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Modelo de Retroalimentación Afectiva para Sistemas Tutores Inteligentes

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Opción TESIS

Es propuesto, por los C. Dres. J. Reyes Juárez Ramírez y Víctor Hugo Castillo Topete

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II.- ANTECEDENTES
III.- MODELO PROPUESTO
IV.- IMPLEMENTACIÓN
V.- RESULTADOS
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A mi familia con amor.

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Resumen

Los elementos afectivos son igual de importantes que los aspectos cognitivos en los sistemas de tutoría por computadora. La retroalimentación que brindan los tutores es un elemento esencial para mantener la motivación de los estudiantes en los sistemas de aprendizaje. Sin embargo, la mayoría de los sistemas de aprendizaje que reporta la literatura no incluyen este tipo de interacción. En esos casos, los intereses del estudiante o su motivación para aprender pueden ser afectados negativamente, lo que afecta de igual forma el desempeño académico del estudiante, pudiendo resultar en un evento de deserción escolar. El problema de deserción en el nivel superior en países como México es muy marcado. Según cifras de la Secretaría de Educación de ese país, esta suma más de 20% en el ciclo 2016-2017 y se proyectan cifras similares para el ciclo 2017-2018. Es por eso que los sistemas tutores necesitan brindar interacción afectiva a los estudiantes que pueda incrementar su motivación para aprender. Esta tesis propone un modelo de retroalimentación, para Sistemas Tutores Inteligentes (STI), a fin de brindar soporte afectivo a los estudiantes y mejorar su motivación para aprender. Asimismo, se realizó la implementación del modelo de retroalimentación afectiva en un sistema de mensajería instantánea el cual se integró a un STI. El modelo propuesto se evaluó desde dos perspectivas. Primero, se validó de manera cuantitativa y cualitativa el modelo de retroalimentación conceptual, en forma de ontología. Después, se evaluó el efecto del sistema de retroalimentación afectiva, integrado en un STI, en la motivación para aprender de los estudiantes. Para está última evaluación se tomaron en cuenta características de los estudiantes como: género, rendimiento académico y personalidad. El modelo de retroalimentación afectiva impactó de manera positiva a la motivación de los estudiantes para aprender. De acuerdo a los resultados, el modelo propuesto ofreció mayores beneficios a estudiantes mujeres, estudiantes con bajo rendimiento académico, y estudiantes con un nivel de neurotismo bajo o promedio. Además, de los resultados de la investigación se concluye que la integración de la retroalimentación afectiva en los STI impacta positivamente la motivación de los estudiantes hacia el aprendizaje mejorando la interacción de los estudiantes con el sistema. Lo anterior eventualmente podría evitar problemas educativos importantes, como el bajo rendimiento académico, o la deserción escolar.

Palabras Clave: *Afectividad, Motivación, Sistemas Tutores Inteligentes.*

ABSTRACT

Affective components are as important as cognitive ones in tutoring assisted learning process. Feedback from tutor is an essential part to keep student's motivation. Affectivity and motivation are also significant in computer-based tutoring systems. However, several educational frameworks do not include this kind of interaction between students and tutoring system. In those cases, the student learning interest and motivation to learn could be negatively affected, and student profits from the system could be decreased, what affects, in the same way, the academic performance of the student, which could result in a school dropout event. The problem of desertion at the undergraduate level in countries like Mexico is very marked. According to data from the Ministry of Education of that country, this sum more than 20% in the 2016-2017 cycle and this institution projects similar numbers for the 2017-2018 period. Considering the previously described, if tutoring systems provide direct and affective interaction to students, these systems would encourage them and increase their motivation to learn. This thesis proposes a feedback model, for Intelligent Tutoring Systems, to provide affective support to students and improve their motivation to learn. The evaluation of the feedback model was from two perspectives. Firstly, the conceptual feedback model, in the form of ontology, was evaluated quantitatively and qualitatively. Then, the effect of the affective feedback system, integrated into an STI, on the student's motivation to learn was evaluated. This evaluation took into account characteristics of the students such as: gender, academic performance and personality. The affective feedback model positively impacted students' motivation to learn. The findings of this study suggest that this integration benefits more the motivation to learn of female students, students who face learning difficulties and students with a low score of neuroticism.

Keywords: *Affectivity, Motivation, Intelligent Tutoring Systems.*

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Chapter 1

Introduction

Learning is the process by which a student acquires skills, new strategies, and knowledge, through learning material and under the guidance of a tutor [4]. This process consists of four main elements [5–7]: 1) tutor, 2) student, 3) learning material, and 4) feedback.

The student is the leading actor of learning [8]. The main objective of the learning process is that the students acquire knowledge. The learning process considers several student characteristics such as [4]: learning style, cognitive level, motivation to learn, learning interests and objectives, and emotional states.

The tutors are learning advisors [8]. They provide support and instruction during the learning process. Also, they transmit information to the students using learning materials [4]. The learning materials are elements that tutors used to support the learning process. These can be books, maps, photos, theorems, videos, software, and project supplies [9].

Expert tutors can recognize student emotional states during the process. This recognition helps to adapt tutoring strategies and impact to the student positively [10]. The tutor-student interaction is the process of tutoring. For this work, tutoring is the process of support students during learning process [11]. This support consists of activities such as: presenting learning materials, explaining information and clarifying doubts.

Feedback is the most common strategy used in tutoring [7]. Feedback monitors student behavior and supports students during the learning process [7]. From this perspective, the primary role of the tutor is to supervise students, locate the errors, and provide support to correct them or to answer doubts of the student [7].

1.1 Problem Statement

Feedback is one of the most important elements in the learning process regardless of context and learning environment [12]. However, the students have several problems to establish communication with the tutor [13]. There are several reasons for this lack of interaction [14, 15], for example, student learning interest, student personality, the difficulty of the topic, or the absence of an affective environment.

The lack of student-tutor interaction during the learning process could cause any of the following problems [7, 14, 16]: demotivation in the students, students drop out school, the student does not acquire significant knowledge, and the tutor does not detect that the student does not understand a concept. These problems could cause a low academic performance on students. The problem of desertion at the undergraduate level in countries like Mexico is very marked. According to data from the Ministry of Education of that country [17], this sum more than 20% in the 2016-2017 cycle and this institution projects similar numbers for the 2017-2018 period.

According to Jiménez et al. [18], the attitude of the tutor affects the student-tutor communication. In this context, the affection provided by the tutor could motivate students to communicate with the tutor. Affective learning environments could generate various benefits such as improving motivation to learn or reducing student stress during learning process [19]. For that reason, it is important to consider these elements in different contexts and learning environments.

The learning process using computers started three decades ago. Researchers developed several computer-based learning systems during these years. Computer-based learning systems are particularly appropriate for remote teaching and learning at any time and place, away from classrooms and do not necessarily require the presence of a human instructor [20]. There are several types of computer-based learning systems such as Computer Assisted Instruction (CAI), Cognitive Tools (CT), and Intelligent Tutoring Systems (ITS).

An ITS is a computerized system that attempts to mimic human tutors and provide personalized instruction to students using the one-to-one tutoring approach [21, 22]. An ITS aims to replicate the benefits of one-to-one, customized tutoring, in contexts where students would otherwise have access to one-to-many instruction such as traditional classrooms, or no teacher at all, e.g., online homework [23].

VanLehn [23] states that an ITS is more effective in tutoring than another learning systems such as MLS. However, they are less effective than a human tutor. It is a fact that human tutors are more effective than computer tutors proved in the same context. The effectiveness of human tutoring perhaps may be due to the motivational strategies, and effective feedback used [23].

Timely feedback and direct error analytic guidance can help learners tackle a learning drawback get to know the quality of their work, based on which learners can reflect and adjust learning ways to achieve the purpose of effective learning [24]. Regular communication between the tutor and the student has positive effects on student motivation such as [14, 15, 25]:

- The tutor will understand better how the presentations of the topic are received and the tutor can adjust the lectures to the audience.
- The student may receive elucidation of a particular point and benefit from the rest of this particular lesson.

For that reason, the integration of feedback into ITS became a priority to improve student motivation, attitude and learning outcomes [26, 27]. These systems need to provide direct interaction with the students [28] because the lacking of communication could lead to inopportune student support in the learning process [29]. It is essential not only integrate feedback to ITS, but also the inclusion of affective support is necessary for learning.

Affective support can encourage students and improve their motivation [30]. However, several systems do not include this kind of interaction between students and tutors. In those cases, the student learning interest and motivation to learn could be negatively affected, and student profits from the system could be decreased [30]. For that reason, tutoring systems need to provide direct and affective interaction to students; it can encourage them and increase the motivation to learn.

Several studies, for example, [22, 31], integrate and evaluate affective and motivational aspects and they conclude that students are receptive to affective feedback. Only a few works have analyzed the influence of affective feedback on student motivation to learn [31–33]. Otherwise, D'Mello et al. [29] investigated the impact of negative and positive written phrases but in learning outcomes. However, this study did not examine the effect of written affective feedback on student motivation. This lack of analysis is significant because the interaction between ITS and student mainly occurs in written form. For that reason, there is a need to design written feedback models that consider affective aspects for the system-student interaction.

1.2 Thesis Objectives

The primary objective of this work is as follows: to provide affective feedback to students when they use intelligent tutoring systems.

Likewise, the following list of specific objectives guide this thesis:

Specific Objective 1: To determine dialogue models in ITS.

Specific Objective 2: To identify dialogue acts in face-to-face tutor-student interaction scenarios.

Specific Objective 3: To provide affective support for improving student motivation to learn.

Specific Objective 4: To integrate the feedback model into an ITS.

Specific Objective 5: To determine the impact of the feedback model on student motivation to learn.

1.3 Research Questions

The definition of the objectives leads to the following research questions. The first of them relate to the analysis of the feedback models reported in the literature to determine dialogue models in ITS:

- Which are the most important feedback models integrated into ITS?
- How is integrated the affection in the ITS?

The analysis of the tutor-student interaction in face-to-face environments was fundamental to understand which factors influence in student-tutor communication and to identify tutor-student communication patterns in face-to-face scenarios. It generates the following research questions:

- Which words/phrases are considered affective by students?
- Which are the most used communication patterns in student-tutor?
- Which are the most important affective elements in a face-to-face communication scenario?

This thesis proposes to design a feedback model for providing affective support to improve students motivation to learn. Also, it proposes the implementation of the feedback model and its integration in an ITS. The above suggests the following research questions:

- Which are the most important elements for designing a feedback model?
- Which are essential components for providing affective support to students?
- How can the affectivity improve student motivation to learn?
- How can be implemented a feedback model?

- How can be integrated a feedback system in an ITS?

Finally, to determine the impact of the feedback model on student motivation to learn:

- Is it possible to improve student motivation to learn using an Affective Feedback Model?

1.4 Research Methodology

A methodology composed of six steps guided this thesis: 1) literature review, 2) formal non-participant observation, 3) the design of an Affective Feedback Model (AFM), 4) the implementation and integration of the designed AFM in an ITS, and the 5) evaluation of the AFM. The following section outline the research strategies, methods, process, data collection techniques and types of data analysis.

Literature Review

The first step was to conduct a Systematic Literature Review (SLR) based on Kitchenham methodology [34]. This SLR identified from the literature the most diffused feedback models integrated into the ITS. Also, this stage led to analyze the affective aspects used for providing feedback to students using an ITS.

Formal non-participant observation

This stage considered a non-participant observation study. The study consisted of following up a professor during his/her duties in an Object Oriented Programming (OOP) course. It considered twenty students of four grades enrolled in an OOP course of an undergraduate program. The study consisted of two phases. The first of them considered the participant observation, and the second one comprised data collection.

The observer analyzed the following aspects: characteristics of professor feedback to students, professor-student dialogues involving negative or positive affection, and professor-student dialogue classification during the session. This study helped to analyze and classify feedback characteristics in empirical learning environments.

Design of an Affective Feedback Model

The literature review and the non-participant observation based the design of the AFM. It has three elements: a dialogue act taxonomy, a context-free grammar, and an affective database.

The literature review and the non-participant observation helped formulate the dialogue act taxonomy. Undergraduate students, from four different regions of México, proposed a set of affective words/phrases. Also, it was introduced a context-free grammar to structure affective sentences.

Implementation and Integration of the Affective Feedback Model in an ITS

An MVC *(Model-View-Controller)* pattern founded the implementation of the AFM. The implementation required Web technologies such as HTML5, CSS3 and JavaScript for the *views*; and Python 2.7 for the *controllers* and *models*. The system used Google App Engine framework for running. The implementation considered the three elements proposed in the feedback model.

Evaluation of the Affective Feedback Model

Undergraduate students were the main actors in this evaluation. The evaluation was from three perspectives. The first assessment based on the supposition that the affective feedback approach motivates students to learn differently, according to their characteristics. For that reason, the evaluation focused on analyzing students motivation to learn from three student attributes: gender, academic performance, and personality. The second assessment perspective examined the student motivation to learn prior and post interaction with affective feedback approach. These experiments had a within-subjects design. Finally, the third evaluation analyzed the effect of an Affective Feedback System (AFS) on student motivation to learn. In this evaluation, students interacted with the AFS and with a non-AFS. This experiment had a between-subjects design.

1.5 Document organization

This thesis is composed of seven chapters. The first chapter is constituted of the current introduction and aims at presenting the scientific context, problem statement, the objectives, research questions and the methodology. The other chapters are organized as follows.

Chapter 2. Feedback and Affectivity in Intelligent Tutoring System

This chapter provides the theoretical framework of the main topics to contextualize the reader on the domain knowledge. Also, it discuses some selected empirical studies of four main issues: tutoring systems, feedback process, affective feedback, and motivation.

Chapter 3. A Model for Providing Affective Feedback

This chapter defines and explains the AFM proposed in this thesis. The design of the conceptual model comprises two parts. Firstly, it considers the construction of an affective learning ontology and its validations. Secondly, it defines the three elements composing the AFM: 1) an affective dialogue act taxonomy, 2) a context-free grammar, and 3) an affective database. This chapter explains these elements.

Chapter 4. Implementation of the Affective Feedback Model

This chapter presents the design and implementation of the AFM following the guidelines previously described. In the same way, it explains the details of AFM log data, user-system interaction and user interface. Also, it describes several features of TIPOO, the tutoring system used in this study: general architecture, course structure, some functionality, and implementation details. Moreover, this chapter explains the integration of the AFM in the tutoring system.

Chapter 5. The Impact of the Affective Feedback on Student Motivation to Learn

This chapter describes two study aspects, the design of the instrument research, and the proposal assessment from three perspectives. The first assessment based on the supposition that the affective feedback approach motivates students to learn differently, according to their characteristics. For that reason, the evaluation focused on analyzing students motivation to learn from three student attributes: gender, academic performance, and personality. On the other hand, the second assessment perspective analyzed the student motivation to learn prior and post interaction with the affective feedback approach. Finally, the third approach examined the effect of an AFS on student motivation to learn. In this evaluation, students interacted with an AFS and with a non-AFS.

Chapter 6. The Impact and Applicability of the Affective Feedback

This chapter discuses the results of the AFM proposed in this thesis. This chapter highlights the theoretical and empirical implications of the proposal and points some limitations of the study.

Chapter 7. Conclusion and Future Work

Finally, this chapter summarizes the obtained results of this study and and it exposes a conclusion. This chapter lists some of the principal contributions of this works and the peer-reviewed published papers. Also, it states some directions of future work.

Chapter 2

Feedback and Affectivity in Intelligent Tutoring Systems

The learning process using computers started three decades ago. Several computer-based learning systems have been developed during these years. Computer-based learning systems are particularly appropriate for remote teaching and learning at any time and place, away from classrooms and does not necessarily require the presence of a human instructor [20]. There are several types of computer-based learning systems such as: Computer Assisted Instruction (CAI), Cognitive Tools (CT), and Intelligent Tutoring Systems (ITS).

Recently, most empirical studies investigate the importance of Intelligent Tutoring Systems as an affective tool. The focus of this thesis is to emphasize on the integration of affective elements on ITS to provide an affective support to the students. The present chapter responds to the research questions *Which are the most important feedback models integrated into ITS?* and *How is integrated the affection in the ITS?* providing a conceptual background and selected theoretical and empirical studies of ITS, feedback models, and affective feedback. Finally, this chapter answers the research question *How can the affection improve student motivation to learn?* presenting a detailed description of motivation.

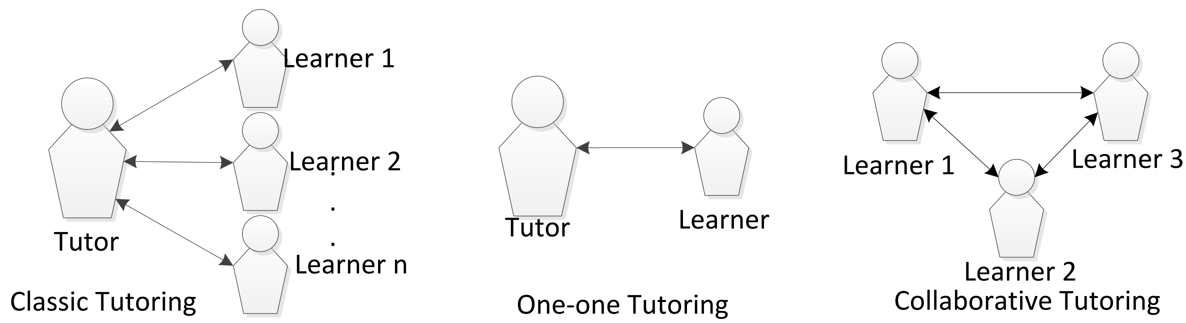

Figure 2.1: The most important types of tutoring process.

2.1 Intelligent Tutoring Systems

The dictionary defines a tutor as a person who gives individual, or group instruction. Tutoring is to help students help themselves, and to assist or guide them to the point at which they become independent learners, and thus no longer need a tutor [11].

The type of tutoring is a factor that significantly affects the learning process. There are three main types of tutoring: Classic tutoring (group tutoring), collaborative method and Socratic tutoring (one-to-one tutoring).

The classic tutoring occurs when one tutor supports many students. This type of tutoring is the most used in traditional classrooms [8, 35]. The technology allows an interactive relationship between the tutor and the student through computer tools such as Blackboard or Moodle. However, in these tools one tutor advises many students remotely.

In the last years there has been an increase on the adoption of collaborative learning. Collaborative method is based on social relationships between students, where they share information for the cognitive development and knowledge creation [35]. The social environments of the Internet begin to specialize in collaborative tools such as Wikipedia, because they are attractive and profitable to achieve educational purposes. However, collaborative learning has some problems such as the organization of the groups, unfair labor, learning rate, among others [35].

Finally, Socratic tutoring occurs when one tutor helps one student; this type of tutoring is more effective than group tutoring and collaborative method [36, 37]. Independently of using collaborative or classic method, the student needs personalized attention at some point of the learning process. In that scenario, the student interacts with the tutor for individualized feedback. Human tutors are not available at all the time for all the students under his/her guide [5]. For that reason, technology bring personalized support with learning systems such as ITS [5].

According to Vaessen et al. [38], ITS are specialized programs that provide feedback and personalize tutoring to automate the learning process when a human tutor is not available. ITS are computational agents whose purpose is to facilitate learning, usually without the help of a human teacher [21,39]. Such systems may be designed for tutoring a particular area of knowledge, or be quite general. Examples of ITS include, among others, tutors of geography, mathematics, physics and computer programming.

There are many benefits associated with the use of ITS in learning environments [40]:

- These systems can help students when instructors may not be present.
- These systems automate the learning process by evaluating decisions instead of outcomes and by providing decision-making practice with feedback.
- These systems improve student's problem solving skills.
- These systems can adapt the information to student characteristics.

In the last years, tutoring systems have become a new trend in research. Thus, the study of ITS predominantly embrace the following aspects: design and development [41], integration of feedback [42], adaptivity of the system to student needs [36], and considering student emotions [43].

The structure and design of ITS vary according to user needs. Most of the ITS present a four module architecture. The following section will provide general information about the design and structure of an ITS.

2.1.1 Intelligent Tutoring System Architecture

In [44] the authors examined and classified the ITS architectures into three categories: 1) the three-module architecture, 2) the four-module architecture and 3) the new-generation architecture. The following subsections describe them.

Three-module and four-module Architecture

The three-module architecture (TMA) includes the student module, the domain module and the tutor module. Fig. 2.2 shows this type of architecture.

In a TAM, the student module records demographic information regarding the student and represents the beliefs of the system about the student. In this ITS architecture, the ITS takes into account the user characteristics and defines a personalized user model. The completeness of the student model

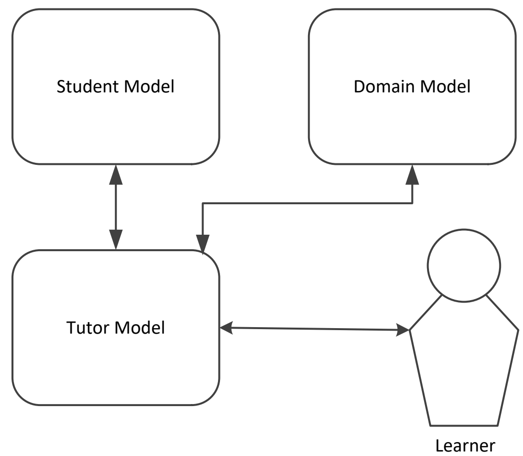

Figure 2.2: ITS architecture based on three modules (plus learner).

is important because is the responsible for representing student's preferences, knowledge, goals, performance history and other relevant aspects. This kind of information is stored for each learner. Based on this information the system gives to student an individualized instruction. In general, student's characteristics recorded in the student model are as follows:

- Demographic information.
- Performance history.
- Learning style.
- Cognitive state.
- Knowledge related to the teaching course.

The domain module contains knowledge and teaching materials regarding the courses provided by an ITS, the course structure and course content. The course structure refers to the basic concepts of the course concerning the domain, usually provided by the curricula of the subject. Every concept has a number of general attributes such as the concept name, concept level, etc. Different relations among them representing the network structure of the course can link these concepts together. Secondly, the course content comprises the teaching materials presented to students such as videos, images, electronic documents, and links to the WEB.

The tutoring module acts as the backbone of the tutoring system. It represents the teaching process and supports the knowledge infrastructure for adapting the course structure and content to a particular

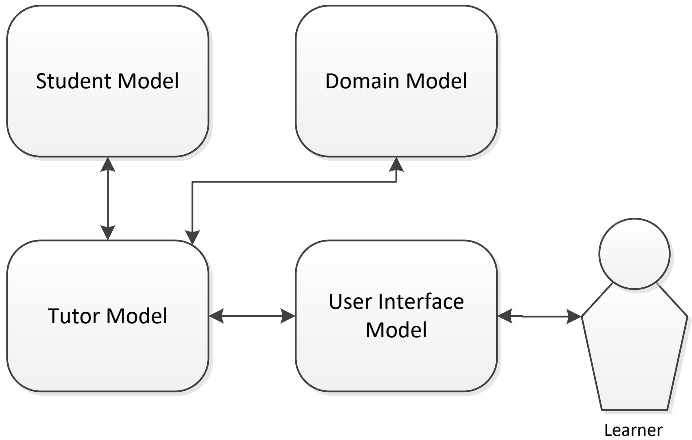

Figure 2.3: General architecture of an ITS (plus learner).

student model. Considering a student model, the tutoring model helps to define what to teach, how to teach, when to review, when to present a new topic, and which topic can be present, in accordance to the student module.

By the other hand, the four-model architecture (FMA) retained the three major components of the traditional TMA, and added the user interface as a fourth component. This architecture became an standard architecture for developing ITS [44]. Fig. 2.3 shows the FMA.

In the FMA, the user interface model is an intermediary between the student and the tutoring system. Using the interface the system can show information, teaching materials or providing student with feedback to student. The user interface model supplies a ITS-student interaction process, collects student input and solves exercises [45].

New Generation Architectures

ITS architectures are related to the influence of one or more of the following aspects: application domain, design paradigms, architectural styles, software development advances, and modern learning and instructional theories. All these factors generate different architectures to design tutoring systems. New generation architectures employ traditional models of three and four models using techniques such as multi-agent systems to develop the structure of the ITS, Fig. 2.4 shows an example of a new generation architecture.

New-generation ITS architectures emerged from the need to build specific functionality for specialized application domains, embrace important trends in software development, namely modular and

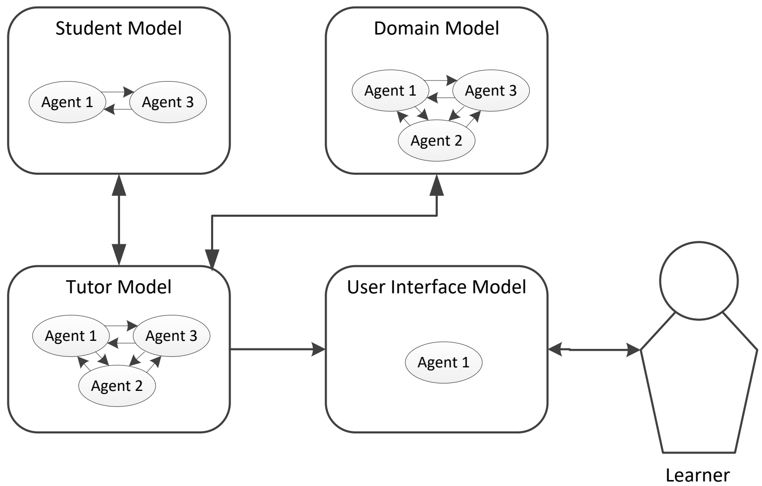

Figure 2.4: An example of an ITS architecture based on multi-agent systems.

incremental development, global sharing of knowledge, as well as incorporate current trends in learning and instruction [44].

2.2 Affective Feedback in Learning Environment

As mentioned earlier, this text focused on the integration of affective elements in ITS to provide students with affective feedback. This section describes the concept of feedback and its importance in learning and how to provide an affective interaction from tutor to students.

2.2.1 Feedback in Learning

Feedback is a key element in the educational process, commonly used to provide support to students during their learning process [46]. Feedback is one of the most powerful influences on learning and academical achievement, but this impact can be either positive or negative [46]. According to Hattie et al. [1], feedback is conceptualized as information provided by an agent (e.g., teacher, peer, book, parent, self, experience) regarding aspects of one's performance or understanding. Feedback is a process in which students and tutors share specific information aimed to encourage them to improve student academic performance, Fig. 2.5 shows feedback process.

Feedback could be informal or formal. For example, an informal feedback is day-to-day encounters between teachers and students or trainees, between peers or between colleagues. Moreover, written or

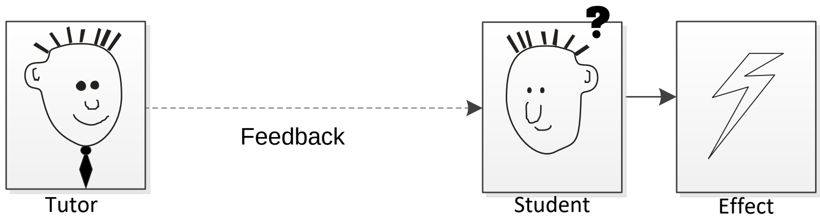

Figure 2.5: Feedback process in learning context.

clinical assessment are examples of a formal feedback [1]. Also, feedback can be classified in three types: motivational, evaluative and descriptive. Motivational feedback has the goal to make the student feel good establishing a respectful learning environment. Evaluative feedback has the goal to measure the student achievement with a score or a grade, but does not convey the information and guidance that students can use to improve their performance. On the other hand, effective feedback provides students with detailed, specific information about improving their learning. The main objectives of feedback are to [47]:

- Justify to students how their mark or grade was derived.
- Identify and reward specific qualities in student work.
- Guide students on what steps to take to improve.
- Motivate them to act on their assessment.
- Develop their capability to monitor, evaluate and regulate their own learning.

Hattie and Timperley [1] propose a model of feedback with four levels (Fig. 2.6). First, feedback about the task associates with whether answers were right or wrong or directions to get more information. Second, feedback about the processing of the task, it is a feedback about strategies/methods used, or that could be used, to achieve or perform the task. Third, feedback about self-regulation is a response about student self-evaluation or self-confidence. Finally, feedback about the student as a person, are pronouncements regarding a student is good or smart.

Feedback in essence is a communication process. There are two types of communication [13]: non-verbal and verbal (see Fig. 2.7). The non-verbal communication is composed by elements such as: intonation, posture, eye movements, gestures, facial expression and voice tone. Verbal communication is concerning to messages, language, words and grammar.

Figure 2.6: A model of feedback to enhance learning proposed by Hattie and Timperley [1].

These communication elements can be used to provide positive affective feedback to create an adequate learning environment. The Psychology Dictionary defines emotional or affective feedback as: the reassurance, encouragement and understanding that are exchanged by people [48]. Affective support is the type of *feedback about the student* or motivational feedback [49]. Affective feedback is important in learning as it can encourage a learner and improve his/her motivation [30]. We elucidate these concepts and make the following statements for this study.

- **Gesture:** is defined as a movement that can indicate an attitude or replace spoken words.
- **Facial expression:** is defined as a form of non-verbal communication manipulating facial muscles.
- **Voice tone:** is considered as speech message using an affective intonation.
- **Intonation:** is the use of melodies to support or just improve the dialogue.
- **Posture:** is the position of the body.
- **Eye movement:** is a coordinated movement of the eyes, most of the times as a reaction in a conversation.

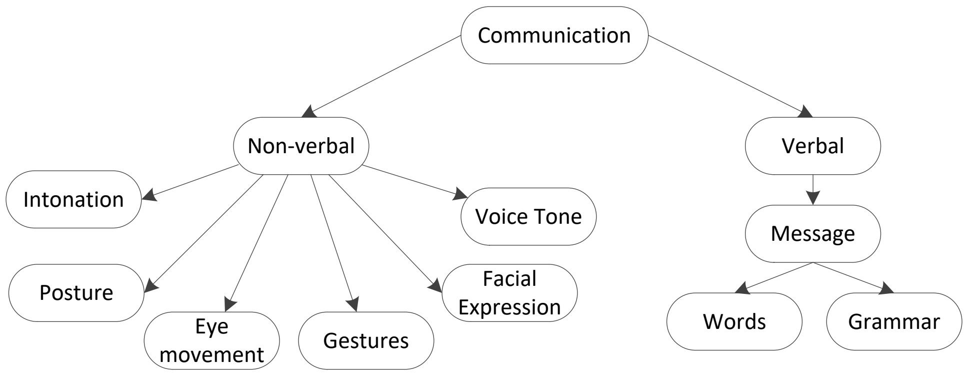

Figure 2.7: Communication elements.

- **Message:** is a text phrases used to provide affectivity to students.
- **Word:** is the basic element in a dialogue.
- **Grammar:** is a set of rules to dialogue in a language.

Provide affective support leads to increased user satisfaction and system likability and can indeed impact student's emotions, attitude and motivation.

2.2.2 Affective Interaction between Tutor and Student

Tutors are more than information transmitters, they are also responsible for creating an adequate learning environment [50]. We refer to tutors as the responsible to guide learning and teach students new knowledge. It is important that these tutors have affective competences when they are teaching to students.

Shephard [51] propose a list of abilities that tutors should have in an affective learning: active listening, answer student questions with immediacy, a positive attitude according the situation and student. In the same way, García [52] suggested to tutors to practice the following affective competences: authenticity, respect and empathy. These competences should improve learning environment, student attitude to learn and eventually, it enhances learning. Likewise, Lara [53] proposed that tutors should be constructive, they must have a friendly attitude, they should take into account student opinion. Also, it is important that tutors congratulate and eulogy students when they reached a goal or when they did an effort. For a better tutoring, tutors should bring individual and personalized support to students. However, it is well known that there are not one human to tutor for each student.

Table 2.1: Tutor, dialogue and students elements considered in affective learning.

Tutor	Feedback	Student
Active listening	Phrases	Personality
Immediacy	Eulogies	Objectives
Authentic	Congratulations	Gender
Empathy	Friendly gestures	Academic performance
Respectful	Friendly voice	Emotions
Friendly attitude		Motivation
Individual support		
Courteousness		
Relax		

The tutor must have a positive, courteous and relaxed attitude. In the same way, the voice, gestures and corporal language should show positivism during the communication. For this reason, it is important that the tutor gives feedback on affective aspects. Tutors need to take into account student needs and adapt dialogue to impact them positively [46, 54, 55]. Emotional support is characterized by empathy, friendliness, encouragement, esteem, and caring, whereas instrumental support is characterized by tangible support, for instance, when teachers help students solve a problem or accomplish a difficult task.

As we mentioned earlier, integrate affectivity into feedback could generate a lot of benefits in students. However, it does not impact in the same way to all students. The affectivity impacts different in each student depending of some factors such as personality [56, 57], gender [58], academic performance (grade point average) [59], objectives, motivation, emotional states, among others. Table 2.1 shows a list of elements that tutors, students and feedback need to achieve affective learning.

These elements have been used in face-to-face learning environments with human tutors to create an affective environment. For that reason, it is important to integrate affective feedback in tutoring systems.

Affective Words

In any dialogue, the words and phrases are the principal components to transmit information [60]. In recent years the integration of affectivity and emotions to the lexicon has become a popular research line. That's why several researchers are focused on analyze the affectivity of different lexicon such as ANEW in Spanish language [61], English lemmas [62], or Emotional connotation in German language [63]. This line of research has focused on proposing new methods of text classifying, relating words to emotions, or creating new methods for evaluating words.

The affective theory suggests two ways to represent an emotional state: categorical and dimensional.

The categorical approach classifies the words in discrete classes (positive or negative) or in a multi-class scale (one of the six emotions proposed by Ekman). Representing affectivity in the categorical approach has three disadvantages [64]. First, the emotion categories should be stated before the classification. This categorization may led out some of the words/phrases of a category. Second, considering the culture or language, may define the same class using a different name leading to difficulties in sharing classes. Third, when the field of the application is changed, the categories need to be redefined.

Therefore, the continuous dimensional representation possibly represents a better option. In the dimensional approach, the affectivity is evaluated using 2-3 dimensions [65]: arousal, valence, and dominance. The most commonly used approach is based on valence-arousal scale, which represents the affectivity in two-dimensional continuous space (see in Figure 2.9). Valence can be defined as the dimension of a pleasant emotion (i.e., positive and negative). Arousal, on the other hand, describes the level of the emotions activation (i.e., excited and calm). Based on this approach any affective state can be marked as a point in the valence-arousal coordinate plane. This method can avoid inconsistency and incompleteness and is a commonly used [61, 64, 66, 67].

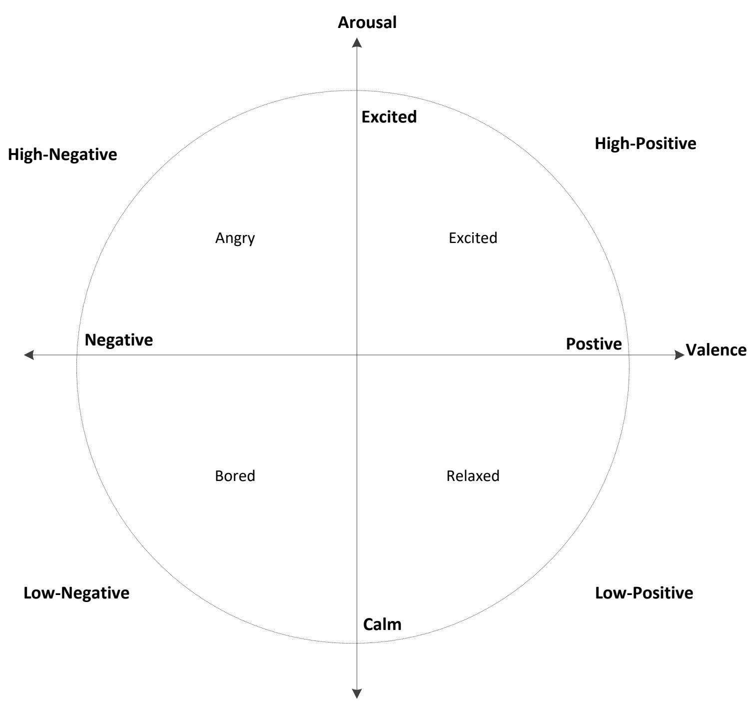

Figure 2.8: The valence-arousal space associated with an emotion.

The related work suggests several methods used to build the affective lexicon. Several types of regression can be used such as linear regression, support vector machine regression, ridge regression and lasso regression. Bradley and Lang developed the manual self-assessment manikin (SAM) as a nonverbal pictographic measure to evaluate three dimensions of pleasure, arousal and dominance [68]. This method provides affective pictures, which can help to determine more precise rating to the words/phrases. The three dimensions use a 9-point Likert Scale with visual representation, an example of this scale is shown in Figure 2.9.

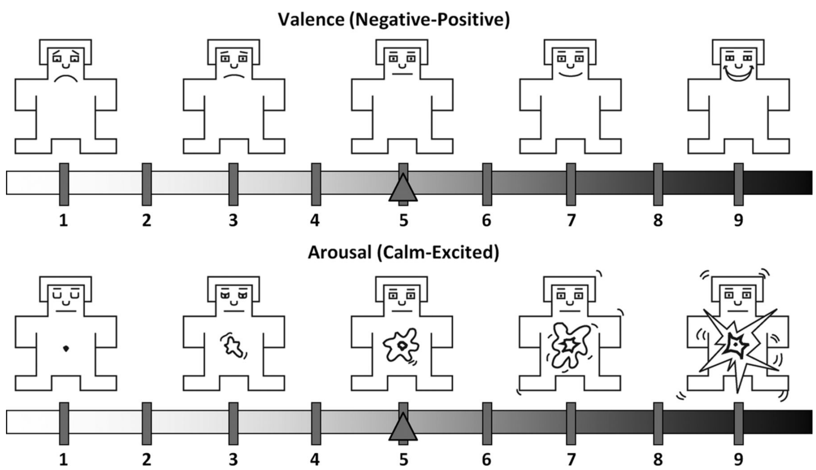

Figure 2.9: Self-Assessment Maniki (SAM) scale for measure the arousal and valence dimensions.

For instance, Redondo [67] analyzed the arousal and valence of 478 nouns using the SAM evaluation. A total of 360 participants evaluated a set of nouns in Spanish. The evaluation was divided into four sets of 120 nouns evaluated by 90 participants each one. The sampling for the words was random to homogenize the distribution [67]. The relation between the valence and the arousal provide an affective value to each word. For example, a word with a high arousal value but a low valence indicates excitement but negatively.

Several studies suggests a relation between the arousal and valence value to an emotion [64,65,69]. According to Wang et al. [64], a high arousal and low valence indicate anger; a high arousal and high valence indicate excitement; contrary, low arousal, and low valence indicates sadness; and low arousal and high valence indicate relaxation.

In the same way, Hinojosa et al. [61] analyzed 875 words in the arousal and valence dimension using the evaluations of 660 participants. Also, they associated each word to one emotion proposed by Ekman [70].

On the other hand, Baca-Gómez et al. [71] selected a set of words of the educational domain. It was developed a Facebook App to extract a set of phrases in Facebook automatically, and they measured the polarity of the phrases. It was considered five categories for the polarity evaluation: very positive,

positive, neutral, negative and very negative. The set of comments was integrated by 1400 comments, of which 500 was positive [71].

Also, Díaz [69] presented a methodology for the creation of dictionaries linked to an emotion and polarity. They tagged the words to one of the basic emotions proposed by Ekman. Also, the words were associated with a probability value, called probability factor affective (FPA), used with the tagged emotional sense.

These contributions are important for the creation of databases for future researchers where qualitative aspects were measured. State of the art describes the analysis of different sets of words. An inconvenient of this proposal is that most of the studies analyzed the affectivity in nouns, but not in adjectives.

The study of Mohammad et al. [72] proposed an emotion lexicon; their dataset is composed of adjective, nouns, adverbs, and verbs. They evaluate the words/phrases with the dimensional approach in a multiclass classification where the words are associated with an emotion.

In summary, the previous work reports that the most popular method to represent a word in the affective domain is using a two dimension categorization approach (valence-arousal scale). There are also several methods to apply the valence-arousal evaluation, but one of those that facilitate the evaluation to the user is the SAM. Most of the studies analyzed nouns of different domains, those works that focused on the educational domain do not examine the affective representation of words. These words are only classified into three groups: positive, negative and neutral.

2.3 Affective Feedback in Intelligent Tutoring Systems

In recent years, education points to the independent study and distance learning through computational tools [8, 36]. This is where the ITS is a viable option to support the student in the independent study. However, as we mentioned above, it is important that these systems provide feedback to the student through dialogue [73]. Feedback is crucial in the learning process. Timely feedback and direct error analytic guidance can help learners tackle the problem, get to know the quality of their work, based on which learners can reflect and adjust learning ways to achieve the purpose of effective learning [24]. For that reason, the integration of dialogue into ITS became a priority to improve student's motivation and learning performance [26, 27].

When ITS emerged, they provided effective support to students taking into account factors such as cognition and learning style of the student. However, the ITS unknown emotional aspects of the student during the tutoring, which are also important factors during the learning process [74, 75]. As we mentioned earlier, in traditional tutoring, human tutors detect the emotional state of the student and provide feedback according to the detection to positively impact the student performance [10]. It leads to the integration of affective aspects in ITS.

Then the research works focused on detect emotional states student during the tutoring [?, 29, 58, 59, 76–86]. The research about this area progressed in providing to computers the ability to recognize the emotional state of the student such as human tutor does.

Current research on learning systems describes the importance of taking into account not only the cognitive abilities but also the affective capabilities, such as motivation [87]. Such as cognitive components, motivational ones are important in tutoring strategies [88]. One of the main problems in ITS is the absence of rich feedback to students. This problem arises because the ITS design does not take into account the teaching aspects. After many years, the feedback in the ITS has been improved, but it still insufficient and these systems become cold.

Affective feedback could improve different aspects of learning, one of them is student motivation to learn. In this way, [32] hypothesized that affective feedback could improve student motivation to learn, but this work do not find a significant relationship between this two variables. The study considered experiments on 12 students of six years old. The results were not conclusive; this could be because learners were too young to understand the questions. Also, the instrument to measure motivation includes one question, which make more difficult the motivation assessment.

The influence of verbal communication in student learning outcomes was analyzed too [78, 89]. Wolf et al. [89] examined the relationships between affective responses and student learning outcomes. They generated automatic responses to students using an animated pedagogical agent that express emotions such as confidence, excited, boredom, focused, frustrated and anxious. Also, they [89] used a database with 50 messages emphasizing the importance of effort and perseverance; the responses also include cognitive help to resolve math problems and affective message. They proposed three types of responses: messages to encourage students, effort affirmations generated after a student invests effort and strategic messages created when students are not succeeding at problem-solving. They concluded that the affective feedback benefited student learning outcomes to some degree. D'Mello et al. [78] confirmed this asseveration, they found that affective feedback based on phrases improves student learning outcomes. They integrated a set of positive, neutral and negative phrases to provide affective feedback. However, they included negative feedback that could affect negatively to students. The study of D'mello et al. [78] shows that affective feedback improves learning to some degree, but not in the same way to all students, student profile plays a significant role in this situation. Student profile contains the relatively constant attributes of the student such as gender, academic performance, age, personality traits [90]. Previous studies suggested that affective feedback improves student learning, but they can not support each student in the same way. This support is dependent on student academic performance [78, 89]. Also, several studies show that affective feedback is more beneficial to students with low academic performance than students with high academic performance [78, 89]. A possible explanation could be because students with high academic performance have a high level of intrinsic motivation to learn and they do not need external factors. Empirical results suggested that female students were more benefited by affective feedback than males [91]. In [91] report a strong relationship between gender and affective needs, but it could be because of student personality. By nature, female students are more emotional than males. However, this could be influenced by student personality too.

Personality is related to affective aspects and motivation [30, 56]. Letzring et al. [56] analyzed to relate the five factors of personality, based on the Big Five personality factors. The five factors have been defined as openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, often listed under the acronyms OCEAN. So, openness to experience has relation with a general appreciation for art, emotion, adventure, unusual ideas, imagination, curiosity, and variety of experience. By the other way, conscientiousness has relation with a tendency to display self-discipline, act dutifully, and strive for achievement against measures or outside expectations. Besides, extraversion has relation with talkative, energetic, and assertive traits. Also, agreeableness is linked to sympathetic, kind, and affectionate traits. Finally, neuroticism has a link with a tendency to experience negative emotions. Their results hypothesized that extroversion factor is the most related to affectivity [56]. The literature suggested that student profile rules how the affective feedback is perceived by students [56, 78, 89].

Previous works concentrated on analyzing the impact of affective feedback on learning outcomes. Nonetheless, learning outcomes using learning systems are dependent on other variables such as the quality of materials, student cognitive abilities, prior knowledge, system usability, interest in the subjects, student motivation to learn, among others. For that reason, it is essential to focus on each one of these variables to eventually improves learning outcomes. As mentioned earlier, motivation is one of the most important elements that increase student learning interest and learning outcomes.

2.4 Motivation Assessment

According to Ohran et al. [92], the term motivation derives from the Latin word *movere*, meaning to move. In the present context, motivation represents the process that arouses, energizes, directs, and sustains behaviour and academic performance. Motivation is the process of stimulating people to action and to achieve a desired task. In brief, it can be said that a person is motivated when he/she wants to do something.

Motivation could improve some human activities such as learning process, workers effectiveness, or athletes performance. It is well known that motivation influences student behaviors, attitudes and in some cases the interest in learning [88, 90, 93]. Many factors influence student's motivation to learn

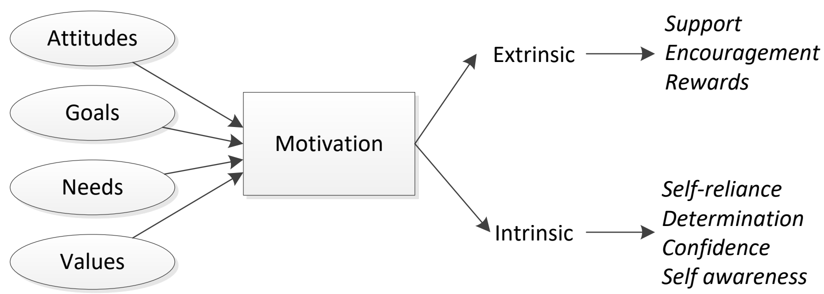

Figure 2.10: Types of motivation and other variables that influence it, adapted from [2].

including interest in the subject matter, perception of the usefulness of studying, the desire to achieve, perception of one's ability, and persistence to achieve [94].

Motivation in education is very difficult to measure. This is partly because, operationally, motivation to learn is very difficult to describe [2]. The key to measuring motivation must be to look for student behaviors indicating high motivation and low motivation. The tutors can easily identify those students who are highly motivated characterized by commitment and enthusiasm. For learning to be successful, there has to be attention and interest. Thus, motivation is a significant aspect [2].

Motivation towards learning may arise from intrinsic or extrinsic factors. Fig. 2.10 shows some of these factors proposed in [2].

In a school scenario, extrinsic motivation can arise in numerous ways. For example, praise, teacher rewards, and the expectation of good grades can all act as extrinsic motivators and are not necessarily bad [92]. Orhan [92] see intrinsic motivation as the inbuilt tendency to connect the interests of individuals to the development and use of the capacities of individuals. Thus, when learning is satisfying and meaningful, when learning outcomes are perceived as a valuable asset by the student, and when there is confidence and purpose, then motivation will be intrinsic, bringing considerable benefits.

The same figure illustrated motivation can be seen as a variable that depends on others such as attitudes, perceived goals, needs and values. It can be exemplified specifically in the context of learning. The student needs to have some kind of purpose for learning in terms of needs (*I need to gain a perfect grade*) or in terms of a goal (*I want to understand this concept because ...*) or even in terms of value (*Passing this course gives me status*). However, the whole area of attitudes underlies the concept of motivation. For all the above, motivation is an important element in the learning process [92, 93].

According to John Keller's ARCS Model of Motivational Design Theories [93], there are four steps for promoting and sustaining motivation in the learning process: Attention, Relevance, Confidence,

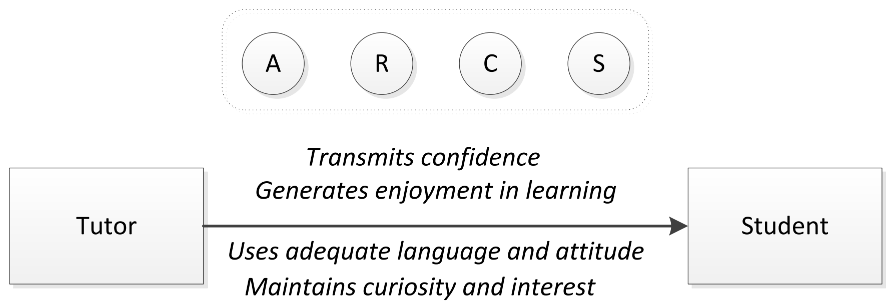

Figure 2.11: Developing motivation in learning context.

Satisfaction (ARCS). Keller developed the model in response to previous behaviorist and cognitive approaches to instructional design which Keller argued focused too much on external stimuli and paid insufficient attention to students motivation.

Attention dimension refers to maintain the curiosity and interest in students. Also, the ARCS model suggests establishing *relevance* to increase a learner motivation using an adequate language. *Confidence* focuses on developing success expectation among learners, and success expectation allow learners to control their learning processes. There is a correlation between confidence level and success expectation. There is direct relation between motivation and *satisfaction*. Learners should be satisfied of what they achieved during the learning process [93]. Summarizing, tutors attitude and behavior could influence student motivation to learn seen from a extrinsic motivation using the support provided by an external actor (tutor). There are some ways to encourage these outcomes. Some of the ways forward can be summarized in Fig. 2.11.

This leads to some important practical ways forward in enhancing and developing motivation with the students. Thus, the learning process must be related to what is important in the life of the learners while group activities can be powerful motivators [2].

Motivation to learn influences learning. In turn, there are a variety of factors that influence motivation. The motivation to learn drives students to act in certain ways to reach their learning goals. In fact, goals, needs, interests, incentives, fear, anxiety, social pressures, attributions, self-confidence, curiosity, values, expectations, reinforcement all serve as motives that energize, direct and maintain behavior [2]. Fig. 2.12 suggests some factors that influence motivation.

Of the six factors which might influence motivation, attitudes are extremely important. Without a positive attitude towards the learning task, it is difficult to generate the necessary motivation to perform

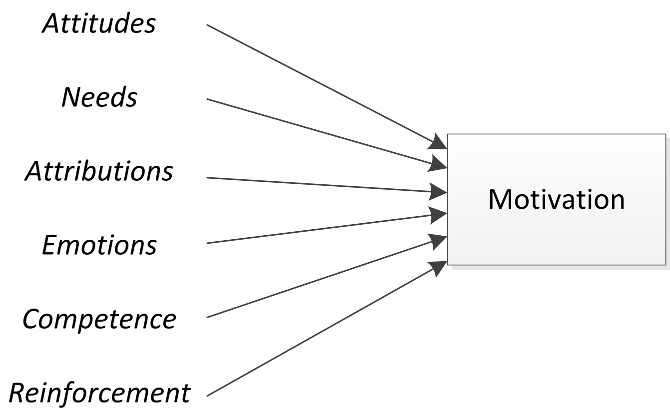

Figure 2.12: Factors influencing motivation.

a task and certainly almost impossible correctly fulfill it [2].

Certainly, motivation has an important role in learning context, face-to-face environments and distance environment with tutoring systems [88]. Because of that, several tutoring systems were designed to motivate students during the interaction [90, 95–98].

Several studies such [90, 95–98] proposed seven indicators to measure motivation to learn: 1) the choice of a task, it indicates motivation to perform the task; 2) the effort, it suggests motivation; 3) persistence, it suggests performing an activity for a long time; 4) achievement, it indicates choice and persistence raise task success; 5) latency, it is the time to respond to a stimulation; 6) willing to reach goals is when a student is motivated to learn if he/she wants to reach goals; 7) indicators of emotions, student actions are accompanied by the feeling of pleasure or displeasure that could indicate a motivation level.

2.5 Summary

Human tutors are not available at all the time for all the students under his/her guide [5]. For that reason, technology would bring personalized support with learning systems, such as ITS [5]. According to Vaessen et al. [38], ITS are specialized programs that provide feedback and personalize tutoring to automate the learning process when a human tutor is not available. ITS typically consist of a domain model, student model, tutor model and interface model. Each of these models play an important role in teaching a subject effectively to students.

One of the main problems faced by ITS is the lack of rich feedback to students because the ITS was not designed to know how it teaches. After many years, the provision of feedback by ITS has been improved, but it is still insufficient and unreal because ITS interaction interfaces are cold. In face-to-face scenarios, tutors are the responsible for creating an adequate environment to motivate students to learn. It is well known that motivation influences students behaviors, attitudes and, in some cases, the interest for learning [88, 90, 93].

The literature suggests that the integration of affective feedback in tutoring systems is as effective as in face-to-face learning environments. Previous studies [32, 78, 89] investigated the influence of affective feedback on student motivation to learn, student academic performance, and the degree of enjoyment in study time. For that reason, the present study suggests an affective feedback approach for ITS to improve student motivation to learn. The next section presents the proposal of the affective feedback approach.

Chapter 3

A Model for Providing Affective Feedback

A model is a physical, conceptual, or mathematical representation of a real phenomenon. Scientific models are used to explain and predict the behavior of real objects or systems and are applied in a variety of scientific disciplines [99]. The objectives of a model include three aspects: (1) to facilitate understanding by eliminating unnecessary components; (2) to aid in decision making by simulating what-if scenarios; and (3) founded on past observations, to explain, control, and predict events.

An ontology is a formal specification of a conceptualization [100]. Conceptualization means to use a set of concepts and relations for expressing, or representing, an abstract model of a phenomenon. Besides, formal means to organize theoretical terms, and its relations, to represent a domain. An ontology helps to structure and define the meaning of a set of terms. For that reason, the design of the proposed model to provide affective feedback follows an ontological structure.

As the previous chapter describes, the literature suggests some essential concepts for creating an affective environment in the learning process, so-called affective learning. The proposed model includes affective elements in computer-based learning systems to provide feedback to students in virtual environments. This chapter responds the research question *Which are the most important elements for providing affective support to students?* and *Which are the most important elements for the construction of a feedback model?*.

Table 3.1: Glossary of relevant concepts of the affective domain.

Actor	Concepts
Student	Motivation, objectives, gender, academic performance, personality.
Tutoring system	Authenticity, courteousness, friendly attitude, immediacy, respect, individual support, active listening, empathy.
Feedback	Affective phrases, Gestures, Voice Tone.

3.1 Ontology conceptual Design

The conceptual design of the proposed model follows Methontology [101]. Methontology [101] is a comprehensive ontology engineering methodology for building ontologies. Methontology enables the construction of ontologies at the knowledge level, i.e., the conceptual level. The methodology comprises the following steps: 1) build a glossary of terms, 2) build a taxonomy, 3) state relations, make a dictionary of concepts and 4) ontology evaluation.

3.1.1 Glossary of Concepts

Concepts are the basic ideas which attempt to be formalized [100]. This glossary of concepts includes all the relevant terms of the affective learning domain. First, it is necessary to identify the three main actors in a learning setting: student, tutoring system and feedback. Then, for each identified actor, it is convenient to collect the necessary elements to create an affective environment in a learning setting. Table 3.1 presents the list of concepts, gathered from a literature review process.

The model proposed for providing affective feedback suggests includes elements from Table 3.1 in the learning process to achieve an affective learning domain, which could create a suitable environment for learning. Students are the principal actors in a learning scenario. Aimed to improve their motivation and learning process, it is significant to to consider some aspects such as their learning objectives, gender, learning academic performance, personality, and emotions.

An appropriate interaction between a tutoring system and a student occurs if the former considers student's needs. In a perfect scenario, tutoring system must be authentic and expresses with a friendly attitude and respect to students. Students need individual support with immediacy. As previous work states [52], the proposed model suggests that tutoring systems should be empathic and courteous with students.

Also, feedback plays a significant role in tutor-student interaction; tutoring systems should provide motivational feedback sending affective phrases such as eulogies or congratulations. Finally, the gestures and voice tone are essential to provide affective feedback.

Table 3.2: Description ans representation of the relations used in the proposed taxonomy.

Relation	Definition	Formal Representation
contributes	a concept is involved in achieving another concept	$\forall x C_{(x2)} \overrightarrow{contributes} C_{(x1)}$
must_has	a concept has other concept necessarily	$\forall x C_{(x1)} \overrightarrow{must\_have} C_{(x2)}$
has	a concept has a direct relationship with other concept	$\forall x C_{(x1)} \overrightarrow{has} C_{(x2)}$
brings	a concept offers another concept	$\forall x C_{(x1)} \overrightarrow{brings} C_{(x2)}$
type_of	a concept is a type of another concept	$\forall x C_{(x2)} \overrightarrow{type\_of} C_{(x1)}$
uses	a concept uses other concept	$\forall x C_{(x1)} \overrightarrow{uses} C_{(x2)}$

3.1.2 Taxonomy

The second step of Methontology prescribes the taxonomy design. A taxonomy or taxonomic scheme is a particular classification of concepts. A taxonomy is a hierarchy of concepts, Fig. 3.1 shows the proposed taxonomy of four levels.

The affective learning taxonomy has four levels. As a domain representative, the concept *affective learning* is the first level in the proposed taxonomy. The next level has three actors: student, tutoring system and feedback. The third and four levels contains the concepts described in the glossary of concepts. The concepts listed in Table 3.1 are subclasses of each sub-domain.

An ontology can express arbitrary complex relations between concepts. For that reason, the next step of Methontology [101] prescribes the depiction of relationships between concepts.

3.1.3 Relations

Relationships (also known as relations) between concepts specify how concepts related each other [101]. Typically a relation is of a particular type that specifies in what sense an object relates to another object in the ontology. There are three significant relationships in ontologies [100]. Firstly, subsumption is an important type of relation (is-a-superclass-of, the converse of is-a, is-a-subtype-of or is-a-subclass-of). This defines which objects are classified by which class. The addition of the is-a-subclass-of relationships creates a taxonomy; a tree-like structure that depicts how objects relate each other. In such a structure, each object is the child of a parent class. Secondly, mereology is a significant type of relation, written as part-of, which represents how objects combine to form composite objects. Much of the power of ontologies comes from the ability to describe relations with conventional language. This type of relation are sematic relations, it describes the semantics of the domain. The proposed ontology comprises semantic relations. Table 3.2 describes the definition of relations in the proposed ontology, where $\rightarrow$ represents relations and C concepts.

The formal representation in Table 3.2 describes how should read the relation between two concepts,

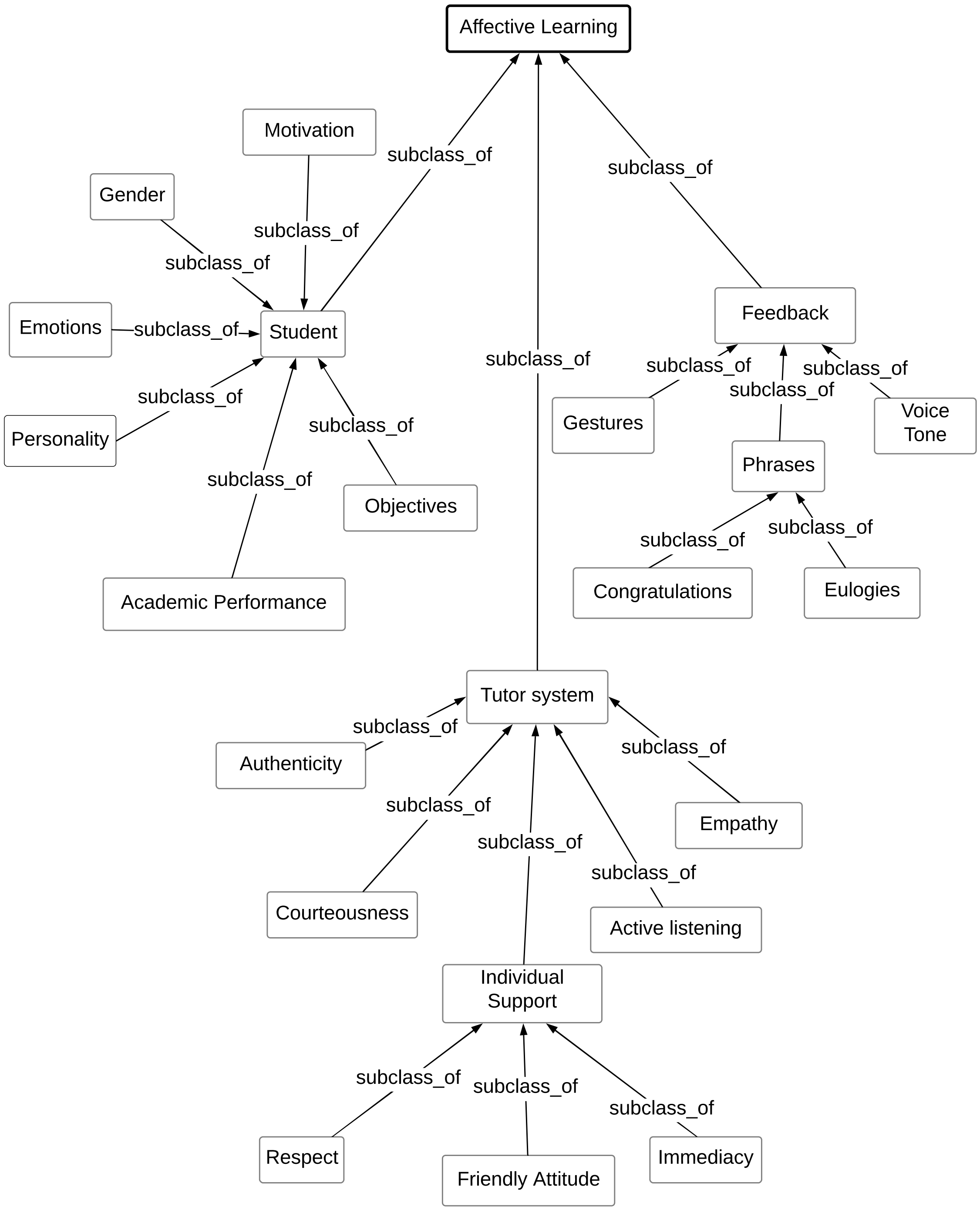

Figure 3.1: The proposed affective learning taxonomy.

Table 3.3: Definition of student concepts.

Concept	Definition	Relation
Student	The person who acquires knowledge [16].	$student \overrightarrow{_{has}} affective\_learning$
Motivation	An emotional state, having a strong reason to act or to accomplish something [50].	$student \overrightarrow{_{has}} motivation$
Emotions	The ability to [54]: a) perceiving emotions, b) using emotion, c) understanding emotions, d) managing emotions.	$student \overrightarrow{_{has}} Emotions$
Objectives	The goals that students are trying to achieve [50].	$student \overrightarrow{_{has}} objectives$
Academic performance	The extent to which a student, teacher or institution has achieved their short or long-term educational goals, commonly measured by examinations or tests.	$student \overrightarrow{_{has}} academic\_performance$
Personality	The total sum of the physical, mental, emotional, and social characteristics of an individual.	$student \overrightarrow{_{has}} Personality$
Gender	The state of being male or female (typically used with reference to social and cultural differences rather than biological ones).	$gender \overrightarrow{_{has}} Personality$

where $C_{(x1)}$ is a subsumption (father) and $C_{(x2)}$ is a subsumed (son). For example, the relation $\forall x C_{(x1)} \overrightarrow{_{uses}} C_{(x2)}$ means that the concept $x1$ uses the concept $x2$. The next section shows the definition of each concept in the glossary of concepts.

3.1.4 Dictionary of Concepts

This section presents a set of definitions which integrates the proposed affective learning ontology. The dictionary has the three main actors: student, tutor system and feedback. Table 3.3 shows the concepts related to student domain. The ontology includes six principal concepts of a student needed when a tutoring system should provide affective feedback to him/her. For instance, it proposes that some student elements, such as academic performance, gender, and personality, determine how the students perceive the affective feedback.

Table 3.4 describes the concepts related to a tutoring system. As mentioned earlier, tutoring systems need to create a friendlier environment to provide affective support to students which eventually improve the student-system interaction. The proposed model incorporates the concepts of Table 3.4 as necessary to ensure affective support.

Table 3.4: Definition of the tutoring system concepts.

Concept	**Definition**	**Relation**
Tutoring system	It is a computation-based tool for teaching and personalizing learning.	$tutor\overrightarrow{_{contributes}}affective\_learning$
Authenticity	It is the ability to behave taking into account feelings [52].	$tutor\overrightarrow{_{has}}authenticity$
Individual Support (IS)	It is the process of close interaction between tutor and student [52].	$tutor\overrightarrow{_{brings}}IS$
Respect	It is a way of treating or thinking about something or someone [52].	$IS\overrightarrow{_{must\_has}}respect$
Friendly attitude (FA)	It is a kind disposition of tutors that make ease the communication and contribute to building a sense of communication in learning [46].	$IS\overrightarrow{_{must\_has}}FA$
Immediacy	It is a characteristic that suggest the promptness to bring feedback to students [46].	$IS\overrightarrow{_{must\_has}}Immediacy$
Courteousness	It is showing good manners, verbally and non-verbally [52].	$Tutor\_system\overrightarrow{_{has}}courteousness$
Active Listening	It is when a tutor includes in his/her speech a student's phrase [102].	$Tutor\_system\overrightarrow{_{uses}}ActiveListening$
Empathy	It is the ability to understand student's feeling and response according to them [52].	$Tutor\_system\overrightarrow{_{has}}empathy$

Finally, Table 3.5 presents the definitions of the concepts related to feedback domain. The feedback domain is where the student-system interaction takes place, and it should be affective. As mentioned earlier, gestures and tone voice are important to transmit emotions. However, phrases and words are more important in communication. For that reason, the model proposed to use affective expressions such as congratulation and eulogies to provide affective support to students during their interaction with the system.

Table 3.5: Definition of feedback concepts.

Concept	**Definition**	**Relation**
Feedback	It is a powerful tool that supports the interaction between tutor and student [16].	$dialogue \xrightarrow[contributes]{} learning$
Voice Tone	It is a particular quality, way of sounding, modulation, or intonation of the voice [102]. The tone of voice helps to give meaning to communication.	$dialogue \xrightarrow[has]{} voice\_tone$
Gestures	It is a movement of the face that is expressive of an idea or emotion [102].	$dialogue \xrightarrow[has]{} gestures$
Congratulations	It is a phrase used by a person to express joy in the success of other people.	$Congratulation \xrightarrow[type\_of]{} Phrase$
Eulogies	It is a speech or writing in praise of a person or thing.	$Eulogies \xrightarrow[type\_of]{} Phrase$

The present ontology replaces the taxonomic relations by the semantic relations proposed in Table 3.2. Fig. 3.2 shows the ontology. This ontology describes how should be the affective learning to provide affective feedback to students during their interaction with a tutoring system.

Most of the ontology development methodologies include evaluation. The evaluation of the proposed ontology considered two perspectives: quantitative and qualitative. It is necessary to assess the quality of an ontology for recognizing the areas which need some improvements.

3.1.5 Ontology's Quantitative Evaluation

OntoQA [103] is a set of metrics designed to evaluate some particular aspects of ontologies. OntoQa divides the evaluation parameters in two categories: schema metrics and instance metrics. A schema metrics supported the evaluation of the proposed ontology, which address the design of the ontology. Although we cannot state if the ontology correctly models the domain, these metrics can indicate the richness, width, depth, and inheritance of a ontological schema [103].

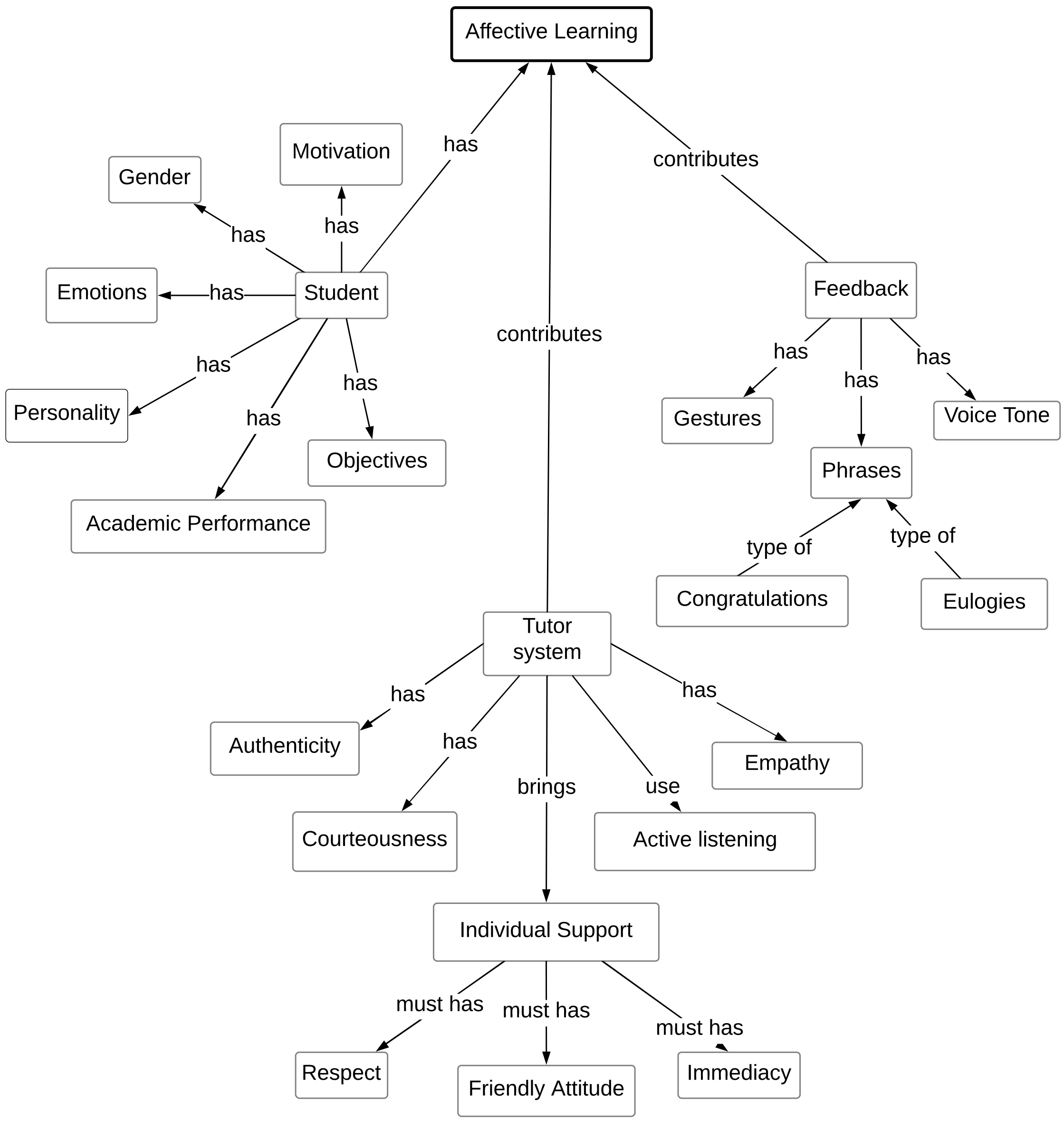

Figure 3.2: Affective learning ontology.

Relationship richness

This metric reveals the variety of relations in an ontology. An ontology that contains many different relations from class-subclass relations is richer than an ontology containing only class-subclass relationships. The relationship richness (RR) of a schema is the number of relationships (P), divided by the number of subclasses (SC) (inheritance relationships) plus the number of relationships (P). The Equation 3.1 calculates the RR value:

$$RR = \frac{|P|}{|SC| + |P|} = \frac{|20|}{|2| + |20|} = 0.9090 \tag{3.1}$$

The proposed ontology has 22 relations. Twenty are relations different of class-subclass relation, and two relations are class-subclass relations (type of). Substituting in the equation we obtain a $RR = 0.9090$, which indicates that the proposed ontology has relationship richness. An RR value close to 0 would suggest that most of the relationships are class-subclass relationships. In contrast, an ontology with an RR close to 1 would indicate that most of the relationships are other than class-subclass (semantic relationships).

Inheritance richness

This measure describes the distribution of information across different levels of a ontology's inheritance tree. This metric indicates the degree to which the ontology knowledge has a proper division into different categories and subcategories.

This measure can distinguish a horizontal ontology from a vertical ontology. A horizontal ontology is an ontology that has a few inheritance levels, and each class has a relatively large number of subclasses. In contrast, a vertical ontology contains many inheritance levels where classes have a few subclasses. The inheritance richness of the schema (IRs) defines the average number of subclasses per class. The number of subclasses (C_1) for a class C_i is $\left|H^C(C_1, C_i)\right|$ (Equation 3.2).

$$IR_s = \frac{\sum_{C_i \in C} \left|H^C(C_1, C_i)\right|}{|C|} \tag{3.2}$$

We need to count the total of children of each concept such as $I = IndividualSupport$, $S = Student$, $T = Tutor$, $P = Phrases$ and $D = Dialogue$.

$$IR_s = \frac{|(I,C_i)| + |(T,C_i)| + |(S,C_i)| + |(P,C_i)| + |(D,C_i)|}{23}$$

Substituting the values, we calculate the *IR*.

$$IR_s = \frac{|3|+|6|+|7|+|2|+|3|}{23} = 0.9130 \tag{3.3}$$

An ontology with an IRS value close to 0 would be a particular type of knowledge that the ontology represents (vertical nature). The suggested ontology has an IRS close to 1, it indicates that it has a horizontal view, which outlines a wide range of general knowledge. An $IR = 0.9130$, means that the proposed ontology represents a general understanding of the domain.

A quantitative evaluation allows ontology designers to analyze a ontology richness regarding classes, relationships, and inheritance. So, it is needed to assess the impact of these ontological elements in an empirical setting. The next section presents the qualitative evaluation.

3.1.6 Ontology's Qualitative Evaluation

Ontology evaluation is a crucial activity during the ontology lifecycle [104]. Zemmuochi and Ghomari [104] proposed a methodological baseline for ontology assessment by humans (domain experts or end-users) via questionnaire. It is intended to detect mistakes and inconsistencies that occur in the ontology development process. The following sections describe this aspect.

Experimental Design

Twenty four domain experts completed the questionnaire. The domain experts were professors teaching in engineering undergraduate programs at the Autonomous University of Baja California and Technological Institute of Tijuana. The 24 professors were from México. The study participation was voluntary.

First, the design questionnaire considered the ontology relationships depicted in Fig. 3.2. Two concepts linked by a relationship integrates a statement of the questionnaire. For example, in a relation such as $C_1 \overrightarrow{_{uses}} C_2$, the statement is: C1 uses C2. The instrument has 22 statements derived from the ontology. In each statement, the participants indicated the degree of agreement with the sentence. Judgments made on ontology relationships were carried out on a three-point ordinal scale, ranging from one (agree) to three (disagree). An electronic instrument, from Google Forms, supported the gathering of data about expert opinions. SPSS v1.0 helped to conduct the descriptive statistical analysis. The questionnaire statements were in Spanish.

Results

Table 3.6 shows the descriptive statistics about judgments on the ontology statements. As a significant finding, the percent of expert agreement with the statements about the proposed ontology was over 70%. So, the most of the experts consistently agreed with the way in which the proposed ontology model the domain.

Table 3.6: The domain expert's responses (N=24).

Questions	**Agree**	**Neutral**	**Disagree**	**Agree (%)**
Student has affective learning	21	2	1	87.5
Student has motivation	17	2	5	70.83
Student has academic performance	23	0	1	95.83
Student has objectives	16	6	2	66.66
Student has emotions	17	4	3	70.83
Tutor system brings individual support	17	5	2	70.83
Individual support must has friendly attitude	21	2	1	87.5
Individual support must has respect	24	0	0	100
Individual support must has immediacy	14	8	2	58.33
Tutor system contributes learning	21	3	0	87.5
Tutor system has empathy	18	6	0	75
Feedback has gestures	21	2	1	87.5
Feedback has voice tone	22	1	1	91.66
Feedback has affective phrases type of congratulation and eulogies	23	0	1	95.83

All the professors agreed that the individual support, provided a by tutoring system, must consider the value of respect. In the same way, 23 professors (95.83%) agreed that the following relationships are correct: student has academic performance and feedback has phrases. The 87.5% of professors agreed with the statement *feedback contributes affective learning*.

An ontology hypothetically establishes the prevalent relations between two elements, but in real scenarios, some conditions are different. Answers with a low percentage suggest that experts are not agreed with the statement, or maybe they considered that, based on their experience, a statement does not represent a reality. For example, only the 58.33% of the professors think that the student has learning objectives. Aforementioned represents a chance for making improvements in tutoring systems; it is crucial to promote the inclusion of learning objectives in the design of these systems to eradicate this deficiency that affects in real scenarios.

In the same way, the 66.66% of the teachers believe that the student support must be immediate. It is possible that the professors think it is not necessary that the feedback occurs in real time. It makes sense in traditional scenarios, where teachers can advise students in the next class session, however, in the context of computer-based tutoring systems, it is better to provide feedback in real time.

From described results, the affective feedback ontology proposed in this work is a guideline to implement feedback modules in intelligent tutoring systems (ITS) to improve the student-system interaction. Also, these results give some insights about the way in which a new generation of ITS could provide affective support to students. The ontological approach help to design the conceptual view of a model. Next, it is necessary to design the components of the Affective Feedback Model (AFM).

3.2 Affective Feedback Model

The proposed AFM responds to students when they interact with a tutoring system and consists of a set of affective written phrases. The AFM consist of an affective dialogue act taxonomy, a context-free grammar, and a set of affective words and phrases. Thus, the dialogue act taxonomy classifies the expressions and discomposes the dialogue complexity. Then, the grammar helps to structure the sentences and defines an admissible string of a language. Opinions from undergraduate students helped to design the set of affective phrases and words. Next sections describe the procedure followed in the AFM design process.

3.2.1 Exploratory study of the characteristics of feedback

Observation is a method of data collection in which researchers observe within a specific research field. This provide researchers with ways for checking for nonverbal expression of feelings. Also, observation helps them to understand and determine how students interact and it supports a quantification of time utilized for developing student activities [105, 106].

Participant observation allows researchers to check definitions of terms that participants use in interviews. Also, it enables to observe events that informants may be unable or unwilling to share because of it may be impolite. Finally, observation also permit to note situations described in interviews by informants, thereby making researchers aware of distortions or inaccuracies in the description provided by those informants [105, 106].

Study procedure

The implementation of proposed AFM consider as a case of study the course of Object Oriented Programming (OOP) at a public university in Tijuana, BC, México. The study consisted in following up a professor during his/her duties in an OOP course. It considered twenty students of four grades enrolled in the OOP course of an undergraduate program of the university. Before beginning the study, the professor received advise about how the exploratory experiment would be carried out and asked him/her for authorization.

The study consisted of two phases. The first of them considered the participant observation, of only observation and the second one comprised data collection. The study lasted four weeks; two weeks consisted of observation and two of data collection. A week consisted of five sessions of 45 minutes. The study design promoted the observation of teacher's activities during his/her class. These activities divided into two types: 1) the teacher exposes and explains the topics of the OOP curricula; and 2) the students do exercises or practices.

Each session divided into three parts for analyzing the following aspects: characteristics of feedback, dialogues involving negative or positive affection, and dialogue classification during the session. The observation was approach was non-participative.

The objective of the study was to answers the research questions *Which are the most used communication patterns in student-tutor?* and *Which are the most important affective elements in a face-to-face communication scenario?*. The study included some paper-based records of student/professor dialogs in-class sessions. At the end of each session the dialogues were classified into a type of dialogue act proposed by several studies [107–110]. The classification of dialogue acts helps to break down the complexity of the dialogues. Also, the structure of the dialogue used was analyzed.

As a result of the exploratory study and considering dialogue classifications of some studies [107–112], a dialogue classification in learning systems resulted. Table 3.7 shows the classification and the dialogue acts of each classification.

The proposed dialogue act taxonomy based on two elements: a) a classification proposed in previous work [111, 112]; and 2) a set of dialogue acts for each classification element. The description of each classification in the learning context is as follows.

- **Affirmations**. These are exclamations, explications or statements of some data, information or concepts.
- **Interrogations**. These are questions that have not been clarified, doubts or, simply, questions.
- **Directives**. These are the requests for an action or information.

Table 3.7: The proposed dialogue acts taxonomy of learning environments communication.

Classification	**Dialogue act**
Interrogative (I)	Information (IN) Affirmation (AF) Direction (DR) Evaluation (EV) Wh (WH) Factual (FC)
Directive (DR)	Repeat (RP) Wait (WT) Directive (DI) Ask for help (AS)
Affirmation (AF)	Explanation (EX) Information (AIN)
Responses (RS)	Yes/No (YN) Factual (FC)
Affective (AFF)	Greeting (G) Goodbye (GB) Apology (AP) Acknowledge (AK) Congratulation (C) Encouragement (E) Eulogy (EG)

- **Responses**. These are usually reactions/answers to the questions.
- **Affective**. These exclamations are used to express cordiality, respect and friendly attitude.

As a result of the exploratory study, interrogative dialogues has six dialogue acts subdivisions. Firstly, interrogatives of information question about some practice, activity or task, for example, *The job is for tomorrow?*. Secondly, interrogatives of confirmation help corroborate if something is the way you think should be, for example, *Is okay the line six of my code?*. Thirdly, interrogative of direction, usually used by students to ask which direction to follow, for example, *what do we do now?*. Fourthly, interrogative of evaluation, traditionally made by the teacher, is used to assess if knowledge was acquired, i.e., *was it clear?*. Fifthly, the Wh questions are used to explore any situation or data, for example, *have any questions?*. Finally, it exists interrogatives of factual information, used to ask questions related to a topic, for example, asking for a definition, example, application or clarification of a particular concept.

On the other hand, affirmation is given in the form of a statement.This classification has two dialogue acts: explanation and information. The explanation exposes some idea of general information (personal/motives) or technique, can be used by students or tutors. The information details some instruction of a procedure, task or practice, usually used by tutors.

Besides, the directive classification includes four dialogue acts. The directive is usually used by a teacher to give students an instruction, for example, *execute the program*. The waiting act is used by students to ask teacher for more time to complete a task, for example, *teacher, please give me more time to finish*. When the student says phrases like, *please repeat it!*, he/she is using a repeat dialogue act. The dialogue act ask for help is commonly used by students, for example, *can you help me?*. The classification of responses helps to answer the questions. There are Yes/No responses and factual responses that contains technical information of a topic.

Finally, the affective dialogue has five dialogue acts: the greeting, the goodbye, the acknowledgment, the apology and the positive exclamations. As highlighted throughout the document, it is recommended that the tutor use a positive vocabulary. Also, it is suitable to divide the positive exclamations into three sub-dialogue acts such as congratulating students for a good performance, encouraging them to go ahead and improve their work, praising the work well done and the effort made by students.

Also, the exploratory study assisting in identifying which actors perform each dialogue act, Table 3.8 shows this information.

The proposed AFM aims to provide affective support to students. For that reason, the AFM considered all the dialogue acts of the affective classification and it was selected a scenario to prove the affective approach. The selected scenario was when a student has a doubt and requires support from the tutor. Table 3.9 shows the dialogue acts included in the AFM to carry out this scenario.

Greeting is essential in communication, independent of the type, therefore is advisable that the ITS greets students. Also, we suggest personalizing this greeting using student name. In the same way, it is recommendable to say *goodbye* when the student logs out. The *acknowledgment* is the action of expressing or displaying gratitude or appreciation for something. If student frequently uses an ITS, the system could support them with this dialogue act. Also, *apology* is a regretful admission of an offense or failure. It should be presented when a student asks a doubt/question about a concept, and the system does not know the answer that he/she is looking for. Finally, in positive exclamation sub-dialogue acts, such as *congratulation*, could express joy in the success of the student for instance when he/she gets a good grade, completes an exercise or exam, finishes a topic or a subject or when stays a long time in the system. Furthermore, *eulogy* expresses warm approval or admiration of someone or something, in this case, the ITS provides a eulogy phrase when a student is studying some topic and he/she improves his/her GPA or finishes the course. Finally, an *encouragement* phrase helps to inspire a student with courage, spirit or confidence. ITS should provide this type of sentences when a student asks questions or doubts, or when student interacts with the system.

Table 3.8: Relation between the dialogue acts and who perform each one.

Classification	**Dialogue act**	Tutor	Student
Interrogative (I)	Information (IN)	x	x
	Affirmation (AF)		x
	Direction (DR)	x	
	Evaluation (EV)	x	
	Wh (WH)	x	x
	Factual (FC)	x	x
Directive (DR)	Repeat (RP)		x
	Wait (WT)		x
	Directive (DI)	x	
	Ask for help (AS)		x
Affirmation (AF)	Explanation (EX)	x	x
	Information (AIN)	x	x
Responses (RS)	Yes/No (YN)	x	x
	Factual (FC)	x	x
Affective (AFF)	Greeting (G)	x	
	Goodbye (GB)	x	
	Apology (AP)	x	
	Acknowledge (AK)	x	
	Congratulation (C)	x	
	Encouragement (E)	x	
	Eulogy (EG)	x	

Each dialogue act has an associated variable in the grammar. The previously described helps to structure an ITS affective response. Furthermore, each student action is an event that triggers a system dialogue act.

3.3 Context Free Grammar

A context-free grammar is a mathematical structure with a set of training rules that define the chains of admissible characters in a formal or natural language [113]. Formal grammars appear in several different contexts: mathematical logic, computer science, and theoretical linguistics, often with different methods and interests [114].

A context-free grammar is defined by a 4-tuple $G = (V, \Sigma, P, S)$ where:

Table 3.9: The dialogue acts considered by the AFM.

Dialogue act	**Tutor**	**Student**
Factual		x
Explanation	x	
Greeting	x	
Goodbye	x	
Apology	x	
Acknowledgment	x	
Congratulation	x	
Encouragement	x	
Eulogy	x	

V is a set of non-terminal character or a variable.

Σ is a set of terminal variables.

P is a set of rules or productions of the grammar.

$S \in V$ is the start variable.

Using a formal grammar to represent a language provides three advantages [113]. Firstly, it gives a precise mathematical definition that defines certain types of languages. Furthermore, the fact that it is a formal definition implies that context-free grammars are computationally implementable. Finally, it provides a convenient visual notation for structuring sentences.

In this way, the proposed grammar facilitates computational implementation of the proposed dialogue act. Each affective dialogue act has a variable in the grammar. Also, it has other types of variables such as student name, adjectives, verbs, concepts and links. Besides, each affective dialogue act possesses static words such as *is, your, you are* and *the topic*. The grammar is presented as follows.

$\langle Dialogue \rangle$ ::= $\langle PositiveExclamation \rangle$ | $\langle Greeting \rangle$ | $\langle Goodbye \rangle$ | $\langle Explanation \rangle$ | $\langle Apology \rangle$ | $\langle Ack \rangle$

| $\langle Greeting \rangle$ ::= $\langle GreetingPhrase \rangle \langle Name \rangle$

| $\langle GreetingPhrase \rangle$ ::= $gp_1 \mid gp_2 \mid gp_3 \mid \ldots \mid$

| $\langle Name \rangle$ ::= name | ε

| $\langle Goodbye \rangle$ ::= $\langle GoodbyePhrase \rangle \langle name \rangle$

| $\langle GoodbyePhrase \rangle$ ::= $bp_1 \mid bp_2 \mid bp_3 \mid \ldots \mid$

| $\langle Ack \rangle$ ::= $ack_1 \mid ack_2 \mid ack_3 \mid \ldots \mid$

| $\langle \textit{PositiveExclamation} \rangle$ ::= $\langle \textit{Congratulation} \rangle | \langle \textit{Eulogy} \rangle | \langle \textit{Encouragement} \rangle$!
| $\langle \textit{Congratulation} \rangle$ ::= ‘`your`’ $\langle \textit{Act} \rangle$ ‘`is`’ $\langle \textit{Adj1} \rangle$ | $\langle \textit{CongratPhrase} \rangle$!
| $\langle \textit{CongratPhrase} \rangle ::= cp_1 \mid cp_2 \mid cp_3 \mid ... \mid$
| $\langle \textit{Adj1} \rangle ::= ad1_1 \mid ad1_2 \mid ad1_3 \mid ... \mid$
| $\langle \textit{Word} \rangle ::= p_1 \mid p_2 \mid p_3 \mid ... \mid$
| $\langle \textit{Eulogy} \rangle$ ::= $\langle \textit{Name} \rangle$ ‘`you are`’ $\langle \textit{Adj2} \rangle$!
| $\langle \textit{Adj2} \rangle ::= ad2_1 \mid ad2_2 \mid ad2_3 \mid ... \mid$
| $\langle \textit{Encouragement} \rangle ::= e_1 \mid e_2 \mid e_3 \mid ... \mid$
| $\langle \textit{Explanation} \rangle$ ::= $\langle \textit{Verb} \rangle$ ‘`the topic`’ $\langle \textit{Concept} \rangle$ ‘ `is`’ $\langle \textit{Adj3} \rangle$ ‘`.`’ $\langle \textit{Verb2} \rangle$ $\langle \textit{Link} \rangle$
| $\langle \textit{Adj3} \rangle ::= ad3_1 \mid ad3_2 \mid ad3_3 \mid ... \mid$
| $\langle \textit{Verb} \rangle ::= v_1 \mid v_2 \mid v_3 \mid ... \mid$
| $\langle \textit{Verb2} \rangle ::= v2_1 \mid v2_2 \mid v2_3 \mid ... \mid$
| $\langle \textit{Link} \rangle ::= l_1 \mid l_2 \mid l_3 \mid ... \mid$

In the proposed grammar, the *Act* is a variable that represents a student's action such as effort, work or tenacity. The variable *Adj1* is an adjective that describes the *Act*, for example, your work is amazing. The *Adj2* represents the student, for instance: Jon you are intelligent. The variable *Adj3* is used to describe the easiness or importance of the topic, for example: Let's see, the topic HTML is easy.

The variables *Verb* and *Verb2* represent actions suggested to a student by the ITS to study a concept, such as analyze, look, read, listen, among others. The variable *Concept* is asked by a student when he/she unknowns a concept or has doubts about it. The ITS responds to this question with a *Link* indicating the electronic location where resides the material that responds to the student question. Also, this explanation is followed by a positive exclamation.

After defining the grammar, the next step for implementing the affective feedback approach is to identify the affective phrases, words, verbs, and adjectives from a student point of view. The following section presents this analysis.

3.4 Setting Affective Dataset of phrases

Undergraduate students proposed a set of affective words/phrases. This section responds to the research question *Which words/phrases are considered affective by students?*. The study included 166 native Spanish speakers (38 female and 128 male; aged between 19 and 25). The participants were students enrolled in engineering undergraduate programs of four different regions in México. They provided demographic information, such as gender, academic performance, and affiliation.

Table 3.10: Some examples of phrases proposed by students.

Greeting	Goodbye	Encouragement	Congratulation
welcome to the site	bye!	you can do this and more!	well done!
welcome	have a nice day!	go ahead!	good job!
good morning	see you!	do not give up!	great!
how are you	see you soon!	you are doing it very well!	excellent!
hello	see you tomorrow!	you have to trust in you!	very good!
can I help you?	good luck!	you can do it!	you did it very well!
Hi	take care!	come on!	I knew you can do it!
how are you doing?	goodbye!	I trust in you!	you did it well!
do you need any help?	my pleasure	keep trying!	congratulations!

Table 3.11: Some examples of words extracted from phrases proposed by students.

Act	Verb	Verb2	Adj1	Adj2	Adj3
effort	let's see	Look	amazing	able	suitable
job	let's talk	check this out	brilliant	dedicated	clear
constancy	let's study	analyze	efficiency	ready	confused
tenacity	let's learn	read	extraordinary	genius	questionable
endeavor	let's check	listen	surprising	unique	difficult
task	look	see	wonderful	nice	excellent
homework	let's work	study	great	the best	easy

The construction of the educational lexicon based on the dialogue act taxonomy described previously. The dataset of phrases considers five affective dialogue acts: apology, greeting, positive exclamation, goodbye, and acknowledgment. The positive exclamation divided into three sub-dialogue acts: congratulation, eulogy, and encouragement. An electronic instrument, designed in Google Forms platform, helped to collect the study information. Such instrument allows each participant to describe phrases for each dialogue act that he/she wants to listen from a tutor in a tutoring interaction. For example, *Which phrases do you like to listen from a tutor to congratulate you?*, *Which phrases do you like to listen from a tutor to apologize you?*, or *Which phrases do you like to listen from a tutor to encourage you?*. Participants could propose more than one phrase for each question. Table 3.10 shows some examples of expressions proposed by students for greeting, goodbye, encouragement and congratulation.

After the data collection process, the phrases went through a text cleaning process where the punctuation signs, stop words and conjunctions were eliminated to extract the relevant words. Then the words were categorized in variables of the proposed grammar such as *Verb2, Verb, Adj1, Adj2, Adj3*. Table 3.11 shows some examples of the previously described.

Table 3.12: Some examples of words extracted from phrases proposed by students.

Type	Word/Phrase	Valence	Arousal
Phrase	well done	8.5	6
Phrase	you do it well	7.66	4.66
Adj	brilliant	8.0	6.42
Adj	confuse	3.85	4.21
Verb	look	6.15	5.07
Verb	listen	6.28	3.92

3.4.1 Evaluation of the Affective Dataset

The affective evaluation of words uses the SAM scale. It uses a scoring range from 1 to 9 for both dimensions, and each number is associated to a visual representation. The middle position represented neutral (five). It was developed a Web system to conduct this evaluation (http://evaluacion-afectiva.appspot.com).

A total of 184 Spanish native speakers completed the evaluation of the affective lexicon. There were 39 female and 145 male students of undergraduate programs in México. The students were enrolled in four different undergraduate programs related to computer science. The participants were aged between 17-28 years, mean= 20.14 and SD= 1.26.

Each participant assessed 50 randomly assigned words on the two dimensions. Words were presented one by one while participants were asked to provide their ratings. Participants completed the survey, on average, in 25 min. The study was performed using the Web system. On average, the word was evaluated thirteen times in each dimension. Then, it was calculated an average of valence and arousal for each word/phrase. Table 3.12 shows some examples of evaluated words. The complete dataset is available (https://goo.gl/yNMhQB).

3.5 Summary

This chapter presents the affective feedback model proposed in this thesis. Firstly, this chapter describes the construction of an affective learning ontology which suggested a set of characteristics for providing affective support in a learning environment. There were two types of validation: quantitative and qualitative. The quantitative validation used a set of mathematical metrics proposed by OntoQA. On the other hand, the qualitative approach uses a human assessment methology where experts in the field validate the ontology using by means of a questionnaire. The quantitative validation showed that the structure of the ontology has richness of relationships and a horizontal view which outlines a wide range of knowledge. The qualitative validation suggested that the elements of the ontology are representative to define the domain of affective learning.

Also, this chapter describes the results of a non-participative observation study which proposes a set of dialogue acts in student-tutor interaction. A dialogue act taxonomy resulted of the exploratory study. The affective feedback model includes the dialogue acts taxonomy, a context free grammar and an affective database. The context free grammar structure the sentences. Undergraduate students proposed a set of affective phrases for each dialogue act of the taxonomy.

The proposed elements of the affective feedback model would be implemented in a system to provide affective support to students. The implementation would be useful to test if the affective approach improves student motivation to learn.

Chapter 4

Implementation of the Affective Feedback Model

Attending the previously described design guidelines, this chapter presents the design and implementation of the Affective Feedback Model (AFM) to answer the research question *How can be implemented the AFM?*. Moreover, this chapter also details the AFM log data, user-system interaction and user interface. Also, it presents TIPOO tutoring system, used in this study. The description includes its general architecture system, course structure, some functionality and implementation details. This section of the document also relates the integration of the AFM in the tutoring system responding to the research question *How can be integrated the proposal in an ITS?*.

4.1 TIPOO

TIPOO (in Spanish *Tutorial Inteligente para la Programación Orientada a Objetos*) is an ITS prototype developed by a research group at the Universidad Autónoma de Baja California, Tijuana, México [36]. It was born as an initiative to support the course of Object Oriented Programming, which is part of the curricular block of Software Engineering in undergraduate program of Computer Engineering at the University. TIPOO is a web-based tutoring system, in which students learn Object Oriented Programming topics by interacting with the platform.

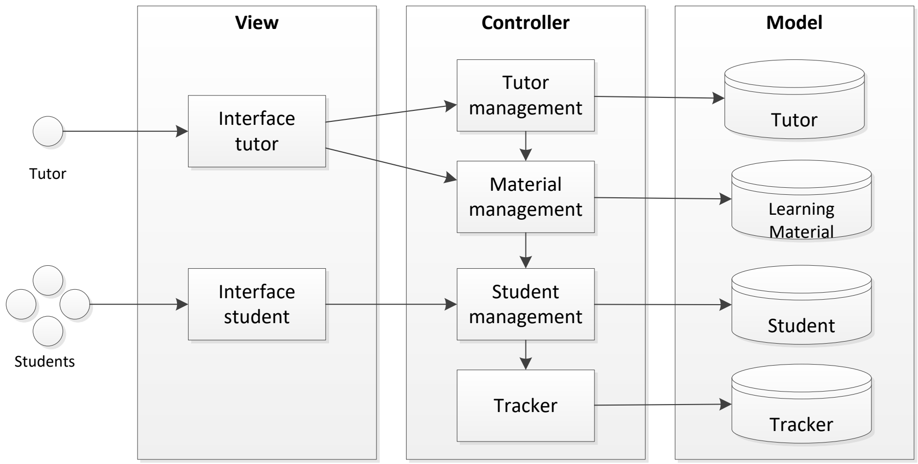

Figure 4.1: TIPOO general architecture.

Fig. 4.1 depicts TIPOO system; it follows a typical FMA. Moreover, TIPOO uses the MVC (Model-View-Controller) design pattern for each module of the traditional architecture (Tutor, Student, Domain, Interface). In other words, the student module has three sections, Model (definition of entities and relationships with the student), View (modules relating to the user interface for viewing and configuration aspects of the student) and Controller (they are all the rules concerning the student entity interactions). The systems provides users with course portability and accessibility. TIPOO was developed using technologies such as HTML5, CSS3, and Javascript for implementing the View side. The server side is running under Python 2.7 in Google AppEngine platform. It uses a non-relational storage system App Engine Data-store to store information about the tutor, student, and the ITS, as well as media content of teaching materials for each lesson. The query language for this system is GQL database; a SQL-like language provided by Google to manage non-relational databases.

4.1.1 TIPOO Views

TIPOO is a web-based learning system, in Spanish, available from Internet browsers like Mozilla Firefox or Google Chrome. Therefore, TIPOO is accessible from several computer platforms, such as laptop, desktop computer, tablet, or smart phone. As TIPOO is responsive, its access is comfortable from mobile devices, such as smart phones and tablets. There are two types of accounts: student and tutor. In TIPOO, after successful registration, each student logs in with his/her e-mail account and password. The student can select a topic, or a learning material showed in the interface.

Similar to the student interface, TIPOO has a tutor interface for professors where they can structure the course and load learning materials. Also, the teacher can track student interaction with the system.

The systems messages in TIPOO are in Spanish. Although TIPOO was born to support an Object Oriented Programming course, currently it supports different courses. Fig. 4.2 shows a sample of TIPOO interface.

Figure 4.2: TIPOO screen showing the different types of learning materials.

4.1.2 TIPOO Models

TIPOO has four models in its database: tutor, learning materials, student, and tracking. Fig. 4.3 shows the class and attributes of each model.

The tutor model records information of the tutors such as university, subject and career. The tutor provides this information when he/she creates an account in the system. Tutors can log in the system with his/her account and can create a course, and structure the topics. Also, tutors are capable of

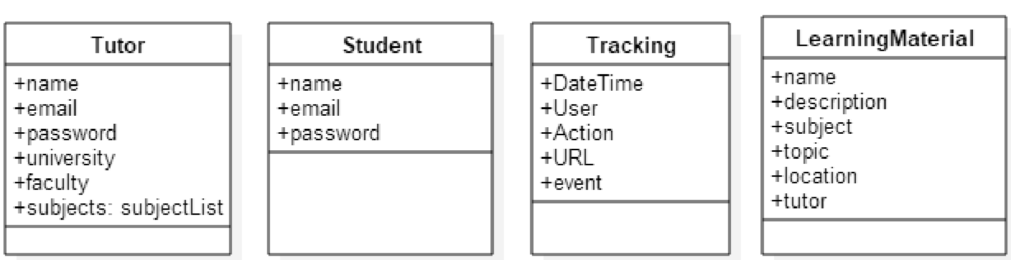

Figure 4.3: Detailed models of TIPOO.

uploading the learning materials; each learning material is associated with a topic, subject, and course. The learning material model records the name of the material, description, subject, topic, location, and tutor.

The student information is captured from the browser and stored in a separate database called the student model that has the following information: student grade, school curriculum, the overall student progress and personal details of the students such as name, age, and gender. Also, this model records the account information of the student, such as e-mail i.e.: user ID and a password.

Finally, the tracking model records the student-system interactions. The tracking model also holds other user interaction details, such as: user ID, topic, learning material, clicks, mouse-overs, amount of time to study at day, number of exercises to be performed daily, level of complexity of teaching materials, etc.

4.1.3 TIPOO Controllers

TIPOO provides students with a computer-based tool for auto-didactic learning sessions. TIPOO focused in learning contents instead of the open web-based environments of learning. The student management controller allows students to interact with the learning material and evaluations. Also, this controller manages student information. The tutoring system will enable tutors to prepare the course structure with subjects and topics, and to load the learning materials for each topic. These actions take place in the tutor management controller. TIPOO also supplies an evaluation module to assess the knowledge acquired by the students in a course.

TIPOO provides different types of learning material for each topic such as text documents, videos, audios and web links. The structure of the courses follows an inheritance tree $<Course><Subject><Topic>$ (Fig. 4.4).

TIPOO stores the student-system interactions in log files. The tracker controller tracks user actions in the system such as clicks, mouse-overs, amount of time to study at day, number of exercises to be performed daily, and level of complexity of teaching materials. All these actions are saved to be subsequently analyzed and for providing recommendations to students. Using the tracking information, tutors can see student learning patterns and preferences when they study.

4.2 Affective Feedback System

The AFM focused on the responses of the system to students. Student actions are significant because he/she starts the interaction with the ITS. The ITS considered a typical sequence when a student asks a question/doubt to the Affective Feedback System (AFS). A state diagram allows modeling sequences

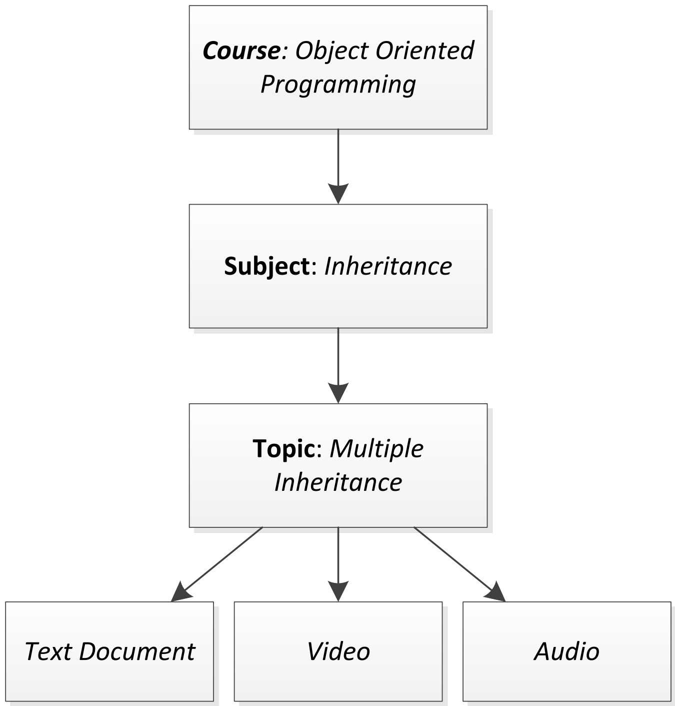

Figure 4.4: General structure of the courses in TIPOO.

of a system during its existence in response to some stimulus, with the corresponding reactions and actions [115]. According to Mora et al. [115], a state transition diagram can represent the dialogs of a system: the circles indicate states of the system in a particular moment, and the arrows are transitions from one state to another. These transitions are labeled with the actions of the user that triggered the action of the system and the response that the system provides. State diagrams are represented by finite state automaton and transitions tables. Sidorov et al. [116] use this technique to represent the dialogue model between users and a guide robot in a museum. They proposed to represent the dialogue model in a 5-tuple $\{Q, U, q, f, \delta\}$ where:

$Q:$ is a set of states

$U:$ is a set of user actions

$q \in Q$ is an initial state

$f \in Q$ is a final state

$\delta : Q \times U \rightarrow Q$

Moreover, the AFM has two types of states: responses r_x and the monitoring m_y. In the monitoring state, the system is waiting for user action. A user action triggers the responses states. Then, these states associate with the dialogue acts presented in the previous section. Table 4.1 shows this correspondence.

Table 4.1: Correspondence between states of the transition diagram and dialogue acts of the AFM.

States	**Dialogue acts**
r_1	Greeting
r_2	Congratulation
r_3	Encouragement
r_4	Eulogy
r_5	Explanation
m_1	monitoring user actions

In a regular interaction with the feedback system, a student logs in the system, next the system sends a greeting phrase to the student. Then, the system is in a monitoring state waiting for user action. At this time, the student could ask for a concept definition A and the system respond with an explanation followed by an affective phrase (congratulation, encouragement, eulogy). Fig. 4.5 depicts the state transition diagram, which represents the workflow of the system.

4.2.1 Formalization of the affective approach

This study considered an affective ITS as a 3-tuple $T = < K, D, S >$. In the 3-tuple, K is the domain knowledge model, as mentioned earlier, this model contains the subject curricula. D is the dialogue module, where the tutor provides the affective feedback. Finally, S is the student model where the student information is recorded.

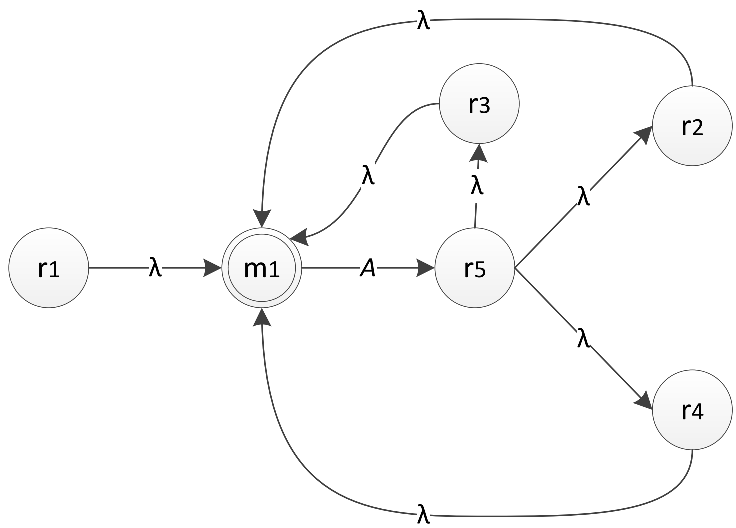

Figure 4.5: State transition diagram of the AFS.

Domain knowledge is structured in subjects, for example; Math, Object Oriented Programming, Web programming, among others. In this way, K is a set of learning subjects $K =< S_1, S_2, ..., S_{|K|} >$. Subjects are divided in a set of units $S_x =< U_1, U_2, ..., U_{|S|} >$ where $U_x =< c_1, c_2, ..., c_{|U|} >$ is a set of concepts; concept c_y is the atomic unit of knowledge in the proposed ITS.

The student model is stated as a 4-tuple $S =< B, N, I, A >$. In this tuple, $B =< g, a, p >$ is basic student information such as gender (g), academic performance (a) and personality (p). N is a set of student needs such as questions or doubts, $N =< n_1, n_2, ..., n_{|N|} >$. In the same way, $I =< i_1, i_2, ..., i_{|I|} >$ is a set of user interactions with the system. It contains messages and dialogues. The proposed model comprises student actions as the first interaction, student actions are a sequence of actions $A =< a_1, a_2, ..., a_{|A|} >$.

Dialogue D is defined as a 3-tuple $D =< M, R, e >$. In this 3-tuple, $M =< m_1, m_2, ..., m_{|M|} >$ is a set of tutor (ITS) responses to students, the tutor provides two types of response: an explanation or/and an affective feedback. On the other hand, student messages are created or produced by the function $e : N \times C \times A \rightarrow M$, this function work as follows: a student has a need (doubt/question) (n_x) and he/she asks (a_x) for a concept definition (c_x) to the ITS.

The ITS responses are represented in a 6-tuple $R =< T, G, P, E, V, I >$. In this 6-tuple, $T =< t_1, t_2, ..., t_{|T|} >$ is a set of affective dialogue acts such as greeting, apology, acknowledgment, goodbye, congratulation, encouragement and eulogy. In the same way, G is a context free grammar. Likewise, $P =< p_1, p_2, p_3, ..., p_{|P|} >$ is a set of affective phrases and words. Additionally, $E =< e_1, e_2, ..., e_{|E|} >$ is a set of explanations provided by the system. Finally, $V =< v_1, v_2, ..., v_{|V|} >$ is a set of affective responses.

When a student sends a message ($m_x \in M$) to the system, he/she is looking for a definition of a concept (c_x) and the system responds an explanation ($e_x \in E$) with a link where the question response is situated. This reaction is followed by an affective response ($v_x \in V$). The affective responses are generated by the function $h : T \times G \times P \rightarrow V$. The function h uses a dialogue acts t_x, the grammar G and the set of affective words and phrases P. As mentioned earlier, T is a set of affective dialogue acts such as an apology, greeting, goodbye, acknowledgment and positive exclamation (congratulation, encouragement, and eulogy).

In the present study, ρ is defined as a greeting phrase. When a student is asking for a definition (m_x), it is represented by ω. If the system needs to apologize to students, a phrase of this type is described as α. Moreover, when the system responds the explanation of the concept, Ψ represents an example of this phrase. Then, after the response the system needs to send a positive exclamation such as encouragement phrase, σ symbolizes this type of phrase. The symbol ψ represents for a goodbye phrase, β an acknowledgment phrase, κ a congratulation phrase, and γ a eulogy phrase. Fig. **??** depicts a dialogue sequence when a student asks for a definition of a concept using the formal representation.

4.2.2 Architecture

An instant message system implemented the AFS. The system operates under an MVC pattern (Model-View-Controller) and utilizes Spanish as a response language. Besides, its implementation required Web technologies such as HTML5, CSS3 and JavaScript for the client side; and Python 2.7 for the server side. The system is running under the Google App Engine framework. Fig. 4.6 depicts an overview of the system architecture.

The AFS is autonomous and independent of a tutoring system; it runs on a separate server. However, it needs some resources provided by an ITS databases, such as the curricula structure, the learning materials, and student model. Fig. 4.7 depicts the architecture of the AFS, next section describes it.

Views

The view of the system has two perspectives: student interaction and system response. Firstly, from the user perspective, the students interact directly with a chat-box interface where him/her can ask for the definition of a particular concept. The chat-box is available in all the ITS views (only when students

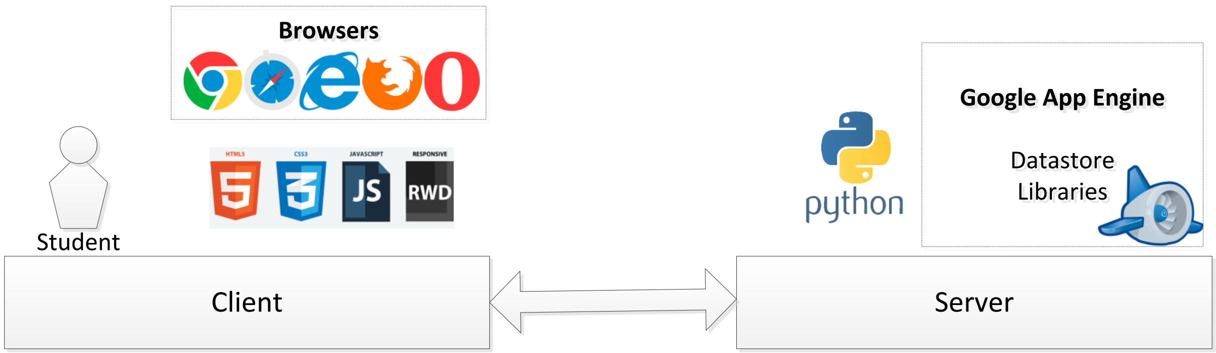

Figure 4.6: An overview of the architecture and the technologies used in the AFS implementation.

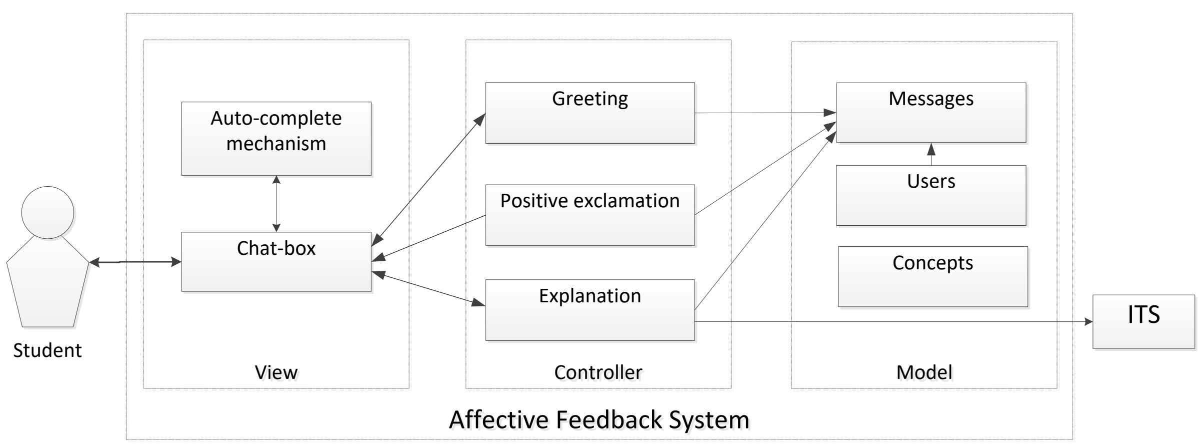

Figure 4.7: General architecture of the AFS.

logs in the system), and it appears on the right of the screen. Currently, student questions must comply with a definition of concept. The chat-box is only available if the user logs with a student account.

Otherwise, from a system perspective, when a student logs in the system, the greeting controller sends a greeting phrase to the chat-box module (user interface) using the name of the user, extracted from the ITS database. As mentioned earlier, this is where the question-answer interaction takes place. The chat-box uses the auto-completion mechanism module to help students write their question. After that, the chat-box has the entire question of the student; and it sends a request to the explanation controller. Fig. 4.8 shows an example of the AFM view.

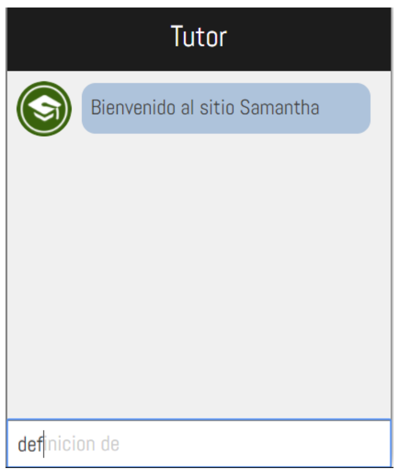

Figure 4.8: Screen of the chat-box with an example of the auto-completion mechanism.

Controllers

When a student logs in the system, the *greeting* controller sends him/her automatically a greeting phrase. On the other hand, the *explanation* module builds a technical answer to a student question. This controller needs ITS resources, such as learning material and web links, for sending a response to the chat-box view. Then, the *positive exclamation* controller is activated, and it generates an affective phrase according to a student action (congratulation, exclamation, affective phrase). The Listing 4.1 shows a code example of the congratulation phrase generation process.

Listing 4.1: A code example for the congratulation phrase generation process

```
elif message_type == 'congratulation':
adjective = random.choice(ADJECTIVES['1'])
word = random.choice(WORDS)
sentence_format = "Es␣{adjective}␣tu␣{word}"
```

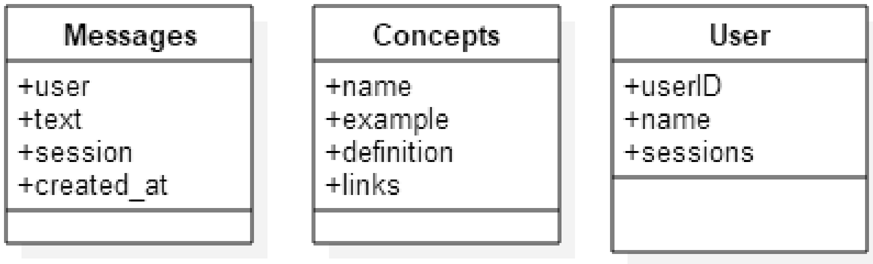

Figure 4.9: Detailed models of the AFS.

```
if debug:
sentence_format = "Es|{adjective}|tu|{word}"

sentence = sentence_format.format(
adjective=adjective,
word=word
)
```

As mentioned earlier, the chat-box uses an auto-complete mechanism to enter the student question into the system. The auto-complete mechanism indicates to the user a series of suggestions, of which each is a suffix or termination of the user entry [117]. Systems that require user input uses this mechanism because it saves effort and time to the user [117]. One of the main advantages of the auto-complete mechanism is the saving of time because the user avoids unnecessarily typing, which saves not only time but also supports cognition [118]. Several systems use an auto-complete mechanism, such as entering email addresses, URLs, dictionaries, programming, Google and other search engines, and mobile devices. Auto-completion facilitates communication between computer and user [118]. For example, in programming languages, auto-completion solves problems such as grammar, syntax, spelling errors, typos, etc. Internet search engines use it to assist users to find what they are looking for quickly; it helps users who are not sure how to perform a search or what are they looking for themselves [118].

Models

The AFS has two models in its database. Fig. 4.9 shows the classes with attributes of both models. The message model logs all the messages between student and ITS, it records all the student-system interaction. The class of message model is composed of the following attributes: message, user id, and date. In the AFS, the students do not need to provide their information. The system has an API that fills out this information using the data recorded on the ITS.

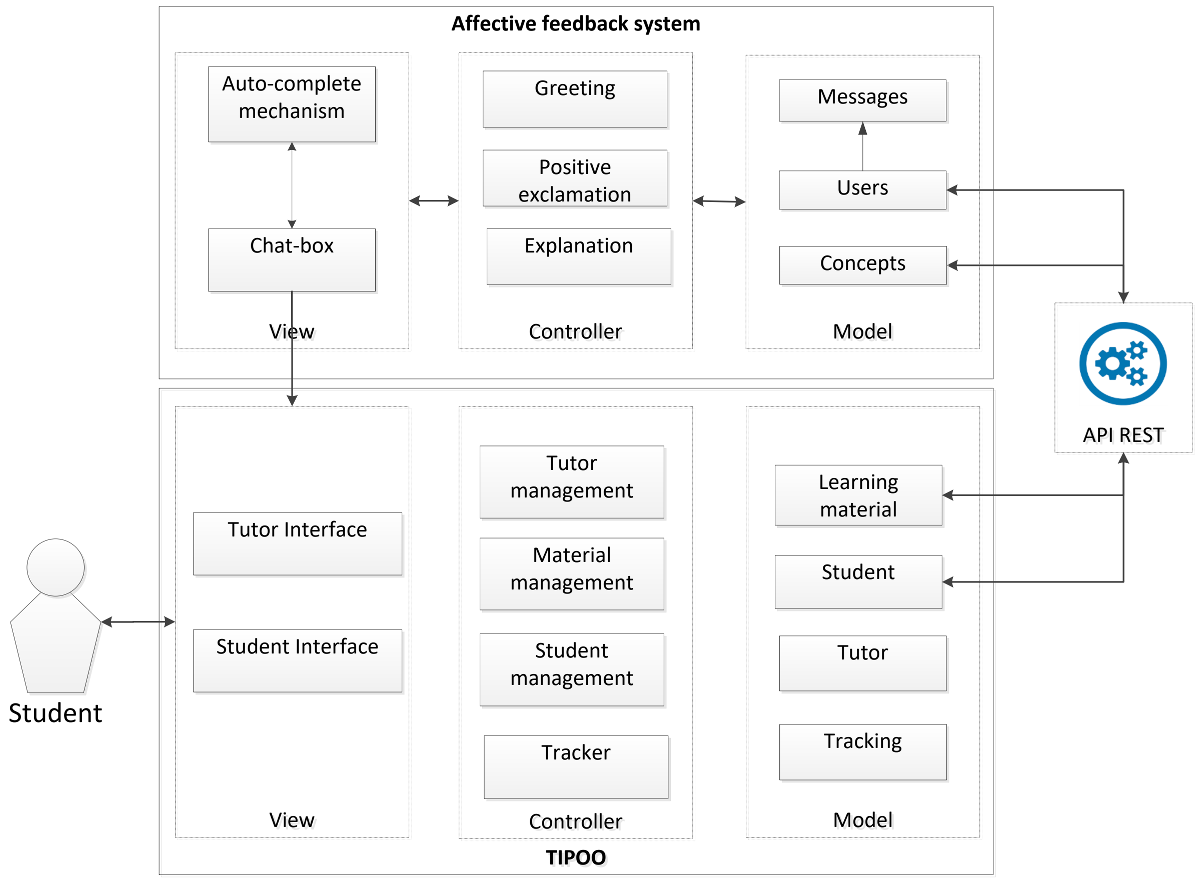

Figure 4.10: General architecture of the integration of the AFS and TIPOO.

4.3 Integration of the Affective Feedback System in a Intelligent Tutoring System

For providing affective assistance to students using an ITS, it is necessary to implement an API for deploying the proposed support model. The REpresentational State Transfer (REST) architecture permits integrating that model to the ITS. REST is an architectural style that defines a set of constraints and properties based on HTTP. Web Services that conform the REST architectural style provide interoperability between computer systems on the Internet. REST-compliant web services allow the requesting systems to access and manipulate textual representations of web resources by using a uniform and predefined set of stateless operations. Fig. 4.10 shows the architecture of this communication.

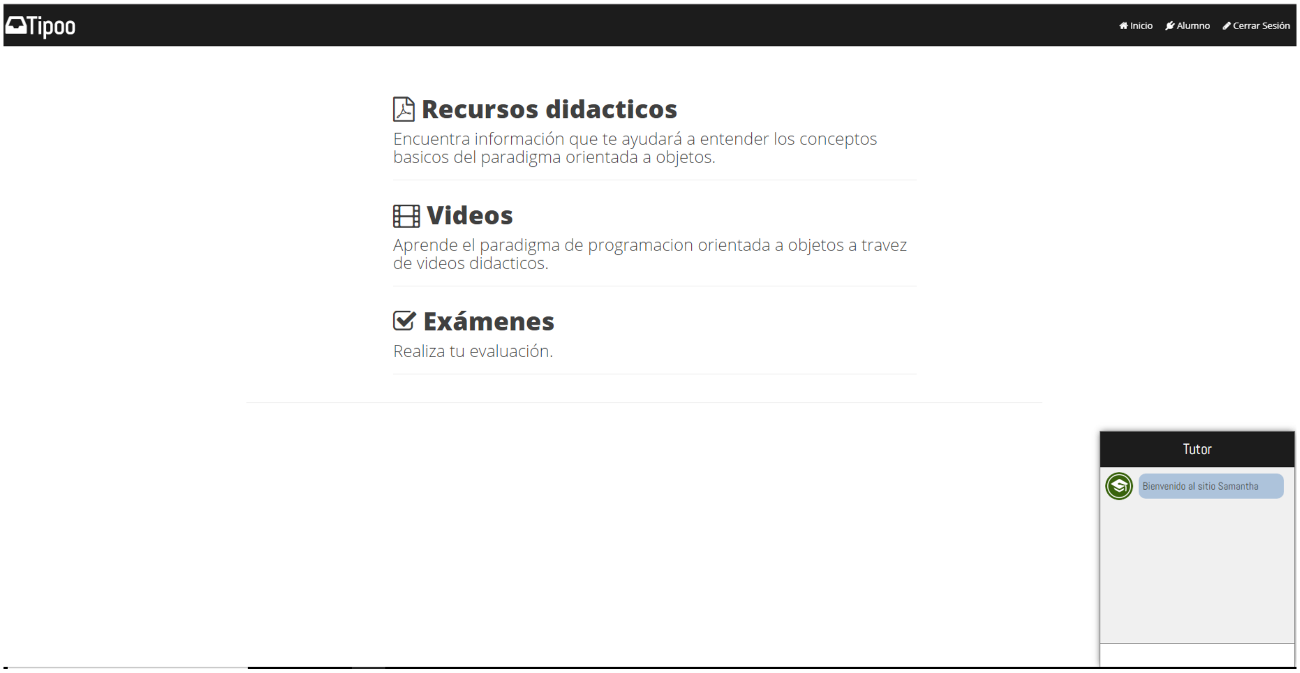

Figure 4.11: TIPOO graphic user interface with the affective feedback view integrated.

After the communication occurs, the AFS can explain concepts and learning material supported in TIPOO database. The AFS was carried out independently of the ITS; it is independent enough to be integrated into TIPOO or any other ITS that has similar characteristics such as the described in previous sections. The communication between the AFS and TIPOO was successful. Also, the chat-box view was integrated into all the views of TIPOO, Fig. 4.11 shows the views integration of views.

4.4 Summary

This section presents TIPOO, an ITS prototype based on a four-model architecture. TIPOO implementation uses an MVC pattern model for developing of web system. TIPOO records students interactions; this information can provide students learning patterns and preferences when they study. Also, the tutoring system supports different types of learning material that can be updated by the tutors and accessed by students.

Moreover, this chapter described details of the implementation of the AFM, also based on a MVC pattern. The implementation of the AFS uses all the elements described in the previous chapter, such as dialogue taxonomy, grammar, and affective database. The system uses an auto-complete technique when the student asks for a definition of a concept. The AFS is an independent system, but it uses resources provided by TIPOO. An API REST supports the communication between the resources provided by TIPOO and the affective system.

CHAPTER 5

THE IMPACT OF THE AFFECTIVE FEEDBACK ON STUDENT MOTIVATION TO LEARN

This chapter describes two study aspects, the design of the instrument research, and the proposal assessment from three perspectives. The main objective of this chapter is to respond the research question *Is it possible to improve student motivation to learn using an AFM?*. The first assessment based on the supposition that the affective feedback approach motivates students to learn differently, according to their characteristics. For that reason, the assessment focused on analyzing students motivation to learn from three student attributes: gender, academic performance, and personality. On the other hand, the second assessment perspective analyzes the student motivation to learn prior and post interaction affective feedback approach interaction. Finally, the third approach the effect of an Affective Feedback System (AFS) on student motivation to learn. In this evaluation, students interact with the AFS and with a non-AFS.

5.1 Instrument

Data were collected using an online questionnaire, which contains two sections. The first of them helped to obtain student's demographic information. The second part assisted on gathering judgments made on the perceived impact of the AFS on student's motivation to learn. These judgments conducted on a five-point ordinal scale, ranging from one (strongly disagree) to five (strongly agree).

The motivation construct, included in the second part of questionnaire, comprises variables proposed by several authors in the literature to measure motivation to learn: 1) the choice of a task, it indicates motivation to perform the task; 2) the effort, it suggests motivation; 3) persistence, it recommends performing an activity for a long time; 4) achievement, it points out that choice and persistence raise task success; 5) latency, it is the time to respond to a stimulation; 6) willing to reach goals which is when a student is motivated to learn if he/she wants to reach goals; 7) indicators of emotions, student actions are accompanied by the feeling of pleasure or displeasure that could indicate a motivation level.

Motivation Assessment Instrument

As previous section depicts, the second part of the instrument has six multiple-choice items closing the participant's answers to a five-point ordinal scale, ranging from one (strongly disagree) to five (strongly agree). The items in the instrument redacted in Spanish. The participants are Spanish native speakers. The instrument helped to identify how much motivation has a student after he/she receives affective feedback.

As a whole, six sub-variables evaluated the motivation construct with one questionnaire item measuring each sub-variable (see Table 5.1).

Instrument's Reliability Analysis

Cronbach α coefficient measure the item internal consistency of a construct. This analysis aims at determining whether the items selected for the questionnaire were measuring the variables that they were targeting. According to Sampieri et al. [99], an optimal reliability coefficient should exceed 0.70 with short scales of three or four items and the minimum should be at least 0.60.

SPSS 20 supported the statistical processing for reliability analysis. Cronbach's α for the six affective feedback items was 0.845. Also, the instrument was revised for the format of the questions and understandability of the wording. Likewise, three independent researchers, who had experience in the area of Intelligent Tutoring System (ITS), reviewed the questionnaire.

Table 5.1: Motivation assessment variables

Sub-variable	**Item**
Effort	The affective feedback motivates me to learn.
Willing to reach goals	The affective feedback motivates me to reach my goals.
Persistence	The affective feedback motivates me to continue studying in the system.
Interest	The affective feedback arouses my interest in learning.
Choice of task	The affective feedback motivates me to dialogue with the system.
Expressive indicators of emotions	The affective feedback makes nice my study time.

5.2 Analysis of the Relationship between Motivation to Learn and some Aspects of Student Profile

This experiment evaluated the mediator role of the AFS on student motivation to learn with regard the student gender and his/her academic performance. According to several studies, gender and academic performance influence on student motivation to learn. The results are organized in three aspects: the general results obtained, an analysis of the results by gender, and an analysis considering academic performance.

5.2.1 Experimental design

The authors selected a convenience sampling (non-probabilistic) because of the availability and easy access of participant students [99]. The sample included 39 (8 females and 31 males) students of engineering undergraduate programs at the Autonomous University of Baja California, aged between 19 and 29 (M age= 21.46). The participation in the study was voluntary. Participants were students from two academic periods (2016-1 and 2016-2).

The subjects were enrolled in Object Oriented Programming (OOP) courses and used TIPOO with the AFS. TIPOO was designed originally for the OOP course because programming learning is a difficult task for engineering students, and it is difficult to develop their programming skills [22, 119]. However, TIPOO could support any course. The participants had prior experience with the use of computer and Internet.

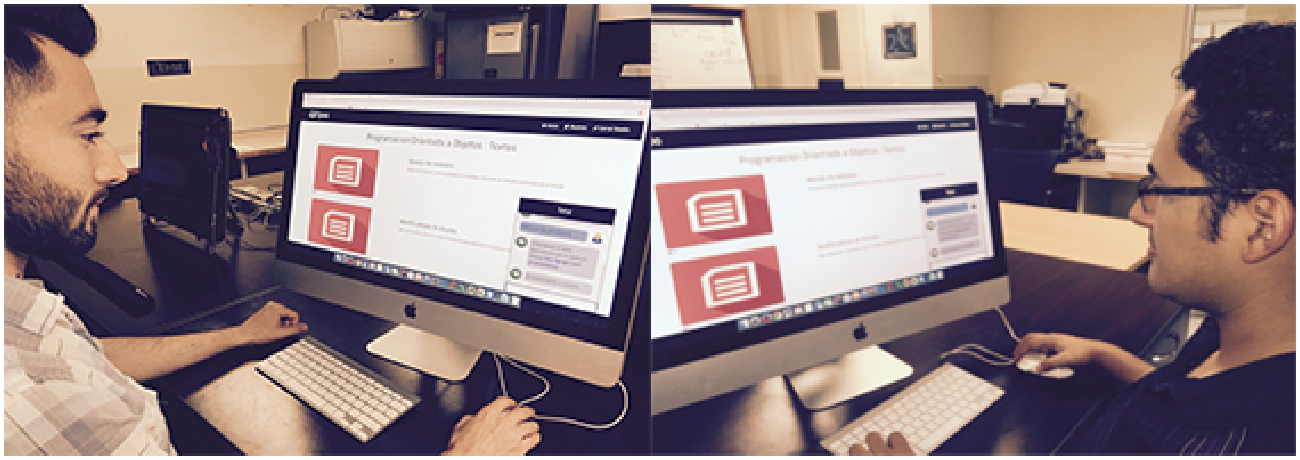

Figure 5.1: Users interacting with the AFS.

The selection of sample size is a difficult task for Human-Computer Interaction studies. Thus, Caine [120] proposed to use a sample size as previous studies determined. This work used a sample and a setting with similar characteristics as previous studies [32, 33, 121].

The experiment required two sessions. In the first one, students completed a questionnaire requiring them demographic information. In the second session, participants interacted with the ITS by 20 minutes, in which studying some concepts of OOP and asking some definitions in the chat-box (AFS). At the end of the second session, students answered the instrument. Their answers help for analyzing how the ITS motivated them for learning. Fig. 5.1 shows user interacting with the AFS.

5.2.2 General Results

Table 5.2 summarizes the experimental results. Most of the students' responses (95 cases) indicated they agreed with the affirmations described in the statements. The second most frequent response suggests that students have a neutral opinion about the instrument statements (82 cases). Moreover, the third most prevalent response of participants indicates that students strongly agree with the instrument statements (39 claims).

In variables such as *motivation to learn*, *motivation to reach goals*, *motivation to study*, and *motivation to dialogue*, “agree" was the option most frequently indicated. For the item, *arouses interest in learning*, “neutral" was the option most voted. Although in most of the variables “agree" was voted most, the difference between the number of votes between “agree" and “neutral" is minimal. For this reason, the analysis of results has two branches. Firstly, the results were classified by students' gender. Secondly, the analysis of results empathized students academic performance: 1) Students without

Table 5.2: Experimental results (n=39).

Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
The affective feedback motivates me to learn.	0	1	14	15	9
The affective feedback motivates me to reach my goals.	0	4	14	17	4
The affective feedback motivates me to continue studying in the system.	0	3	15	16	5
The affective feedback arouses my interest in learning.	0	3	18	14	4
The affective feedback motivates me to dialogue with the system.	1	5	8	16	9
The affective feedback makes nice my study time.	0	1	13	17	8

learning difficulties; and 2) Students facing learning difficulties. Students without learning difficulties have a grade point average higher than 80 while students are facing learning difficulties less than 80.

5.2.3 Gender Analysis

Male students agreed with most of the statements (70 cases). However, “neutral" was also most voted (71 cases). On the other hand, most of the female students’ responses were situated in the “agree" (25 cases) and “strongly agree" (11 cases) options in all statements. Tables 5.3 and 5.4 show the results of 31 male students and 8 female students respectively.

In variables such as *motivates me to learn*, *motivates me to reach goals*, and *motivates me to dialogue* most of male students selected “agree". Contrary, for the variables: *motivates me to study* and *improves interest in learning* most of the male student’ responses were situated in the “neutral" option.

In Table 5.4, we can see that for all variables “agree" and “strongly agree" are the most voted options. Only in the variable *Motivates me to learn*, “neutral" and “strongly agree" have the same number of mentions.

The previously described results helped to design a new variable, called *motivation*. The design involved a visual group calculation in SPSS version 20. Table 5.5 contrasts motivation and gender results.

Table 5.3: Results of male students (n=31).

Variable	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
The affective feedback motivates me to learn.	0	1	11	13	6
The affective feedback motivates me to reach my goals.	0	3	12	13	3
The affective feedback motivates me to continue studying in the system.	0	3	13	11	4
The affective feedback arouses my interest in learning.	0	3	16	9	3
The affective feedback motivates me to dialogue with the system.	1	5	7	12	6
The affective feedback makes nice my study time.	0	1	12	12	6

Table 5.5: Motivation level results contrasted with student gender (n=39).

	Motivation level		
Gender	**Unmotivated**	**Moderately motivated**	**Highly motivated**
Male	1	18	12
Female	0	3	5

A Mann-Whitney U test indicated that motivation to learn for students who used affective feedback was almost the same for women (Mdn=3) and men (Mdn=2), U=93, p=*NS*.

5.2.4 Academic Performance Analysis

It is important to note that for students not facing learning difficulties “neutral" had more mentions than “agree" in most of the statements. On the other hand, for students facing learning difficulties the *agree* option was the most voted; in some cases “strongly agree" was the most voted.

Table 5.6 shows the responses of 27 students with a high-grade point average (more than 80).

The most of the students with high grade point average selected “neutral" for the following statements: *motivates me to learn* (12 cases), and *improves interest in learning* (15 cases). In statement *motivates me to reach goals* (neutral=12 cases and agree=12 cases), “neutral" and “agree" had the same number of mentions. On the other hand, for the statement *motivates me to dialogue* most of the students

Table 5.4: Results of female students (n=8).

Variable	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
The affective feedback motivates me to learn.	0	0	3	2	3
The affective feedback motivates me to reach my goals.	0	1	2	4	1
The affective feedback motivates me to continue studying in the system.	0	0	2	5	1
The affective feedback arouses my interest in learning.	0	0	2	5	1
The affective feedback motivates me to dialogue with the system.	0	0	1	4	3
The affective feedback makes nice my study time.	0	0	1	5	2

agreed with that statement (9 cases).

Table 5.7 presents the results for 12 students with a low grade point average (less than 80). Twelve responses were collected.

In all variables, “agree" and “strongly agree" were the answers most selected by students with a low-grade point average. In any case, “disagree" or “neutral" had more mentions than “agree". Actually, “strongly disagree" was not voted at all. These results suggests that affective dialogue could impact to a greater extent these students. In the same way, as the previous section describes, SPSS visual group supported the design the "motivation" variable (Table 5.8).

Table 5.8: Motivation level results contrasted with student academic performance (n=39).

	Motivation level		
Academic performance	Unmotivated	Moderately motivated	Highly motivated
High	1	17	9
Low	0	4	8

Likewise, the Mann-Whitney U test suggested that motivation to learn for students who interact with affective feedback has statistical significance difference between groups with high academic performance (Mdn=2) and low academic performance (Mdn=3), U=106, p=0.091.

Table 5.6: Results of students with a high grade point average (grade point average >= 80, n=27).

Statements	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
The affective feedback motivates me to learn.	0	1	12	9	5
The affective feedback motivates me to reach my goals.	0	2	12	12	1
The affective feedback motivates me to continue studying in the system.	0	1	15	9	2
The affective feedback arouses my interest in learning.	0	2	15	9	1
The affective feedback motivates me to dialogue with the system.	1	4	8	9	5
The affective feedback makes nice my study time.	0	1	12	11	3

5.3 Relationship between Motivation to Learn and Personality

This experiment evaluated the mediator role of the AFS on student motivation to learn with regard the student personality. The literature states a relation between personality, affectivity, and motivation [30].

5.3.1 Experimental design

According to recent data [122], the student enrollment ratio in the period 2015-2016 had risen to 3.3 million in the tertiary school level in México. According to the latest data available from the Secretaría de Educación Pública (SEP) in Mexico, female students accounted for 51 percent of undergraduates enrolled at universities and males the 49 percent. On average, undergraduate students are aged between 19 and 29 years; most students graduate under 30 years. According to an OECD study [122], the characteristics of the student population in México are similar than other countries such as Colombia, Costa Rica, Spain, Denmark, USA, Brazil, among others. After sample selection, it was verified that the sample had similar characteristics, about age, gender and academic performance, of the student population of countries in the OECD. A total of 29 students from Universidad Autónoma de Baja California of e-commerce course participated in the study, aged between 20 and 23 years (*M* age= 21). The collected data included gender, academic performance, and personality for each student. The 58.6% were female students and 41.4% male students.

Table 5.7: Results of students with a low grade point average (grade point average <= 80, n=12).

Variable	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
The affective feedback motivates me to learn.	0	0	2	6	4
The affective feedback motivates me to reach my goals.	0	2	2	5	3
The affective feedback motivates me to continue studying in the system.	0	2	0	7	3
The affective feedback arouses my interest in learning.	0	1	3	5	3
The affective feedback motivates me to dialogue with the system.	0	1	0	7	4
The affective feedback makes nice my study time.	0	0	1	6	5

In the Universidad Autónoma de Baja California, the grade is between 0 and 100. Students with low academic performance were defined as those who scored lower than 80; almost the 51.7% were this type of students. On the other hand, students with high academic performance were defined who scored higher than 81; the 48.3% were students with high academic performance. Also, all students were assigned with scores for each personality factor (OCEAN Model [3]). Each of the five personality factors has a 3-point scale (low, neutral or high).

The experiment had a duration of three weeks; each week consisted of two sessions of 40 minutes. In this study, the sampling was non-probabilistic [99]. A total of 29 participants joined to six sessions. In the first one, students were asked to fill in a questionnaire data regarding gender, grade point average, personality and on-going semester. The participants answered a short personality test proposed by IPIP-NEO [3]. It has 120 items and provides the scores of each factor.

Then, the participants created an account in TIPOO system. In sessions 2, 3, 4 and 5, students interacted with TIPOO for 40 minutes. In these sessions, the participants were given studying topics about web programming. During the interaction, students were able to ask to the system for a definition of a concept. Then the system sent the explanation followed by an affective phrase. In the final session (6), students answered the motivation assessment instrument. The Shapiro-Wilk (S-W) test was applied to the 29 constructs to analyze the data distribution. The S-W test for normality statistics suggested that normality was an unreasonable assumption. Hence, it was applied a Kruskal-Wallis test (non-parametric) to analyze the relation between the student personality and motivation to learn. For certain items, responses were re-grouped to ensure the feasibility of the Kruskal-Wallis test. The data were collected using Google Forms. The results were analyzed with IBM SPSS software version 20.

5.3.2 General Results

Table 5.9 shows the student's responses to the instrument. Most students indicated they feel motivated to learn when received affective feedback. Specifically, 16 participants selected the *agree* option, nine participants chose the *strongly agree* option, and four selected the *undecided* option. The majority of participants selected the *agree* (15) and *strongly agree* option (8) for the item *affective feedback motivates them to reach goals*, and six participant selected the *undecided* option. It is important to note that in these two items, *the affective feedback motivates me to learn and to reach goals*, the participants who selected the *undecided* option has a low score of conscientiousness in the OCEAN model. Moreover, 15 students selected the *agree* option and seven the *strongly agree* option in the item *the affective feedback motivates me to continue studying*. The two participants who selected the disagree option were students with a low score of openness. Most of the students (15 selected the *agree* option and seven the *strongly agree* option) indicated that the affective feedback arouses their interest in learning, the student with a high score of neuroticism in the OCEAN model selected the *disagree* option. In the item "the affective feedback motivates me to dialogue with the system", 15 participants selected the *agree* option; the student who chose the *disagree* option has a high score of neuroticism.

Table 5.9: General results of student responses (n=29).

Statement	**Strongly disagree**	**Disagree**	**undecided**	**Agree**	**Strongly Agree**
The affective feedback motivates me to learn.	0	0	4	16	9
The affective feedback motivates me to reach my goals.	0	0	6	15	8
The affective feedback motivates me to continue studying in the system.	0	2	5	15	7
The affective feedback arouses my interest in learning.	0	1	6	15	7
The affective feedback motivates me to dialogue with the system.	0	1	6	15	7
The affective feedback makes nice my study time.	0	0	5	16	8

5.3.3 Personality Analysis

The previously described results helped to design a new variable, called *motivation*. The design involved a visual group calculation in SPSS. The most of the students were highly motivated to learn (22 students) after they interacted with the AFS and seven students were moderately motivated. The most of these students have a high score of neuroticism, and no one was unmotivated. These results suggest that the affective feedback impacts student motivation positively to learn. Table 5.10 shows the results of motivation categorized by the five factors of personality.

Table 5.10: Motivation level results categorized by the personality trait in the OCEAN model [3] (n=29).

		Motivation level		
		Unmotivated	**Moderately motivated**	**Highly motivated**
Extraversion	Low	0	1	5
	Average	0	5	11
	High	0	1	6
Agreeableness	Low	0	5	9
	Average	0	2	9
	High	0	0	4
Conscientiousness	Low	0	5	8
	Average	0	1	8
	High	0	1	6
Neuroticism	Low	0	1	7
	Average	0	2	12
	High	0	4	3
Openness	Low	0	5	16
	Average	0	2	4
	High	0	0	2

The Kruskal Wallis test revealed a significant effect of neuroticism on student motivation to learn ($\chi^2 = 10.51$, p= 0.005). Likewise, the same test indicated that there are not a significant effect of openness ($\chi^2 = 0.505$, *ns*), conscientiousness ($\chi^2 = 4.11$, *ns*), extroversion ($\chi^2 = 2.71$, *ns*) and agreeableness ($\chi^2 = 3.58$, *ns*) on student motivation to learn. These results reveal that the motivation caused by the affective feedback is related to student personality, particularly to the neuroticism factor.

Table 5.11: Results of the motivation in prior- and post-interaction with the system classified by neuroticism score (n=29).

Neuroticism Level	**Unmotivated**		**Moderately Motivated**		**Highly Motivated**	
	Prior	**Post**	**Prior**	**Post**	**Prior**	**Post**
Low	0	0	2	0	6	8
Average	0	0	3	0	11	14
High	0	0	1	3	6	4

5.4 Motivation in Prior and Post Interaction with the System

This section depicts the effect of the affective feedback approach on students motivation to learn. The analysis considers students motivation prior and post interaction. This experiment reveals that affective feedback not only impacts student motivation positively to learn, but also improves it.

5.4.1 Experimental design

This experiment follows the same conditions of the personality analysis presented in Section 5.3.1. The experiment had a duration of three weeks; each week consisted of two sessions of 40 minutes. A total of 29 participants joined to six sessions. In the first session, students answered the questionnaire of demographic information and the short personality test. Also, before the student-AFS interaction, students responded about their motivation level (called later motivation to learn prior-interaction).

5.4.2 Results

This section depicts an analysis of the student motivation to learn prior-interaction and post-interaction with the system. The 75.86% of students were highly motivated to learn previous the interaction with the system, and after the interaction, they were still highly motivated. The 17.24% of students incremented their motivation to learn; they were moderately motivated prior-interaction and highly motivated post-interaction. There were some students who their motivation was not changed; the 3.4% of students were moderately motivated prior-interaction and post-interaction. Finally, the 6.9% of students were highly motivated before the interaction with the system, and after the interaction, they were moderately motivated.

It was analyzed which type of students maintained, decreased or increased their motivation considering the relationship between neuroticism factor and motivation to learn, stated in the previous section. Table 5.11 shows how many students were unmotivated, moderately motivated and highly motivated prior and post interaction with the AFS.

Table 5.12: Results of the motivation in prior and post interaction with the system classified by gender (n=29).

Gender	Unmotivated		Moderately Motivated		Highly Motivated	
	Prior	Post	Prior	Post	Prior	Post
Male	0	0	4	1	8	11
Female	0	0	2	2	15	15

Table 5.13: Results of the motivation in prior and post interaction with the system classified by academic performance (n=29).

Academic	Unmotivated		Moderately Motivated		Highly Motivated	
Performance	Prior	Post	Prior	Post	Prior	Post
Low	0	0	3	3	12	12
High	0	0	3	0	11	14

It is important to observe that those students who increased their motivation to learn post interaction with the AFS had an average or low score of neuroticism. Contrary, students who not changed their motivation score and those who decreased it post interaction with the AFS, presented a high score of neuroticism.

Also, it was analyzed the motivation considering student gender. Prior interaction, four male students were moderately motivated, eight were highly motivated. Post-interaction, one male student was moderately motivated, and eleven were highly motivated. Three students increase their motivation after the interaction with the AFS. Female students did not change their motivation prior and post interaction. Table 5.12 shows a comparison of student motivation prior and post interaction with the affective system considering student personality.

The earlier reported results helped to design a new variable, called *motivation*. The design involved a visual group calculation in SPSS. Table 5.13 shows the motivation results of the prior and post interaction classified by academic performance. The students with low academic performance did not changed their motivation score prior and post interaction with the AFS. On the other hand, three students with a high academic performance increased their motivation score after they interacted with the system.

The results suggest that the affective approach has a positive influence on student motivation to learn. Also, the results indicate that the AFS interaction improves student motivation to learn, particularly to male students, students with high academic performance and with a low and average score of neuroticism.

5.5 Affective Feedback vs Non-Affective Feedback

This section shows the results of the motivation stated from participants after they interacted with the interaction with the affective and non-affective systems. Also, it analyses the influence of the affective approach.

5.5.1 Experimental design

We implemented a non-affective version of the feedback system proposed in this study and integrated it in TIPOO. The non-affective version is the TIPOO system without the affective phrases; it uses only the explanation dialogue act to answer student questions. This last version of the system did not provide congratulation, eulogy or encouragement phrases to students. The same participants described in Section 5.3.1 interacted with the non-affective version. After 20 minutes of interaction with this version, students answered the motivation assessment instrument described earlier. We compared the results obtained in the non-affective interaction with the results of the affective interaction. The affective interaction results were the same of the experiment described in Section 5.3.1.

5.5.2 Results

The control group included students interacting with the non-AFS version of the ITS. In this group, one student was unmotivated, five students were moderately motivated, and 23 students were highly motivated. These results indicate that most of the students were motivated using the feedback system without the affective approach. By the other hand, the experimental group comprised students interacting with the affective feedback version of the ITS. This group indicated that motivation to learn improves after system interaction, for example, no one was unmotivated, only three students were moderately motivated, and 26 students were highly motivated. These results show that the affective feedback impact to students motivation positively, Table 5.14 shows this comparison.

Table 5.14: Comparison of student motivation results between affective and non-AFS interaction (n=29).

	Motivation level		
Version	**Unmotivated**	**Moderately motivated**	**Highly motivated**
Non-affective	1	5	23
Affective	0	3	26

Table 5.15: Results of student motivation caused by the interaction with the affective and non-AFS classified by neuroticism score (n=29).

Neuroticism Level	Unmotivated		**Moderately Motivated**		**Highly Motivated**	
	Non-Affective	**Affective**	**Non-Affective**	**Affective**	**Non-Affective**	**Affective**
Low	1	0	1	0	6	8
Average	0	0	0	0	14	14
High	0	0	4	3	3	4

Table 5.16: Results of student motivation caused by the interaction with the affective and non-AFS classified by gender.

Gender	**Unmotivated**		**Moderately Motivated**		**Highly Motivated**	
	Non-Affective	**Affective**	**Non-Affective**	**Affective**	**Non-Affective**	**Affective**
Male	0	0	2	1	10	11
Female	1	0	3	2	13	15

A Wilcoxon Signed-Ranks test indicated that the experimental group (mean rank = 3.13) was rated favorably than the control group (mean rank = 2.5). However, there is not a statistically significant difference between the two groups Z = -1.41, p = *ns*. Thus, the results indicated that there is not a significant difference between groups, despite that, the qualitative analysis showed that the proposed model was consistently accepted.

We analyzed the results of the non-affective interaction from the three perspectives presented in previous sections: gender, academic performance, and personality (neuroticism factor). Table 5.15 presents the motivation results of the two interactions.

From Table 5.15, students with a low score of neuroticism increased their motivation when they used the AFS. The students with an average score of neuroticism have the same motivation score after they interacted with the affective and the non-AFS. Finally, one of the students with a high score of neuroticism increased his/her motivation to learn.

Table 5.16 shows a comparison of the motivation results after the interaction with the affective and non-AFS. One female student was unmotivated using the non-AFS, and her motivation increased when she used the AFS. Also, male students increased their motivation using the AFS.

From Table 5.17, one student with the high academic performance was unmotivated using the non-AFS, and he/she increased his/her motivation. In the same way, students with a low academic performance rise their motivation using the AFS.

The integration of a feedback system in an ITS motivate students to learn; this could be because most of the learning platforms more used in México, such as Moodle, Blackboard or Google Classroom, do not have an instant text message to provide support to students. The automatic responses of the

Table 5.17: Results of student motivation caused by the interaction with the affective and non-AFS classified by academic performance (n=29).

Academic	Unmotivated		**Moderately Motivated**		**Highly Motivated**	
Performance	**Non-Affective**	**Affective**	**Non-Affective**	**Affective**	**Non-Affective**	**Affective**
Low	0	0	4	3	11	12
High	1	0	1	0	12	14

system could be one of the reasons for here presented student motivation score.

5.6 Summary of the Findings

This section presents four different experiments to study the effect of the affective feedback approach on student motivation to learn. The first experiment analyzed the influence of academic performance and gender on a sample of 39 undergraduate engineering students. The second experiment examined the effect of personality traits on student motivation caused by affective feedback. The third experiment consisted of comparing the motivation prior and post interaction with the AFS. Finally, the fourth experiment is a comparison of the student motivation to learn moderated by the interaction with a AFS and with a non-AFS version. The sample for the second, third and fourth experiment was of 29 undergraduate students in an administration educative program in the same university.

From the results, the use of an AFS moderates the student motivation to learn regarding his/her academic performance. Also, the results show a non-statistically significant difference in the mean of motivation results of female and male students.

In view of the results of the second experiment, the use of an AFS moderates the student motivation to learn regarding his/her neuroticism score. The students with a high score of neuroticism were less motivated by the affective approach. In the same way, students with a low and average score of neuroticism were more motivated.

Also, the results of the third experiment suggest that the affective approach improves the student motivation to learn regarding his/her previous interaction with the system-interaction. Only the students with a high score of neuroticism reduced their motivation score when they interacted the AFS.

The findings of the forth experiment suggest that the integration of a feedback system in an ITS improves student motivation to learn.

CHAPTER 6

THE IMPACT AND APPLICABILITY OF THE AFFECTIVE FEEDBACK

Chapter 2 describes the theoretical foundation of the affective feedback model proposed in this book. Also, Chapter 5 shows the assessment of that model. The present chapter highlights the theoretical and empirical implications of the proposal.

6.1 Theoretical Implications

The affective feedback positively influences student motivation to learn. However, it benefited more to some students than others. A possible reason could be that the affectivity level of the feedback was the same for all students. One-size-fits-all approach it is not recommendable for learning because each student is different and has different needs. Therefore the level of affectivity must be adapted for each student to improve the influence of affective feedback on student motivation. For that reason, this study proposes a characterization of a student profile considering gender, academic performance and personality to analyze the influence of affective feedback on student motivation to learn.

Most students without learning difficulties selected the neutral option on the scale. On the other hand, most of the responses of students facing learning difficulties were situated in “agree" or “strongly agree" options. The results of this study agree with the results of other authors [58, 59] that affectivity benefits more students facing learning difficulties. It could be because students facing learning difficulties need more motivation to achieve their goals, need guidance and support during the learning process. On the other hand, students with high academic performance require less support from the teacher, or in case of having a problem they can solve it by themselves due to academic maturity acquired throughout their academic training. These findings suggest the following claim:

Claim 1: The affective feedback approach has positive impact on motivation of students facing learning difficulties.

Despite the previous claim, academic performance is not the unique aspect that impacts affectivity and motivation to learn; gender could influence on student motivation to learn. Female students tend to have more affective traits than male students, and to need more affectivity too [123]. In previous work, Wolfe et al. [58] stated that affective feedback provided with gestures impacts more to female students than male ones. The frequency analysis of this study suggests that female students were more impacted in their motivation to learn caused by the affective feedback approach. It could be because women are more sensitive than men [123]. thus, the results obtained in the present study suggest the following claim:

Claim 2: The affective feedback approach has a positive impact on the motivation to learn by female students.

The analysis of other aspects of student profile could give valuable insights about the impact of affective feedback on motivation to learn, for example, student personality. The literature [56, 57, 124] suggests that personality, particularly extroversion trait, is related to motivation and affectivity. Maybe the affective feedback approach could impact more on the motivation of introvert students than extrovert ones.

Also, the present study analyzed the effect of student personality on motivation to learn caused by an affective feedback. The literature suggests that affectivity is related to two personality factors. Firstly, positive affectivity has a relation to extraversion factor [30, 56]. And secondly, individuals with a high score in neuroticism trait (a psychological characteristics that defines a tendency to experience negative emotions) to be more negative [30].

The present study did not find a significant relation for the first relationship suggested by literature (positive affectivity to extraversion) [125]. On the other hand, the findings of this study support a relationship between neuroticism and affectivity, as previous work stated [30]. The use of affective feedback benefited less the motivation of students with a high score of neuroticism. Thus, students with this psychological trait not increased their motivation to learn, contrary they reduced or not changed their motivation. A student with a high score of neuroticism perceive the affective feedback negatively, and it was more difficult to impact on their motivation positively. There are two possible explanations for this phenomenon. Firstly, the affective feedback does not influence students with a high score of neuroticism because they do not need this type of support, or because they perceive it negatively. Secondly, probably the level of affectivity provided was not the adequate for these students. These findings show that student personality plays an essential role in the perception of affective feedback support as an instrument for promoting student motivation to learn. Thus, the results obtained put forward the next claim:

Claim 3: The affective feedback approach impacts specifically to students with a low and average score of neuroticism.

This study focused on analyzing the influence of affective feedback on student motivation to learn, but it only revealed the importance of written phrases. Affective feedback would be improved by including static gestures to these phrases, such as emoticons. These graphics elements would give a more affective sense to affective sentences, to best of our knowledge the literature does not report studies with this analysis. Also, phrases could be accompanied by an animated gesture like an avatar; several studies prove that animated agents have positive impact on student motivation to learn and learning outcomes [79, 91]. The influence of the same written phrases can also be analyzed but in a spoken form. The results of [126] indicate that the voice could contribute more positively to learning than movements and gestures. These improvements would enhance the positive impact of the affective feedback proposed in this study which based on phrases.

Likewise, the experiment for analyzing the student motivation prior and post interaction with the affective feedback system show that affective feedback not only positively impacts the student's motivation to learn, but can also improve it. These results encourage the following claim:

Claim 4: The affective feedback approach could impact positively student motivation to learn, particularly to female students and students with a low academic performance and low/average score of neuroticism.

This study analyzed the assumption that the use of an automatic feedback system could impact student motivation to learn. This assessment approach provided support to students considering two scenarios. Firstly, students received automatic feedback from an ITS without the affective assistance. And secondly, the students received such feedback, but with an ITS providing affective support. This experiment showed that the affective feedback approach impacts on the student motivation to learn.

6.2 Practical Implications

The theory of affective learning indicates the benefits of affective feedback, however, in scenarios of face-to-face teaching, tutors do not take advantage of affective learning; and it gets worse in computer-based learning systems. This study determined that the integration of affective feedback in computer-based learning systems, such as ITS, not only positively impacts student motivation to learn, but also improves it.

This study presents an affective feedback approach that can be used by teachers to improve student motivation during the learning process. Face-to-face scenarios, such as a classroom or personalized tutorials, could use the affective feedback approach here described. Likewise, it is recommended to use affective feedback in remote situations such as distance reviews, email, or instant messaging. All the above in an interaction with a human teacher.

However, as mentioned above, we do not have a human teacher for each student. Because of that, the creation of learning systems became popular to support student duties when a human teacher is not present. This work describes the integration of a component to an ITS to provide emotional feedback to students. The component is an instant messaging box that could provide emotional feedback to students. Chapter 4 describes in detail the implementation of the component and the integration in an ITS. The component is independent from a particular ITS and can be added to other ITS or learning system. The learning system can be implemented with any technology and under any design pattern because the communication between systems is carried out through HTTP and JSON. However, the learning system must have the following characteristics:

- The ITS database must contain model with an attribute of student name.
- The ITS databases must have a model of learning materials.
- The model of learning materials must have the following attributes: name, location (link) and description.

The objective of this proposal is to create a better learning environment for students. The use of the affective approach will create a better learning environment that will promote the motivation to learn in students. Impacting student motivation can eventually influence student learning interests or academic performance and improve the learning process.

6.3 Limitations

This study presents some limitations. Firstly, the study sample was a small size. However, research in this field (Human-Computer Interaction) suggested that small samples among 12-20 participants could be useful for homogeneous groups [105, 127, 128]. This type of samples could provide a vision of the population behavior [120]. Although the sample is small, it has similar characteristics to the regional population. Also, there are other countries with student population similar to the student population in México. From this perspective, the sample is representative and the results here described could be useful for student populations with similar characteristics in México and other countries.

The language is a limitation in this work because the system provides answers in Spanish and the subjects are native speakers of the same language. Thus, the component proposed in this work could only be used by Spanish speakers. Each language has non-similar features such as the grammatical form to give semantics to writing, which changes with each language [129]. The contribution of the present study would be useful to similar contexts, and future work can be focused on the analysis of the current proposal on different cultural contexts.

Another limitation is the profile of the sample. The validation scenarios were in subjects related to computation and with undergraduate students as a sample. The profile of a student considering previous training, learning interests, and affection needs differs from an educational level and student age. For instance, the affection need of an undergraduate student differs from a student of the elementary school or a post-graduate student. Consequently, the results of this study can be generalized for populations with similar characteristics to those described in Chapter 5.

Chapter 7

Conclusions and Future Work

This chapter summarizes the obtained results of this study and it exposes a conclusion. Also, it lists some principal contributions of this work and the peer-reviewed published papers. Finally, it states some directions of future work.

7.1 Conclusions

The inclusion of feedback in Intelligent Tutoring Systems (ITS) is important to provide support to students when the tutor is not present. Moreover, even more important, is that feedback takes into account affective aspects to improve the student-system interaction. Integrating affective aspects in learning systems improve motivation, study interests and eventually improve learning outcomes. This thesis proposes the integration of an affective feedback model in an ITS. First, this text relates a general view of topics about ITS, feedback and affectivity in face-to-face scenarios and affective feedback in learning systems. After that, based on the information provided by the literature, it defines an Affective Feedback Model (AFM) to improve student motivation to learn. Finally it also describes the implementation of an Affective Feedback System (AFS) in an instant message box and its integration to an ITS.

Beside, this thesis presents an empirical validation of the student-AFS interaction to analyze the influence on student motivation to learn. The evaluation was from three perspectives: 1) the effect of the

AFS on student motivation to learn considering a student profile, 2) the analysis of student motivational level prior and post interaction with the AFS and 3) the analysis of the motivational results of student interaction with the AFS and a non-affective version of the feedback system.

The first evaluation analyzed the influence of the affective feedback on student motivation to learn. The use of the affective feedback system influences positively student motivation to learn. However, it influences different to each type of student. The investigation uses a student profile to analyze the results. The profile has three student characteristics: gender, academic performance and personality. The AFS was more effective to female students and to students with low academic performance. In the same way, there is a statistical relation between student motivational level caused by the AFS and student personality. The AFS was more effective to students with a low or average score of neuroticism. The second evaluation examines the student motivational level prior interaction with the AFS and the motivational level post interaction. The interaction with the AFS improves the level of student motivation to learn, particularly to students with a low or average score of neuroticism. In the same way, students with a high score of neuroticism perceived negatively the AFS. They decreased their motivational level after the interaction with the system.

Finally, the third evaluation compares the motivational level of students after the interaction with the AFS and a non-affective version of the AFS. The non-affective version is the same feedback system but it does not include the affective phrases; it only provides explanation of the concept. The interaction with a feedback system, whether or not it is affective, in intelligent tutors motivates the student to learn. However, student motivation to learn increases if the feedback is affective.

The results of the present thesis pointing out several interpretations. Firstly, that affective feedback has several benefits for students, such as improving motivation to learn. This aspect would eventually enhance student-learning outcomes. Secondly, the characterization of the student profile helps to determine in which student personality traits the proposal has a higher impact. Thirdly, the architectural design proposed in this study could help to develop feedback systems for learning systems.

7.2 Contributions

The research presented in this thesis exposes some contributions to the Computer Science, particularly to the Human-Computer Interaction area. This section describes the main contributions of this research.

Affective dialogue act taxonomy

A taxonomy of speech acts to provide affectivity in the tutor-student interaction. The dialogue classification proposed in related work and the observation of face-to-face learning scenarios based the taxonomy developed in this work. The taxonomy can be useful to classify dialogues or create grammars to structure the dialogues. Section 3.2 of Chapter 3 describes the methodology that defined that taxonomy.

Structure of a student profile that benefits from affective feedback

The use of the AFS by student, described in Chapter 5, allows to identify an student profile for characterizing the impact of the affective feedback approach regarding student personality traits. That definition can help to adapt the affectivity to student characteristics.

An affective feedback model

The proposed AFM gives students several responses when they interact with a tutoring system. These responses consist of a set of affective written phrases. The AFM comprises an affective dialogue act taxonomy, a context-free grammar, a set of affective words and phrases, and a formalization of the model. The Chapter 3 describes the design of the AFM.

A weighted affective dataset

This study outlines a dataset of affective phrases proposed by undergraduate students. Each phrase/word has an affective value. The affective value states on the valence-arousal dimension. The Section 3.4 of Chapter 3 describes the construction of the dataset and its evaluation.

An affective feedback system

This thesis proposes an AFS based on the AFM. Chapter 4 defines the architecture of the system. The architecture comprises the characteristics of the database, the technologies used for the implementation and a diagram of the system structure. The architectural design could help to develop feedback systems for learning systems.

Motivation Assessment Instrument

This thesis proposes an instrument to measure the motivation to learn from students after using an AFS. The instrument is reliable according to the calculated Cronbach alpha. Section 5.1 of Chapter 5 describes the design of the instrument.

7.2.1 Main Contribution Publications

This section presents the published contributions related to this thesis. Each publication is a part of the body of this thesis, and it shows the evolution of this research. The papers are presented by type of publication and in reverse chronological order.

Journal Citation Report Papers

Samantha Jiménez, Reyes Juárez-Ramírez, Víctor H. Castillo, Guillermo Licea, Alan Ramírez-Noriega, and Sergio Inzunza (2018). A feedback system to provide affective support to students. Computer Applications in Engineering Education. http://doi.org/10.1002/cae.21900

Samantha Jiménez, Reyes Juárez-Ramírez, Víctor H. Castillo, and Alan Ramírez-Noriega (2017). Integrating affective learning into intelligent tutoring systems. Universal Access in the Information Society. http://doi.org/10.1007/s10209-017-0524-1

Book

Samantha Jiménez, Reyes Juárez-Ramírez, Víctor H. Castillo and Juan J. Tapia (2018). Integration of Affective Feedback in Intelligent Tutoring Systems: Impacting Student Motivation to Learn. (Beverley Ford, Ed.). London: Springer.

Book Chapters

Samantha Jiménez, Reyes Juárez-Ramírez, Víctor H. Castillo, Alan Ramírez-Noriega and Sergio Inzunza (2018). Affective Evaluation of Educational Lexicon in Spanish for Learning Systems. In New Advances in Information Systems and Technologies (pp. 1–10). Naples, Italy.

Samantha Jiménez, Reyes Juárez-Ramírez, Víctor H. Castillo, Alan Ramírez-Noriega, and Sergio Inzunza (2017). Affectivity Level for Intelligent Tutoring System Based on Student Stereotype, in Recent Advances in Information Systems and Technologies, vol. 206, pp. 97–109.

Samantha Jiménez, Reyes Juárez-Ramírez, Víctor H. Castillo, and Alan Ramírez-Noriega (2016). An Affective Learning Ontology for Educational Systems, in New Advances in Information Systems and Technologies, Á. Rocha, M. A. Correia, H. Adeli, P. L. Reis, and M. Mendonça Teixeira, Eds. Cham:

Springer International Publishing, pp. 1117–1126.

Samantha Jiménez, Reyes Juárez-Ramírez, Víctor H. Castillo, and Alan Ramírez-Noriega (2016). Affective Dialogue Ontology for Intelligent Tutoring Systems : Human Assessment Approach, in Proceedings of the International Conference on Advanced Intelligent Systems and Informatics, pp. 608–617.

Conference Papers

Samantha Jiménez, Reyes Juárez-Ramírez, Alan Ramírez-Noriega, and Sergio Inzunza (2017). A Conceptual Framework for Learning Systems Evaluation, in International Conference of Software Engineering, pp. 1–10.

Samantha Jiménez, Reyes Juárez-Ramírez, and Víctor H. Castillo (2016). An Empirical Analysis of Factors influencing Student-Tutor Dialogue, in Latin American Conference in Learning Objects and Tecnologies, pp. 426–433.

Samantha Jiménez, Reyes Juárez-Ramírez, Raúl Navarro, Arturo Coronel, and Víctor H. Castillo (2016). Architecting an Intelligent Tutoring System with an Affective Dialogue Module, in 2016 4th International Conference in Software Engineering Research and Innovation, pp. 122–129.

7.3 Future Work

The AFM proposed in this thesis improves student motivation to learn. However, future work is needed to extend the benefits of the integration of AFM in ITS. The following sections present a list of topics planned for future research.

Analyze the impact of non-verbal communication

The AMF can be extended by including dynamic or static non-verbal communication. For example, emoticons can provide static non-verbal communication, and an animated agent can provide dynamic non-verbal communication. Providing non-verbal communication by an AFS would impact differently the motivation to learn of students. Studying such an impact will give a most prominent characterization of the phenomenon of supplying affective feedback by ITS.

Evaluate the proposed model in other educational levels

The proposal must be evaluated at different educational levels to determine the impact of affective feedback on subjects of different ages.

Extend the student profile

Also, the affective student profile could be extended considering other characteristics of the student such as learning style, age, or learning interests.

Adapt the affectivity level to the student profile

The integration of an adaptation module to the AFM could improve the results obtained in this work. The adaptation of the affectivity to the student profile could serve those students who did not show benefit with the affectivity level offered in this study.

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