An Affective Model for Semi-open Learning Environments

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ABSTRACT
We have developed an intelligent tutoring system coupled to a virtual laboratory, which constitutes a semi-open learning environment. Now, we are looking for a more personalized environment by means of recognizing the student's affective state and reacting accordingly. We propose a general affective behavior model for intelligent tutoring systems in order to provide students with a suitable response from a pedagogical and affective point of view. Our proposal for the affective state is based on the OCC cognitive model of emotions. The affective behavior model integrates the information from the student cognitive and affective state, and the tutorial situation, to decide the best pedagogical action. For this, we propose the use of a decision network with a utility measure on learning. By using the decision network, the tutor will select the best pedagogical and affective response given the current state of the student. We present initial examples of the performance of the affective behavior model under different situations, and initial results in the construction of the affective student model by using personality questionnaires.

Keywords
Intelligent Tutoring Systems, Affective Student Model, Affective Tutor, Affective Computing.

1. INTRODUCTION
We are developing a *virtual laboratory* as a complementary tool for learning mobile robotics [14]. Since the main goal of the virtual laboratory is to serve as learning tool for students, we have incorporated an *intelligent tutoring system* (ITS).

In most developments of ITS, the tutor-student interaction has been unnatural. However, in the last few years, researchers in computer science have turned towards emotions which were originally believed to be unrelated to computer systems performance [17]. Scientific studies have demonstrated the influence of emotions in human communication [5]; and, a hypothesis is that it can also happen in the human-machine interaction [17]. In an ITS, this hypothesis becomes stronger, since emotions have been identified as important players in motivation, and motivation is very important for learning [10]. When a tutor recognizes the affective state of the student and responds accordingly, he may be able to motivate students. There are several authors who propose to use the affective state of student to give him a more suitable response that fits with his affective and cognitive state [3, 6, 11, 12]. However, the affective state has not yet been used to decide the pedagogical response, because there are still many open questions, such as which affective states are relevant for learning.

In this paper, we propose a model for an affective tutor, which combines the affective and cognitive state of the student to establish the affective and pedagogical actions. The tutor integrates an affective student model based on the OCC cognitive model of emotion [15], represented as a Bayesian network, in a similar way as [3]. We are using Bayesian networks [16] because the process of establishing the affective state involves uncertainty [3]. The main contribution of this work is in the affective behavior model, which integrates the information from the student cognitive and affective state, and the tutorial situation, to decide the best pedagogical action. For this we propose the use of a decision network with a utility measure on learning. By using the decision network, the tutor will select the best pedagogical and affective response given the current state of the student. We present some initial examples of affective and pedagogical responses under different situations, as well as results in the construction of the affective model by using personality questionnaires based on the five factor model [4].

2. SEMI-OPEN LEARNING ENVIRONMENT
In the development of a robotics virtual laboratory, we have considered important aspects of open learning environments. The student is free to explore different parameters to observe their effects inside the virtual lab; however, each experiment has specific objectives that the student needs to achieve. This enables an effective assessment of the exploration behavior.

The key element of this environment is a representation of the student based on probabilistic relational models. The model keeps track of the students' knowledge at different levels of granularity, combining the performance and exploration behavior in several experiments, to decide the best way to guide the student in the next experiments, and to re-categorize him based on the results.

For a detailed description of this architecture see [14]. A screenshot of an experiment in the virtual laboratory is shown in Figure 1.

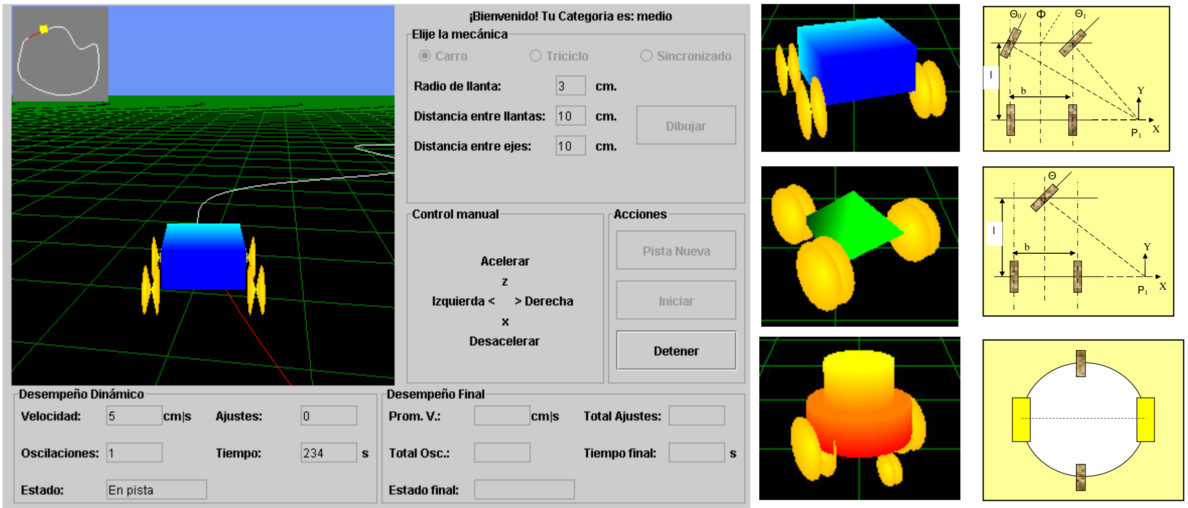

Figure 1. An experiment in the virtual laboratory

3. AFFECTIVE INTELLIGENT TUTORING SYSTEM

An ITS is a computer-based educational system that provides individualized instruction like a human tutor based on knowledge about the student (student model), about teaching (tutor module) and about specific domains (expert module). It also has an interface module, which decides how to present the material to the student in the most effective way. An ITS decides how and what to teach based on the student cognitive state. However, it has been demonstrated that an experienced human tutor manages the emotional state of the student in order to motivate him and to improve his learning process; therefore, the representation of the emotional state of the student is also required in order to provide students with more suitable instruction. In order for the tutor to obtain the capacity to recognize the student's affective state and respond to it, the student model structure needs to be augmented to include knowledge about the affective state. Also, an *affective behavior model* would be added with the ability of reasoning about this affective state in order to provide an adequate response from a pedagogical and affective point of view.

The affective behavior model is integrated to an ITS coupled to a virtual laboratory as shown in Figure 2, the affective components are shown shaded. The affective analysis module obtains the indicators used to infer the affective state and to update the affective student model. With this last structure, the affective behavior model will determine the affective action to be delivered by the tutor.

In this proposed architecture, the student model includes the knowledge state of the student (cognitive model) as well as his emotional state (affective model). The affective behavior model provides elements to determine the next pedagogical action to the tutor model, and it provides the interface module elements for a physical realization of the response, which will depend on the technology used in the user interface. This model has to establish parameters that enable a mapping from affective and cognitive student model to pedagogical responses of the tutor.

In next section, we describe the affective student model, and then we present the affective behavior model.

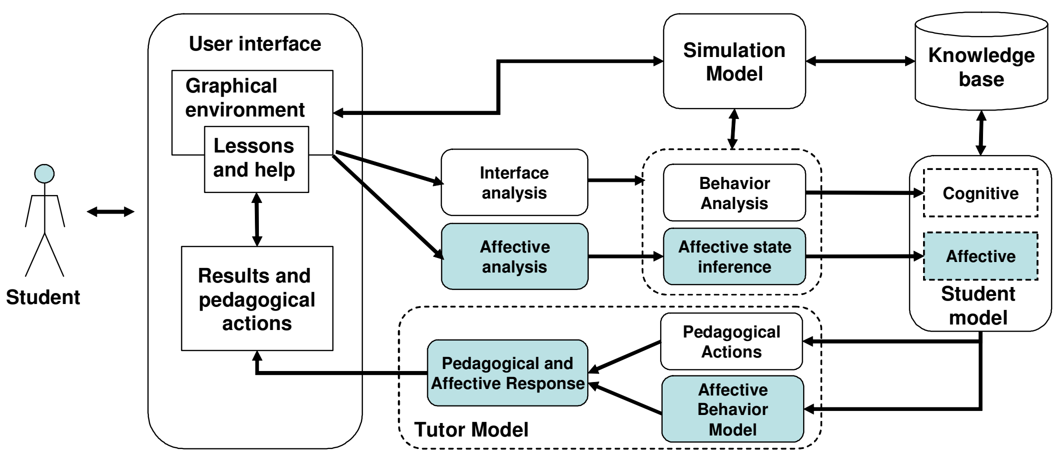

Figure 2. Architecture of the affective ITS

4. AFFECTIVE STUDENT MODEL

The student model must contain knowledge about the affective state of the student, in addition to knowledge about his cognitive state, in order to give him an affectively adequate response and at the pedagogically appropriate time. Several ways to evaluate the emotional state have been proposed: some are based on the detection of physical and biological signs [13], other implementations are based on the use of personality and emotion models [3], and other are based in student interaction [6]. In this work, we use the OCC cognitive model of emotion [15] to establish the affective state. The OCC model establishes the emotional state as a result of a comparison between goals and situation, i.e. how the situation fits with goals. The OCC model is one of the most known emotional models; several authors use it to establish the emotional state or to synthesize emotions [3, 2, 8].

To determine student affective state we use the following factors: 1) personality traits, 2) knowledge state, 3) mood, 4) goals, and 5) tutorial situation. We represent the affective student model by a causal probabilistic network (CPN) as shown in Figure 3. The dependency relations have been established based on literature [1, 9]. This way to represent the affective state is similar to one proposed by [3].

The OCC model establishes emotional state as a cognitive appraisal between goals and situation. We represent this with nodes *goals* and *tutorial situation*, influencing node *affective state*. However, we think that mood influences the emotional state too, so we have *mood* also influencing the affective state. Although sometimes emotional state and mood are used interchangeably, we distinguish them: mood represents the longer term emotional state, while affective state represents the instantaneous emotional state. Mood has an arousal level higher than emotion, i.e. mood changes slower than emotion [19]. We think that both, emotion and mood, affect each other. Currently, we are not using mood to infer the affective student state; we are working on how to get student mood and how to use it to determine the student affective state.

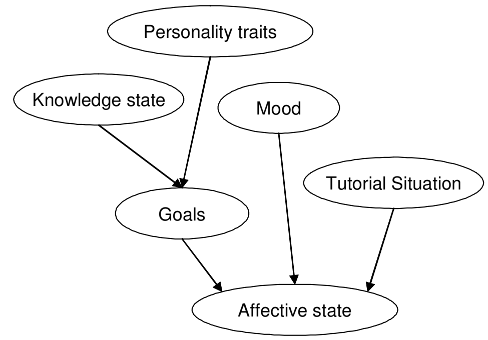

Figure 3. CPN that represents, at an abstract level, the affective student model

Another factor influencing affective state is the *personality traits*. For example, an agreeable person can be more permissive with errors that a neurotic person, therefore distress or shame are less possible to arise in an agreeable person than in a neurotic person.

In Figure 4, we present the detailed CPN for student affective model. According to the OCC model, the goals are fundamental to determine affective state. In order to establish student goals, we have two options: to ask the student, or to infer them. We think that asking the student is not a good option because people, in general, tend to be kind and to give kinder responses, even if the counterpart is a computer [18]. So, we infer them by means of personality traits.

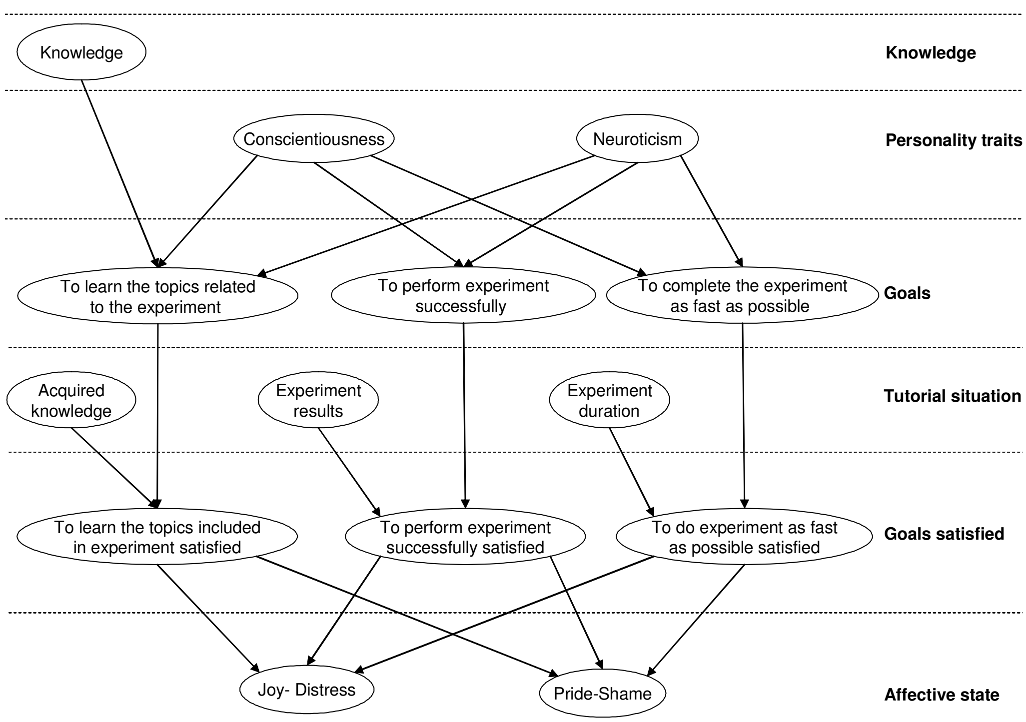

Figure 4. CPN that represents the affective student model (in detail)

We based personality traits on the five factor model [4], which considers five dimensions for personality: *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*. Currently, we use only two of them (*conscientiousness*, *neuroticism*) to establish goals, because there is a stronger relation of these two dimensions with learning [9]. Heinström (2000) also stated a relation between learning and *openness*, but it has not been proved. Although we use only two personality dimensions to infer goals, we think that all five dimensions influence the affective state.

The goals for our domain are: 1) to learn the topics related to the experiment, 2) to perform experiment successfully, and 3) to complete the experiment as fast as possible. In order to know if a goal has been satisfied, we include the nodes *goals satisfaction* (one for each goal), and they are affected by the nodes *goals* and *tutorial situation*. The nodes *goals satisfaction* represent the comparison between goals and situation as established by the OCC model. The nodes *tutorial situation* are variables which have the outcomes of student actions.

Based on the OCC model, we consider four possible emotional states: *joy, distress, pride, shame*. The pair joy and distress as well as pride and shame are complementary.

We have established the conditional probabilities for the affective student model based on the literature [1, 9], and from questionnaires applied to students, which are presented in section 6. Currently, we have a static network, but we are working on integrating the time, by extending the model to a dynamic Bayesian network.

5. AFFECTIVE BEHAVIOR MODEL

Once the affective student model has been obtained, the tutor has to respond accordingly, and in order to do that, the tutor needs a model of affective behavior (ABM) which establishes parameters that enable a mapping from affective and cognitive student model to responses of the tutor. Figure 5 shows a block diagram for the ABM. The ABM receives information from three components: the affective student model, the cognitive student model and the tutorial situation. The proposed model translates these components into affective actions towards the tutor and interface modules.

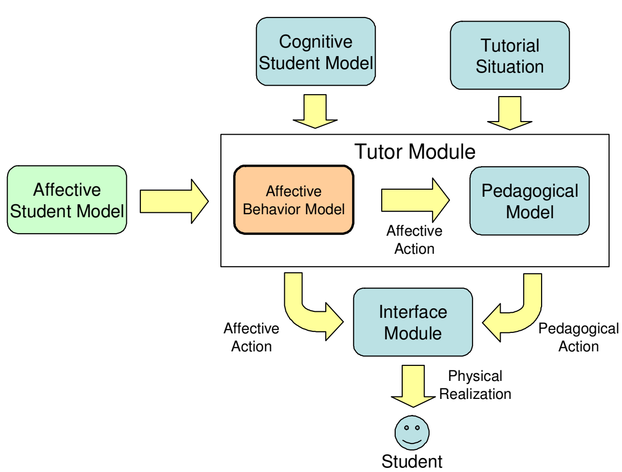

Figure 5. Block diagram of the affective behavior model

The affective action contains knowledge about the overall situation that will help the tutor module to determine the next response to the student, and also will advise the interface module to express the response in a suitable way. Based on the affective action, the tutor module can decide if it is necessary to provide another exercise or to change the topic in turn. For example, if the student's response is incorrect and his affective state is happy, the tutor can encourage the student with another exercise more suitable to the situation in order to maintain high motivation.

In Figure 6, we present a high level representation for the affective behavior model using a decision network. The pedagogical action considers utility on learning of the student. The node *affective state* corresponds to the nodes for *affective state* of the CPN in Figure 4. The node *knowledge* is the knowledge the student has after the experiment. We are currently developing a more detailed representation for the ABM.

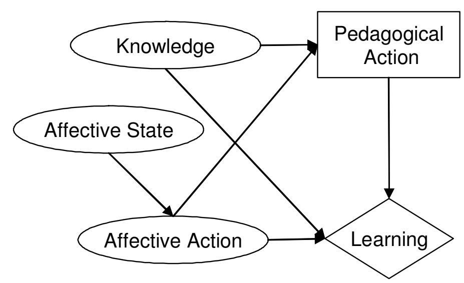

Figure 6. Decision network for the affective behavior model

The affective actions are the product of the ABM. The affective action is composed of the pedagogical sub-action (to the tutor module) and interface sub-action (to the interface module). These sub-actions will be used in a way that will be determined by the specific ITS, and particularly, by its tutor and interface modules; that is, the domain of the ITS and the technology used in the user interface. For the time being, we have identified three classes of affective actions: *neutral*, *moderate* and *strong*. Fundamentally, a neutral or a moderate action applies when the level of motivation is good (the motivation increases or remains at same level), and it determines that the tutor can employ the same pedagogical strategy used at that moment; i.e., the instruction is working. A strong action applies when the student's motivation decreases and it is necessary to execute some action to attract his attention; for example, to change the rhythm of instruction to faster or slower depending on the cognitive student model.

The pedagogical and interface sub-actions represent the basic movements of a human tutor. The pedagogical sub-action tells the tutor module if it must continue on the same topic or move forward or backward, but the pedagogical action must be established by the tutor module. The interface sub-action specifies one of the following three levels of affectivity: 1) when the motivation increases or remains on the same level, because the student is doing well, 2) when the motivation slightly decreases, for example, due to an error, and 3) when the motivation dramatically decreases, for example, when the student has had various errors. This will tell the interface module how the physical realization should be. However, the technology used in the user interface will determine what specific actions are delivered to the student and in what way.

Table 1. Affective state under different conditions

Cases	Knowledge	Tutorial Situation			Affective State	
		Acquired Knowledge	Experiment Results	Experiment Duration	Joy-Distress	Pride-Shame
1	Student knows the topic in turn	Positive	Positive	Positive	Joy	Pride
2		Positive	Positive	Negative	Joy	Pride
3		Positive	Negative	Negative	Joy	Pride
4		Negative	Negative	Negative	Distress	Shame
5	Student does not know the topic in turn	Positive	Positive	Positive	Joy	Pride
6		Positive	Positive	Negative	Joy	Pride
7		Positive	Negative	Negative	Joy	Pride
8		Negative	Negative	Negative	Distress	Shame

In order to show the performance of the affective behavior model, we present in Table 1 and Table 2 some examples of its application to different tutorial situations.

Table 2. Affective and pedagogical actions under different conditions

Cases	Affective Action	Pedagogical Action
1	Neutral	Present another exercise with higher difficulty level
2	Moderate	Present another exercise with same difficulty level
3	Moderate	Present another exercise with same difficulty level
4	Strong	Present another exercise with lower difficulty level
5	Neutral	Present another exercise with higher difficulty level
6	Neutral	Present another exercise with same difficulty level
7	Moderate	Present another exercise with same difficulty level
8	Strong	Explain the topic again

Table 1 shows the affective state established by the model for eight cases. We can observe that the affective state is *joy* and *pride* when the tutorial situation is positive; and it is becomes in *distress* and *shame* when the tutorial situation is becoming negative. For the inferred variables, we show the value with the highest probability.

Table 2 shows the affective and the pedagogical actions for the same eight cases. We can observe that when the affective state is positive, the affective action is neutral and the tutor encourages the student with a harder exercise. When the affective state is negative, the affective action is strong and the tutor presents him another explication of the topic or an easier exercise.

6. EXPERIMENTS

To obtain the initial probabilities for the CPN of the affective student model, we applied a personality questionnaire based on the five factor model to a group of 58 students. From these questionnaires we obtained the initial probabilities for the personality variables. In Table 3, we show the conditional probability table (CPT) for the personality nodes (*conscientiousness* and *neuroticism*). We can observe that both personality traits have the same probabilities, this is a coincidence.

Table 3. CPT for personality nodes

Values	Personality	
	Conscientiousness	Neuroticism
High	0.24	0.24
Average	0.79	0.79
Low	0.02	0.02

These are *a priori* probabilities, but the aim is to apply the personality questionnaire to each student to have a more accurate personality measure and to give him a more suitable instruction.

The personality nodes influence goal nodes. The probabilities for these nodes were established based in the literature [1, 9]. The CPTs for the three goals we have established are shown in tables 4, 5 and 6. In Table 4, we present the probabilities in two parts; first when the value for knowledge is *the student knows the topic in turn*, and second, when the value for knowledge is *the student does not know the topic in turn*.

We are in the process of evaluating the model, but we have already motivating results in the estimation of the affective state and in establishing the pedagogical action. Currently, the affective behavior model is not integrated into the ITS. The model has been implemented in the Elvira system [7].

We performed several experiments to predict the affective state. In one experiment, we set the personality variables to a high level of *conscientiousness* and a high level of *neuroticism*. We consider four situations: 1) the student has a high rate for the three variables representing the tutorial situation; 2) the student has a high rate for two variables; 3) the student has a high rate for one variable; 4) the student has not high rate for any variable. In general, the distributions obtained for the affective state variables seem reasonable, so we are currently validating these with a psychologist.

Table 4. CPT for goal *to learn the topics related to the experiment*

To learn the topics related to the experiment									
Knowledge: Student knows the topic in turn									
Conscientiousness	**High**			**Average**			**Low**		
Neuroticism	**High**	**Average**	**Low**	**High**	**Average**	**Low**	**High**	**Average**	**Low**
Present	0.5	0.4	0.3	0.4	0.3	0.2	0.3	0.2	0.1
Absent	0.5	0.6	0.7	0.6	0.7	0.8	0.7	0.8	0.9
Knowledge: Student does not know the topic in turn									
Present	0.97	0.95	0.9	0.95	0.9	0.8	0.9	0.85	0.75
Absent	0.03	0.05	0.1	0.05	0.1	0.2	0.1	0.15	0.25

Table 5. CPT for goal t*o perform experiment successfully*

To perform experiment successfully									
Conscientiousness	**High**			**Average**			**Low**		
Neuroticism	**High**	**Average**	**Low**	**High**	**Average**	**Low**	**High**	**Average**	**Low**
Present	0.98	0.96	0.91	0.91	0.86	0.81	0.91	0.81	0.71
Absent	0.02	0.04	0.09	0.09	0.14	0.19	0.09	0.19	0.29

Table 6. CPT for goal *to do experiment as fast as possible*

To do experiment as fast as possible									
Conscientiousness	**High**			**Average**			**Low**		
Neuroticism	**High**	**Average**	**Low**	**High**	**Average**	**Low**	**High**	**Average**	**Low**
Present	0.99	0.97	0.92	0.92	0.87	0.8	0.95	0.9	0.85
Absent	0.01	0.03	0.08	0.08	0.13	0.2	0.05	0.5	0.15

7. FUTURE WORK

We are in the process of evaluating the affective student model. Next, we will implement the affective behavior model, and in the next phase, we are going to do the validation of the model.

For the development of the ABM, we have to formalize the mapping from affective student state to pedagogical responses. We are going to implement the model as a decision network. In a manner similar to the way we implemented the student affective model, we plan to construct an initial ABM based on the literature, and then to validate and improve the model with empirical tests. We are also preparing some *wizard of oz* experiments that may provide additional insight for the formalization of the model.

8. CONCLUSIONS

In this paper, we proposed an affective behavior model for an intelligent tutoring system coupled to a virtual laboratory. Our main contribution is establishing a pedagogical response given an affective state. We have presented an affective student model based on the OCC model, and an initial affective behavior model that combines the cognitive and affective states to establish pedagogical and affective responses. We have presented some initial examples of affective and pedagogical responses under different situations, and initial results in the construction of the affective model.

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