, characteristics and constrains, and thus, they might not be re-usable for other kinds of DEGs.

Table 1: Set of behavioural indicators

#	Behavioural Indicator	Operationalization and Explanation
1	Click rate (*cr)*	The amount of mouse clicks per time slice
2	Mouse movements (d_{MM})	The Euclidian distance between the mouse pointer´s position *t* and *t* + *Δt* is calculated. The sum of all Euclidian distances per time slice is d_{MM}.
3	Distance of "view" - movements (d_{VM})	The amount of vertical and horizontal "head movements" of the learner´s avatar; counted in units of visual angle changes. Considered as an indicator for search behaviour in the virtual environment.
4	Relative exploitation of available tools (p_t)	Number of actually used tools divided by the total number of available tools.
5	Frequency of tool-usage (of the different available tools) (f_t)	$ft = \frac{fT_1 + \ldots + fT_n}{n} \cdot \frac{T_W}{Tts}$ Indicator for the average usage frequency of tools T_i. (T_W / T_{ts}) acts as a weight so that the indicator takes on a high value only if the learner made use of the tools to gain information through an exhaustive conversation.
6	Frequency of communication tool-usage (f_{ct})	Number of chat tool usage
7	Frequency of interactions with NPCs (f_i)	Number of lines entered in the chat tool
8	Frequency of expressing positive emotions	Number of function key presses representing positive emotions (e.g. the key F3 leads to the expression of "Joy")
9	Frequency of expressing negative emotions	Number of function key presses representing negative emotions (e.g. the key F6 leads to the expression of "Anger")
10	Within-patch processing (T_W)	Units of time spent on communicating with NPCs (see section 4.2)
11	Between-patch Processing (T_B)	Units of time spent for exploring the *environment (*see section 4.2)
12	Inactivity (T_{ia}*)*	Units of time the learner doesn`t press any keys and doesn`t move the mouse.
13	Extent of NPC-interactions weighted by Within-Patch processing (I_{NPC})	

#	Behavioural Indicator	Operationalization and Explanation
		$I_{NPC} = nNPC \cdot \frac{T_w}{T_{ts}}$ Number of NPCs contacted by the learner, multiplied by weight (T_w / T_{ts}). The indicator takes on a high value if NPC-interactions are accompanied by an exhaustive conversation
14	Information gained (*G*)	$G = \lambda * T_B * g$ (see equation1 in section 4.2)
15	Rate of Information Gain (*R*)	$R = G / (T_B + T_W)$ (see equation 3 in section 4.2)
16	Profitability (π)	$\pi = g / t_W$ (see equation 4 in section 4.2)

The remaining behavioural indicators 10 to 16 are mainly based on the theory of information foraging. These indicators possess the potential to be re-usable for other kinds of TEL-applications, such as other DEGs or Learning Management Systems. They are further exemplified in the next section.

5.2 Applying the Theory of Information Foraging

The description of the indicators derived from the information foraging theory is embedded into an example of a game scenario in which a learner consecutively talks to two NPCs. As described above, the whole duration of a game-play is split into time slices, whereas the following example extends over the period of one time slice (30 seconds). In the following, the variables T_W and T_B represent the number of seconds spent on Within- and Between-Patch processing (see section 3), respectively.

At the beginning of our example the learner may continue with an explorative activity (e.g. searching for an NPC). After *three* seconds the learner may find the targeted NPC telling the learner to look for a new contact person, an NPC designed to practise negotiation skills. It takes the learner *eight* seconds to receive this instruction, i.e. to conduct this exploitive activity. Then, after *three* seconds of inactivity, in which the learner doesn´t move the mouse or doesn´t click any keys, the search for the assigned contact person starts and lasts only *five* seconds due to a very clear instruction. Afterwards the conversation with the next NPC starts, lasting until the end of the time-slice (i.e. 11 seconds). In this example, T_B sums up to *eight* seconds: three seconds for the first, and five seconds for the second period of exploration. T_W amounts to 19 seconds because the learner has spent eight seconds on the first and 11 seconds on the second period of exploitation.

Besides T_B and T_W, additional variables that are taken from Pirolli & Card (1999) have to be gathered to obtain an indicator for the rate of valuable information. For that, *G* has to be computed, which represents the total amount of information gained and is given by equation (1),

$$G = \lambda \cdot T_B \cdot g \tag{1}$$

where λ is the prevalence, the average rate of encountering patches (i.e. NPCs) and *g* is the average gain per patch. λ is simply given by equation (2),

$$\lambda = 1/t_b \tag{2}$$

where t_b represents the average time in seconds between processing patches. Referring to the example above, where the learner spent three seconds on searching for NPC 1 and another five seconds on looking for NPC 2, the value for t_b is four seconds [= (3+5) / 2] and therefore, λ is 0.25 (= 1 / 4). The higher the value of t_b the lower is λ, the rate of encountering NPCs, either reflecting low clearness or low motivation. Finally, as previously described, *g* represents the average gain per patch (i.e. during the conversation with an NPC), which is in our case the number of relevant propositions extracted during the conversation. To simplify the assessment process, the number of propositions may be equated with the number of relevant content words used by an NPC. Relevant content words are terms (nouns, adjectives and verbs) referring to topics that have to be addressed by the learner in order to succeed in the negotiation process. By means of WordNet (http://wordnet.princeton.edu/), a psycho-linguistic database, a list of such content words can be arranged beforehand. To continue our example, let's suppose that the conversation with NPC 2 during the second half of the time-slice encompasses 15 words, whereby ten words were uttered by NPC 2. Furthermore, let's suppose that four of the ten words are content words that belong to the semantic field of project management. At that point, G can be computed, since empirical values for all variables (λ, T_B and g) are available. In this example G would be 8 (= 0.25 * 8 * 4).

Finally, R, the rate of valuable information gained per time-slice can be obtained. It is given by

$$R = G / (T_B + T_W) \quad (3)$$

When inserting the corresponding values from above, R amounts to 0.307 [= 8 / (8 + 19)]. The more information is extracted during conversations and the less time is needed for this information gain, the higher the value of R.

Finally, the so called Profitability π can easily be calculated. It is the ratio of gain per patch to the cost of within-patch processing and is given by

$$\pi = g / t_W \quad (4)$$

The variable *tw* is the average time in seconds spent on within-patch processing and is computed by simply dividing *Tw* by the number of phases in which within-patch processing took place. Hence, in case of TARGET´s DEG, π stands for the efficiency of a learner's search behaviour. It represents the amount of valuable information (s)he actually extracts from conversations, taking into account the amount of time needed for this process.

5.3 Combining Behavioural Indicator´s Values

After gathering the *raw values* of all BIs at the end of each time slice, they have to be combined to get a single value x_i for each of the five dimensions i (Clearness, Approach Motivation, Avoidance Motivation, Valence and Activation). For the combination, we apply a multiple regression model. This is in line with the suggestion from Margolis and Clauser (2006). The indicators, respectively their raw values BI_j serve as predictors in the multiple regression equations. A linear combination is preferred over a multiplicative one in order to allow small values on a particular indicator to be compensated by higher values on other indicators.

For each dimension i we apply one regression equation, initially consisting of the following input-variables: i) a constant intercept d_i, ii) the 16 predictors, and finally, iii) the 16 predictors' weights w_{ji}. This leads to the following equation (5):

$$x_i = d_i + w_{1i} * BI_1 + ... + w_{ji} * BI_{ji} + ... + w_{16i} * BI_{16i} \quad (5)$$

At the time of writing, the realization of validation studies is in progress. However, as a starting point, the weight of each BI for each regression equation has been estimated a-priori, based on expert ratings in the field of cognitive psychology. Independent from each other, two experts evaluated the predictive validity of the BIs (i.e. their weights) for each dimension by a 3 point rating scale. The scale comprised the values 0 ("low validity"), 1 (intermediately validity) and 2 ("high validity"). In addition to that, the experts had to evaluate the direction of the relationships between the particular indicator and the dimension (i.e. positive vs. negative correlation). For the overall ratings presented in Table 2 we decided to take the lower value in case of divergent ratings and the mean value otherwise. For instance, referring to indicator 1, the *Click rate* is regarded highly predictive for the learner's activation (as indicated by the value 2), intermediately predictive for approach- and avoidance motivation (value 1) and not predictive for the remaining two dimensions of valence and clearness (value 0).

The actual weight of each indicator and potential redundancies between the indicators will be analysed by a validation study which is briefly outlined in section 6. Those indicators that turn out to be highly correlated with other indicators and which do not contribute substantially to an additional explanation of variance will be dropped. This ensures an economic assessment of the dimensions since the amount of predictors constituting the regression equations will be kept as small as possible.

Table 2: Behavioural indicators and assumed relations to psycho-pedagogical constructs

#	Behavioural Indicator	*Motivation*		*Emotion*		
		Approach	Avoidance	Activation	Valence	Clearness
1	Click rate	1	1	2	0	0
2	Mouse movements	1	1	2	0	0
3	Distance of “view” - movements	1	1	2	0	(-) 1
4	Relative exploitation of available tools	2	1	1	1	1
5	Frequency of tool-usage	2	1	2	1	(-) 1
6	Frequency of communication tool-usage	2	1	1	1	1
7	Frequency of interactions with NPCs	1	1	2	2	0
8	Frequency of expressing positive emotions	1	0	0	2	0
9	Frequency of expressing negative emotions	0	1	0	(-) 2	0
10	Within-Patch Processing	2	0	0	2	0
11	Between-Patch Processing	2	2	0	1	1
12	Inactivity	(-) 1	(-) 1	(-) 2	0	(-) 2
13	Extent of interactions with NPCs	1	0	0	1	0
14	Information gained	1	1	2	1	2
15	Rate of Information Gain	2	1	0	0	2
16	Profitability	1	0	0	0	0

6 Interpretation procedure

The interpretation of a learner´s current state with respect to a particular dimension, as indicated by the dimension´s initial values x_i, depends on the comparison with a baseline. The baseline can be obtained either by the learner´s values in previous time slices of the same game scenario (intrapersonal comparison) or by the values of other learners (interpersonal comparison). The latter approach is feasible when an extensive database of a large number of individuals is available. However, we prefer an intrapersonal comparison which takes the learner´s *gaming history* into account since individual learner´s baselines may differ to a great extent. Thus, the results of the multiple regression equations, x_i, are transformed into *z*-scores for the sake of comparability. The *z*-transformation is done by the following equation:

$$z_i = \frac{x_i - M_i}{SD_i} \tag{6}$$

Whereas z_i and x_i represent the standardized and the raw values of the dimension *i*. The average value of the dimension *i*, represented by M_i, is computed by averaging the raw values of all previous time slices. Thus, M_i does not incorporate the current state. The variability of the dimension *i* is represented by the standard deviation SD_i. Since the reliability of the assessment increases with the amount of incorporated data, the deviation of the current from the average state in terms of standard deviations is not taken into account until the fourth time slice has passed. Hence, the computation of the standardized values of the dimension begins at the earliest 120 seconds after the learner starts to play the game scenario.

The five values z_i for each dimension and each time slice (from the 4th time slice on) represent the individual learner´s *deviation* from the current time slice to the previous ones in terms of standard deviations. We consider open student modelling not only for the competence and skills assessment but also for the constructs the extended micro-adaptivity approach in TARGET. In this case, the z_i values might not be easy to interpret for learners who are not familiar to think in terms of standard deviations. Therefore, we aim to provide manifestations of a continuous variable, with values ranging between 0 and 1.

This aim can be reached by inserting the standardized values z_i into the following logistic function:

$$p(z_i) = \frac{1}{1+e^{-z_i}} \tag{7}$$

With $p(z_i)$ representing the final value of the dimension *i*. Besides the obvious advantage of these $p(z_i)$ values for the purpose of open student modelling, the second advantage is that the logistic function is positively accelerated and differentiates primarily in a range between -3 and +3 standard deviations. In other words, the logistic function leads to a higher differentiation of initially small differences in the standardized values z_i.

7 Current work and Outlook

The content of this final section is twofold: First we outline how the behavioural indicators described in section 4 will be evaluated, aiming to determine their weights for each of the five multiple regression equation. Finally, we will provide a glimpse on the didactical rules and exemplify one intervention targeting to influence the learner´s current level of activation.

7.1 Validation of Behavioural Indicators

For the evaluation of the indicators' validity we adopt approaches suggested by Insko (2003) and Van Reekum et al. (2004) in order to conduct a non-invasive measurement procedure and to elicit the subjective experience of the participants. The subjective experience is part of the emotional trinity comprising physiological, expressive and subjective components and is used as an external criterion to be compared with the BIs.

The subjective experience is measured by self-report that will be gathered by a pop-up screen intermittently occurring during game play. These pop-ups present small sets of items that are extracted from standardized state scales and ask for the current emotional, motivational or problem-solving related state. Similar to Cai & Lin (2011) we will apply the Self-Assessment Manikin (SAM; Lang, 1980) to measure both dimensions of the emotional model (activation and valence). To assess participants' motivational states we will present items from the revised 10-Item version of the *Achievement Motives Scale* (Lang and Fries, 2006). Since standardized questionnaires on the construct clearness do not exist, we will develop items giving information on a participant's current problem representation. All items will be rated through slider scales: by moving the position of a slider between two poles of a graphical intensity-dimension, the learner indicates the extent to which (s)he agrees or disagrees on a particular item. The items will cover different aspects of the cognitive, emotional and motivational dimensions and will be selected randomly for presentation.

Finally, a regression analysis will be conducted to determine the nature and significance of the relationship between the indicators and the self-report. Standardized Beta-Coefficients will support the identification of valid indicators as well as their weights for equation (5). A linear model would be the simplest case; however, we will evaluate whether statistical requirements, such as linearity of the variables' relationship, are met by the data-pattern. Additionally, we will try to find out if other functions, e.g. modelling non-linear relationships, provide a better data-fit. The Generalized Linear Model is able to incorporate non-linear covariates in the coefficients.

7.2 Didactical Rules

The value $p(z_i)$ of each continuous dimension (emotion, motivation and clearness), ranging between 0 and 1, has to be broken up into categories indicating a sufficient, medium or insufficient state for an efficient and sustainable learning process. For that, we introduced the two threshold values 0.50 and 0.80 to assign $p(z_i)$ to "*insufficient*" (if $p(z_i) < 0.50$), "*medium*" (if $0.50 \leq p(z_i) \leq 0.80$) and "*good*" (if $p(z_i) > 0.80$). The combination of these categorizations across the three dimensions represents the learner´s current psycho-pedagogical state. We draw on a set of didactical rules that trigger particular classes of interventions (motivational, emotional and clarifications to increase the learner's problem representation) in response to the current psycho-pedagogical state. We designed three didactical rules for the provision of appropriate interventions: i) *Priority ranking* of intervention-classes, ii) *Selection* of intervention-instances, and iii) *Stopping Rule*.

Based on the learner's psycho-pedagogical state, the priority ranking defines in which order the different classes of interventions should be provided. Our priority ranking is based on the following considerations: If the learner`s clearness state is insufficient, i.e. if he or she simply doesn`t know how to progress within the game scenario, it is impossible to establish and reflect upon self-regulating goals (Elliot and Harackiewicz, 1996). Goals are an obligatory part for self-regulated learning, and highly related to the construct of (achievement-) motivation (Schunk and Zimmermann, 2008). Therefore, a sufficient (“good”) clearness state is seen as prerequisite for a desirable motivational state and for avoiding an undesirable emotional state (e.g. frustration). Thus, interventions aiming to enhance the learner´s clearness state (i.e. clarifications) do have the highest priority. Emotional and motivational interventions share the second highest priority.

Once it has been decided which class of interventions should be provided, a concrete instantiation of this class needs to be selected. It is necessary to consider that some concrete interventions may have been already provided but without reaching the intended outcome, while other interventions may not be appropriate in the current game context (e.g. activating office noise when the learner´s avatar is outside the office building).

The Stopping Rule defines which values of the different psycho-pedagogical constructs are sufficient for an efficient and sustainable learning process, i.e. under which circumstances (i.e. current psycho-pedagogical state) the introduction of interventions should be stopped. As a rule of thumb, interventions should be provided as seldom as possible and as often as necessary. Applying this simple principle should avoid that the learner’s game-flow (Csikszentmihalyi, 1990) is disturbed. As a starting point we take a medium value for the emotional and the motivational state of the learner as sufficient into account. This means that further interventions won’t be provided if the learner´s values remain at least equal compared to the previous time slice. However, for the construct of clearness, only a “good” value seems to be sufficient since less (or non-existent) clearness can be seen as prerequisite for interventions of other classes to be efficaciously.

7.3 Interventions

Within this subsection an example of an intervention-instantiation is presented. We selected an intervention called *field records.* In a DEG that is based on a 3D virtual environment like TARGET, the introduction of field records is assumed to be beneficial out of two main reasons. First, natural background noises increase the perceived level of reality within a game scenario. And second, specifically selected and designed noises can be systematically applied to beneficially affect the learner’s psycho-pedagogical state; in particular his or her emotional and motivational state. The term field records describes sounds naturally occurring in our environment, for instance the chirping of birds, the clicking of a keyboard or the ringing of a phone in an office environment. Most of the time, we would not even notice their appearance. Nevertheless, well-founded psychological research suggests that external stimuli do not have to be processed consciously in order to influence our state of mind. To the contrary, it is known that stimuli which are processed unconsciously can activate our implicit motive system (Bargh et al., 2001), which in turn may lead to affective reactions. Intending to use these effects, we adopt field-records to unleash a non-intrusive, acoustic atmosphere influencing the learner’s motivational and emotional state. To allocate appropriate sound samples we make use of the International Affective Digitized Sounds (http://csea.phhp.ufl.edu/media/iadsmessage.html) initiated by Bradely and Lang (1999). This psychological database of sound-tracks is characterized with respect to the dimensions activation and valence. By that, it is possible to select and provide sounds during the game play that stimulate the emotional state of the learner and are mainly congruent with her or his current state. The provision of sounds that are in accordance with the learner’s emotional state should avoid unpleasant feelings of dissonance (Gembris, 1990). In case of low values on the activation and valence dimensions, the learner should not be confronted with sounds characterized by high activation or very positive valence. In order to improve her or his state in a gentle way, sounds should be selected that are described as moderate with respect to both dimensions. However, a learner with intermediate or even high valence and activation values may be stimulated by activating and happy sounds.

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