Un Tutor Virtual Afectivo basado en la Gestión de las Emociones durante las Interacciones en el Aprendizaje

Tesis presentada por

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Dedicatoria

Οποιοσδήποτε μπορεί να θυμώσει, αυτό είναι κάτι το πολύ απλό. Αλλά να θυμώσει με το κατάλληλο άτομο, στον βαθμό που αρμόζει, την κατάλληλη στιγμή και με τον σωστό τρόπο, αυτό, η αλήθεια είναι οτι δεν είναι τόσο εύκολο.

Aristoteles.

Cualquiera puede enfadarse, eso es algo muy sencillo. Pero enfadarse con la persona adecuada, en el grado exacto, en el momento oportuno y del modo correcto, eso, ciertamente, no resulta tan sencillo.

Anyone can get angry, that is very simple. But being angry with the right person, in the right degree, at the right time and in the right way, it is certainly not so simple.

Qualsevol pot enfadar-se, això és una cosa molt senzilla. Però enfadar-se amb la persona adequada, en el grau exacte, en el moment oportú i de la manera correcta, això, certament, no resulta tan senzill.

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Resumen

Las nuevas tecnologías proporcionan nuevas herramientas y espacios, en los que se desarrollan procesos de enseñanza-aprendizaje en línea, en diferentes modalidades (virtual o semi-presencial). En este sentido, se abren nuevas líneas de investigación para estudiar el papel de la educación emocional en estos entornos. Esta investigación se centra en detectar e interpretar las emociones que tanto el profesor utiliza para inducir el aprendizaje en los estudiantes como las que estos experimentan durante sus procesos de aprendizaje y que les llevan a ***prestar atención*** al proceso que desarrollan, en estos entornos.

Después de un análisis detallado de los trabajos de investigación en curso en este campo, este estudio ha dado lugar al desarrollo de un marco de interacción persona-ordenador. Lo que facilita la expresión de dichas emociones en la comunicación llevada a cabo en el aula virtual. Así como el análisis del discurso de los participantes y su evaluación de los conocimientos, incluso de su estado emocional y de su propia actitud ante el proceso. El objetivo final de este nuevo marco educacional ha sido proporcionar un ambiente seguro, confortable, donde se encuentre valorado y en el que confíe que le ayudará ***a alcanzar su meta.***

El ***problema de investigación*** desarrollado en esta tesis pretende dar respuesta a algunas de las preguntas abiertas actualmente en torno a dos grandes temas, «Emotion Awareness in elearning» y «Emotional feedback in elearning», proponiendo un modelo conceptual y computacional de análisis de la emoción en un entorno CSCL y, en particular, en el discurso educacional que tiene lugar en este contexto.

En esta línea, ***los objetivos*** de esta tesis han sido mostrar las emociones que los alumnos sienten durante su proceso de aprendizaje colaborativo en entornos virtuales y cómo estas emociones influyen en su aprendizaje. Evaluando las emociones obtenidas, clasificándolas y observando su evolución dentro del periodo de tiempo que dure la acción formativa. Estudiando, además, para qué situaciones formativas, los tutores virtuales afectivos pueden resultar efectivos y apropiados y determinar qué capacidades o habilidades deben tener para optimizar los procesos de aprendizaje de los alumnos.

Los resultados muestran que un enfoque integrado que incluye soluciones y estrategias metodológicas constructivistas para la detección e interpretación de la emoción se puede desarrollar y aplicar en este contexto. Entre los resultados obtenidos se destaca la capacidad del sistema de proporcionar ***conciencia y retroalimentación emocional***, y de analizar los efectos de este tipo de conciencia y la influencia de este tipo de retroalimentación en aspectos relacionados con el aprendizaje, la motivación, el compromiso, la autorregulación y los resultados del aprendizaje de los estudiantes así como la gestión del tiempo (time management) y la gestión de uno mismo (self-management) en términos de implicación conductual y cognitiva, autorregulación y rendimiento de los estudiantes.

Descriptores: «*Emotional elearning*», «*Emotion Awareness*», «*Affective Feedback*», «*Emotional Ontology*», «*Sentiment Analysis*», «*Affective Pedagogical Tutor*».

Abstract

New technologies provide new tools and spaces in which teaching and learning processes are developed online, in different modalities (virtual or blended). In this sense, new research lines arise aiming at studying the role of emotional education in these environments. This research focuses on detecting and interpreting both the emotions that the teacher uses to induce learning in students and the emotions students experience during their learning processes that lead them to ***pay attention*** to the process that they are developing in these environments.

After a detailed analysis of the state of the art in this field, this research has led to the development of a framework of human-computer interaction that enables the expression of those emotions during the communication that takes place in the virtual classroom as well as the analysis of the discourse of participants. It also assesses the level of acquired knowledge, the emotional state and the attitude of the student during the process. The ultimate goal of this new educational framework is to provide a safe and comfortable environment, where students are valued and feel confident, and finally to help them ***achieve their goal.***

The ***research problem*** that has been developed in this thesis aims to answer some of the currently open questions on two big issues, «Emotion Awareness in elearning» and «Emotional feedback in elearning», and to propose a conceptual and computational model of analysis of emotion in a CSCL environment and in particular, in the educational discourse that takes place in this context.

In this line, ***the goals*** of this thesis have been to reveal and represent the emotions that students feel during their process of collaborative learning in virtual environments, show how these emotions influence their learning, analyze and evaluate the obtained emotions, classify them, and observe their evolution within the period of time that the learning activity lasts. Moreover, studying particular learning situations, an online affective pedagogical tutor (APT) has been developed that provided efficient and appropriate affective feedback. In addition, our study determined which skills or abilities the APT should have in order to optimize the students learning processes.

The results show that an integrated approach including solutions and constructivist methodological strategies for the detection and interpretation of emotion can be developed and applied. Among the results obtained we highlight the system's ability to provide ***emotional awareness and emotional feedback***, the effects of this kind of awareness and the influence of this type of feedback on issues related to learning, motivation, commitment, self-regulation and students learning outcomes as well as to time management and self-management in terms of behavioral and cognitive involvement, self-regulation and student performance.

Keywords: «*Emotional elearning*», «*Emotion Awareness*», «*Affective Feedback*», «*Emotional Ontology*», «*Sentiment Analysis*», «*Affective Pedagogical Tutor*».

Resum

Les noves tecnologies proporcionen noves eines i espais, en els quals es desenvolupen processos d′ensenyament-aprenentatge en línia, en diferents modalitats (virtual o semi-presencial). En aquest sentit, s‘obren noves línies d‘investigació per estudiar el paper de l‘educació emocional en aquests entorns. Aquesta investigació se centra a detectar i interpretar les emocions que tant el professor utilitza per induir l‘aprenentatge en els estudiants com les que aquests experimenten durant els seus processos d‘aprenentatge i que els porten a ***prestar atenció*** al procés que desenvolupen, en aquests entorns.

Després d‘una anàlisi detallada dels treballs de recerca en curs en aquest camp, aquesta investigació ha donat lloc al desenvolupament d‘un marc d‘interacció persona-ordinador que facilita l‘expressió d‘aquestes emocions en la comunicació que es porta a terme a l‘aula virtual així com l‘anàlisi del discurs dels participants i que avaluen el nivell de coneixements adquirits, l‘estat emocional i l‘actitud de l‘estudiant davant el procés. L‘objectiu final d‘aquest nou marc educacional ha estat proporcionar un ambient segur, confortable, on es trobi valorat i en què confi que l‘ajudés ***a concloure la seva meta.***

El ***problema d‘investigació*** que s‘ha desenvolupat en aquesta tesi pretén donar resposta a algunes de les preguntes obertes actualment al voltant de dos grans temes, «Emotion Awareness in elearning» i «Emotional feedback in elearning», proposant un model conceptual i computacional d‘anàlisi de l‘emoció en un entorn CSCL i, en particular, en el discurs educacional que té lloc en aquests entorns.

En aquesta línia, ***els objectius*** d‘aquesta tesi han estat mostrar les emocions que els alumnes senten durant el seu procés d‘aprenentatge *col · laboratiu* en entorns virtuals i com aquestes emocions influeixen en el seu aprenentatge. Avaluant les emocions obtingudes, classificant-les i observant la seva evolució dins el període de temps que duri l'acció formativa. Estudiant, a més, per quines situacions formatives, els tutors virtuals afectius poden resultar efectius i apropiats i determinar quines capacitats o habilitats han de tenir per optimitzar els processos d'aprenentatge dels alumnes. Els resultats mostren que un enfocament integrat que inclou solucions i estratègies metodològiques constructivistes per a la detecció i interpretació de l'emoció pot ser desenvolupat i aplicat.

Entre els resultats obtinguts es destaca la capacitat del sistema de proporcionar **consciència emocional i retroalimentació emocional**, analitzar els efectes d'aquest tipus de consciència i la influència d'aquest tipus de retroalimentació en aspectes relacionats amb l'aprenentatge, la motivació, el compromís, l'autoregulació i els resultats de l'aprenentatge dels estudiants així com la gestió del temps (time management) i la gestió d'un mateix (self-management) en termes d'implicació conductual i cognitiva, autoregulació i rendiment dels estudiants.

Paraules Clau: «*Emotional elearning*», «*Emotion Awareness*», «*Affective Feedback*», «*Emotional Ontology*», «*Sentiment Analysis*», «*Affective Pedagogical Tutor*».

Índice general

Capítulo 1

Introducción

Durante mucho tiempo el estudio de las emociones ha estado bastante desatendido dentro del campo de la investigación neurocientífica dada la dificultad metodológica que suponía abordar una experiencia subjetiva, que incluso podía llegar a ser inconsciente por el propio sujeto, de manera científica y fiable. No obstante, en las últimas décadas esta tendencia se ha invertido, sobre todo debido a la evidencia de que la corteza cerebral tiene un papel relevante en la conducta emocional.

Los últimos avances en la Neurociencia han puesto de manifiesto la importancia que nuestro sistema nervioso tiene en relación con el aprendizaje y la evolución que el ser humano experimenta durante su vida. En este sentido, nuestro sistema emocional así como el cognitivo tienen un papel fundamental en la capacidad de retención a lo largo del tiempo de las experiencias vividas tanto del aprendizaje que de ellas obtenemos como en la fijación de aquellos hechos o experiencias traumáticas que nos imposibilitan evolucionar y acceder a nuevas experiencias.

La inteligencia emocional es la capacidad de identificar, usar, entender y manejar las emociones de una manera positiva de aliviar el estrés, comunicarse de manera efectiva, empatizar con los demás, superar los retos y los conflictos. Por tanto, el aprendizaje emocional consiste en la adquisición de habilidades para reconocer y manejar las emociones, desarrollar la atención y preocupación por los demás, tomar decisiones responsables, establecer relaciones positivas, y manejar situaciones difíciles con eficacia. Esto es particularmente importante en el aprendizaje colaborativo soportado por ordenador (CSCL), donde se alcanzan los objetivos de aprendizaje en colaboración entre un grupo de estudiantes. Los seres humanos pueden mostrar varios comportamientos afectivos que tienen impacto en la colaboración y el aprendizaje durante CSCL (Feidakis et al, 2012).

Teniendo en cuenta el impacto de las emociones en el aprendizaje, el papel del tutor debe ser mejorado con nuevas competencias y habilidades, tanto para estimular el aprendizaje activo y la construcción colaborativa del conocimiento, como para saber identificar los sentimientos y las emociones, así como para controlar y proporcionar modelos adecuados de expresión, especialmente cuando se trata de emociones negativas que son a menudo más difíciles de comunicar de manera adecuada. Profundizando en nuevas formas de interacción que emulan y mejoran las habilidades de comunicación humana y estimulan el pensamiento crítico, mejorando el aprendizaje.

Las Emociones y relaciones de los usuarios están constantemente presentes en los entornos de elearning, apoyadas en las nuevas herramientas y contenidos de aprendizaje y, como tal, representan un nuevo e interesante campo de investigación (Efklides, 2006). Las últimas realizadas en entornos virtuales de enseñanza-aprendizaje muestran la importancia de tener en cuenta tanto las habilidades y capacidades cognitivas como las afectivas que los estudiantes poseen o deben adquirir en dichos procesos. Desarrollando entornos gráficos facultados por agentes virtuales que funcionan como tutores virtuales y que son capaces de interactuar con el alumno siguiendo el modelo cara a cara humano facilitando la comunicación.

Actualmente, hay dos grandes temas de investigación con cuestiones abiertas: la **conciencia de las emociones** y la **capacidad de manejar los sentimientos** apropiadamente. Ambos constituyen la base para una comunicación efectiva y pueden ayudar a comprender y empatizar con lo que realmente está molestando a otras personas. Estos temas de investigación están ganando el interés y la atención de más y más investigadores en el ámbito del aprendizaje afectivo. Uno de los temas de actualidad en la conciencia de la emoción es como etiquetar (es decir, cuantificar) la conducta humana para la retroalimentación emocional relevante en el CSCL. El objetivo de este trabajo es primero presentar un enfoque eficaz para etiquetar el comportamiento afectivo en el discurso educativo que luego permitirá a un tutor humano (o virtual) poder capturar y manejar las emociones de los estudiantes, hacer que los estudiantes tomen conciencia de sus propias emociones, evaluarlas y proporcionar la información adecuada.

De acuerdo con las áreas de investigación del doctorado en Educación y TIC (elearning) esta investigación se desarrolla en dos ámbitos de investigación (a) Procesos de enseñanza-aprendizaje y (b) Recursos tecnológicos para el aprendizaje que se fundamentan a continuación.

Capítulo 2

Justificación de la investigación

2.1. Fundamentos Biológicos

2.1.1. Emociones

Las emociones se pueden considerar funciones biológicas del Sistema Nervioso que han evolucionado como respuestas conductuales y fisiológicas, especializadas para facilitar la supervivencia, por esta razón, son filogenéticamente antiguas y básicamente inconscientes.

Se considera que la emoción engloba cuatro componentes: (a) **Fisiológico** referido a los cambios en la liberación de ciertas hormonas que alteran el cerebro afectando a cómo responde en aquel estado, (b) **Conducta motora referida a la expresión** facial, el tono de voz o la postura corporal, como etiquetas observables del estado emocional, (c) **Cognición referida a los sentimientos** (representaciones mentales de los cambios fisiológicos emocionales (sentido interoceptivo)), constituye el componente subjetivo de la emoción por el cual nuestro cerebro interpreta un estado somático determinado, representando el componente consciente y el estado de alerta mental, de manera que ayudan a regular la conducta social y (d) **Conducta inconsciente referida a los procesos cognitivos** generados por el estado emocional que influyen en la conducta de manera desapercibida para el sujeto. A veces se habla de intuición o corazonada pero en realidad se trata de una especie de reacción emocional que nos impulsa a hacer algo.

Actualmente, se sabe que nuestras emociones determinan en gran medida nuestra ***conducta***. Son responsables de nuestras reacciones espontáneas, de nuestra manera de pensar; distorsionan nuestros recuerdos, intervienen de forma determinante en la toma de decisiones y en la planificación de nuestro futuro, determinando el modo en el que nos comunicamos con los otros, e incluso nos hacen defender ciertos valores éticos y morales. Y lo hacen de manera más o menos consciente. Finalmente, las ***experiencias emocionales*** facilitan o impiden la interacción social.

Desde el punto de vista ***neurofisiológico***, las emociones se localizan en el sistema límbico que asocia diferentes partes del sistema cerebral (amígdala, hipotálamo, hipocampo y tálamo) con las emociones (LeDoux, 1999). Según LeDoux (1999), existen ciertas reacciones y recuerdos emocionales que tienen lugar sin la menor participación cognitiva consciente. Sugiere este autor que el hipocampo no tiene tanto que ver con la emisión de respuestas emocionales como con el hecho de registrar y dar sentido a las percepciones, es decir con la memoria emocional. La principal actividad del hipocampo consiste entonces en proporcionar una aguda memoria del contexto, algo que es vital para el significado emocional de los acontecimientos. Y la amígdala, especializada en las cuestiones emocionales, está directamente relacionada con los procesos de aprendizaje y memoria.

2.1.2. Cognición

La gente a menudo separa emoción y razón, en la creencia de que las emociones son un obstáculo en la toma de decisiones o el razonamiento pero estudios recientes han demostrado que en todos los casos el proceso cognitivo de un individuo depende en gran medida de sus emociones de forma que estas pueden influir drásticamente en su rendimiento (Damasio, 1994; Spering et al, 2005).

El papel de la razón es el de permitir sentir las emociones de manera adecuada y equilibrada, reconocerlas y expresarlas (propias y ajenas) de forma asertiva, controlarlas y regularlas, saber tranquilizarnos, convertir sentimientos negativos en positivos, asícomo anticipar nuestros estados de ánimo en acontecimientos futuros, aprender a tolerar la frustración y percibir el error como fuente de aprendizaje, etc.

Los seres humanos no somos únicamente racionales, sino que somos primero emocionales y sociales y después racionales. Podemos afirmar que «no hay razón sin emoción» , así que un enfoque emocional en el ámbito educativo es vertebral puesto que determina cómo se producen las experiencias de enseñanza y de aprendizaje (Morgado, 2010).

2.1.3. Funciones Ejecutivas (FE)

La regulación emocional se considera una de las funciones ejecutivas (FE) más importantes. Podemos entender las FE como un conjunto de mecanismos de control cognitivo complejo que facilitan las conductas dirigidas a un objetivo, y que se ponen en marcha o son necesarias especialmente ante situaciones novedosas o poco aprendidas para el sujeto. Estos mecanismos incluyen la planificación, anticipación y creación de expectativas, la monitorización y autorregulación, la flexibilidad mental, la memoria de trabajo, las funciones atencionales, la inhibición conductual y la autorregulación emocional.

Las FE coordinan el funcionamiento de otras áreas cerebrales e integran procesos sensoriales multimodales; el resultado del procesamiento llevado a cabo en otros sistemas relacionados con la atención, la memoria, la emoción y los patrones de respuesta, así como las reacciones emocionales que son necesarias para que la conducta sea eficaz para obtener los objetivos perseguidos, anticipando posibles resultados, sus consecuencias derivadas, autorregulando la conducta, etc.

Los avances en Neuroeducación demuestran que nuestro cerebro es capaz de atender y consolidar de manera más rápida y eficiente los contenidos dados en situaciones de aprendizaje en las cuales se produzcan vivencias emocionales ***(Disonancia Emocional)***. Así, las bases neurobiológicas de la memoria emocional se centran principalmente en la activación de estructuras del sistema límbico, como la amígdala, durante el procesamiento de un estímulo con carga emocional por el individuo se dará que favorecerán la liberación de neurotransmisores activadores como la noradrenalina (NO) y la adrenalina (A) en regiones fundamentales para la consolidación de la memoria, como son el hipocampo y la corteza cerebral. Por este motivo, en un contexto emocional se producirá un aumento de atención, una mayor asignación de valor al estímulo atendido, una potenciación del aprendizaje y un aumento de los mecanismos de plasticidad cerebral que se traducirá en un mejor recuerdo de aquel conocimiento.

2.1.4. Atención

La ***atención*** es un mecanismo esencial que permite seleccionar la información relevante del entrono en función de las necesidades del individuo para garantizar una mejor adaptación al medio. Si bien se asume que los procesos atencionales son varios y participan en funciones cognitivas complejas, se puede afirmar que implica la participación de tres subsistemas: la alerta o atención sostenida, la atención selectiva y focalizada y el control ejecutivo.

Se entiende por ***atención sostenida*** el estado del organismo para procesar información. Este sistema se puede ver afectado por condiciones como la fatiga, el paso del tiempo y las demandas de la tarea. Este sistema implica un elevado coste energético y a partir de aproximadamente 45 minutos de agotamiento mental, son necesarios descansos para poder recuperar la efectividad, y se demuestra la sensibilidad al entrenamiento.

La ***atención selectiva*** se refiere al proceso para elegir la información relevante el del entorno que permita el logro de objetivos deseados, comportarse en sintonía con estos y evitar posibles amenazas. En este proceso de selección, la atención puede orientarse o bien de manera voluntaria de acuerdo con los objetivos y las expectativas de los individuos (atención endógena), o bien de manera involuntaria, guiada por la estimulación externa (atención exógena) (Posner, 1980).

El ***control ejecutivo*** se define como la habilidad para mantener el procesamiento de la información de manera continuada en el tiempo, a pesar de la existencia de distractores. Dando lugar a un comportamiento dirigido a un objetivo. La atención ejecutiva permite el procesamiento de información novedosa para poder dar una respuesta rápida y adecuada a cada situación (Norman y Shallice, 1986).

Por este motivo, hay que tener presente que la atención se verá muy influenciada por los estados emocionales y motivacionales del individuo. Se ha observado que emociones como el miedo, la rabia, la tristeza o la vergenza producían una interferencia directa sobre la atención de las personas, que provocaba un aumento en el número de distracción y una disminución del recuerdo de aquello aprendido. En cambio, la atención se puede ver fomentada en función de la motivación por la actividad y el estímulo que presenta.

2.1.5. Motivación

La ***motivación*** es proceso que dirige el comportamiento hacia un objetivo. La motivación determina la elección de una conducta, el inicio de esta y la persistencia en su ejecución hasta llegar a las metas propuestas. La motivación puede ser autorregulada por factores internos (motivación endógena), como la curiosidad o por determinantes externos (motivación exógena), como son las condiciones ambientales, el reconocimiento o el castigo social y los incentivos ***(Disonancia Cognitiva).***

Teniendo en cuenta la relación entre motivación, atención y aprendizaje es evidente que será más fácil aprender aquellos contenidos que más interesen a los alumnos. Un aumento de la motivación tendrá como consecuencia un aumento de la atención, que implicara que el individuo permanezca más tiempo ante aquella tarea y se fortalezca así la adquisición y el recuerdo de los contenidos aprendidos. El aprendizaje es un proceso satisfactorio por sí mismo, y el hecho de aprender implica la liberación de Dopamina (DA) en nuestro cerebro. La liberación de DA aumentará el nivel de implicación y activación de nuestro organismo, lo que favorece la consolidación de memorias con alto contenido emocional.

2.2. Procesos de Enseñanza-Aprendizaje

2.2.1. Inteligencia Emocional

De la capacidad de gestionar convenientemente los sentimientos utilizando la razón, nació el concepto de Inteligencia Emocional. Definida por primera vez por Salovey y Mayer (1989) fué popularizada después por Goleman (1995). Se considera que la inteligencia emocional es la habilidad para reconocer y expresar de manera equilibrada nuestras propias emociones, reconocer y entender las emociones de los demás y utilizando esta información para guiar la propia conducta y el pensamiento de forma eficaz.

Por un lado, la calidad de vida de una persona depende de su capacidad para sentir sus emociones de forma adecuada y para regularlas en respuesta a las circunstancias de su entorno. En este sentido, las personas necesitamos un equilibrio emocional y éste depende de que lo que sentimos, pensamos, decimos y hacemos vaya en la misma dirección.

Por otro lado, hay que tener presente que si los niveles de respuesta emocional son excesivamente elevados, nos podemos encontrar en situaciones de sobreactivación o estrés emocional. Éste es una respuesta de defensa del propio organismo ante una situación de amenaza. El propio organismo se prepara para poder afrontar aquella situación de la mejor manera posible. Sin embargo, si bien un cierto nivel de activación es útil y positivo para poder resolver y atender contenidos complejos y favorece el procesamiento cognitivo y el aprendizaje (estrés adaptativo o eustrés).Áunque cuando los niveles de activación se sostienen en el tiempo o la situación es demasiado intensa y no tenemos suficientes recursos para hacerle frente, el exceso de percepción de amenaza nos puede conducir a una situación de incertidumbre, miedo o pánico, la cual provocará una disminución de la capacidad de aprendizaje (estrés no adaptativo o distrés).

Es de elevada importancia poder aplicar metodologías pedagógicas que tengan en cuenta el funcionamiento de los procesos atencionales de los alumnos, puesto que, como se ha descrito, sin atención no se puede producir la adquisición y la consolidación de los nuevos aprendizajes.

2.2.2. Educación Emocional

En un análisis reciente del estado de la investigación educativa sobre las emociones, Pekrun (2005) señala la escasa atención que han recibido las emociones en los procesos educativos durante el siglo XX con dos notables excepciones: el estudio de la ansiedad relacionada con la evaluación y el rendimiento (exámenes, tests, etc.) y el estudio de la relación entre emoción y motivación, relacionada con el éxito y fracaso académico (culpa, orgullo, etc.). En su análisis, Pekrun reconoce el escaso conocimiento del que disponemos aún sobre la ocurrencia, frecuencia y fenomenología de las emociones en diferentes entornos de aprendizaje y, muy especialmente, en el aprendizaje en línea.

La relación emocional con nuevas herramientas y contenidos de aprendizaje supone una línea de estudio, especialmente interesante en relación con el *elearning* (Ekflides, 2006; Etchevers, 2005; Aires et al, 2006; Rebollo et al, 2008). Las experiencias educativas llevadas a cabo en entornos virtuales de aprendizaje, requieren una redefinición de los elementos organizativos del aprendizaje, en lo referente a:

- (a) los ***agentes involucrados*** (profesores y estudiantes),
- (b) los ***espacios*** donde se llevan a cabo las actividades formativas,
- (c) los ***tiempos*** y
- (d) las ***secuencias de aprendizaje*** (Pérez, 2002).

En este sentido, debemos tener en cuenta tanto los procesos implicados en la educación (enseñanza aprendizaje) como los actores que intervienen en dichos procesos (tutores estudiantes).

El ***proceso de aprendizaje*** implica en particular tres procesos cognitivos: la atención, la memorización y el razonamiento. Con respecto a cada uno de ellos, la capacidad cognitiva del estudiante depende de sus emociones (Frasson and Chalfoun, 2010). En un contexto de aprendizaje emocional, las emociones pueden ser utilizadas en los contenidos de aprendizaje para incrementar la atención del alumno mejorando su capacidad memorística y de razonamiento, de forma que las relaciones entre objetos o ideas se realizan más fácilmente y promueven la eficiencia y el rigor en la toma de decisiones y resolución de problemas (Isen 2000). El estudio de las resistencias, actitudes y emociones en relación con el uso de las tecnologías como recurso de aprendizaje, se muestra particularmente necesario para reducir los índices de abandono y fracaso que presentan los modelos de *elearning* (Cabrera et al. 2006). En general, estas emociones conducen a un proceso de pensamiento más creativo, flexible y divergente, mientras que las emociones negativas causan un pensamiento más lineal, convergente y secuencial (Pekrun, 2006).

En el ***proceso de enseñanza***, el tutor debe estar preparado para generar un dialogo efectivo con los participantes y entre los participantes. De modo que se favorezca el aprendizaje activo, la construcción e conocimiento cooperativo y/o colaborativo. El tutor ha de saber identificar sentimientos y emociones, controlar y ofrecer los modelos adecuados de expresión sobre todo cuando se trata de emociones negativas que suelen ser más difíciles de comunicar de una forma respetuosa. La inteligencia emocional del profesor influye considerablemente en la creación de un clima en el aula emocionalmente saludable, donde se gestionan de forma correcta las emociones y donde se pueden expresar sin miedo a ser juzgados ni ridiculizados (Ibarrola, 2000).

En definitiva, en este aspecto, se trata de conocer los estados emocionales que se ponen en juego en el aprendizaje en linea así como los comportamientos que estos procesos generan. De forma que nos permita explorar y profundizar en las relaciones entre emoción y entorno virtual, siendo de especial utilidad para describir cómo suceden y cómo son abordadas las emociones en la virtualidad con respecto a los distintos elementos que la componen: herramientas, docente y compañeros presentes en los procesos de aprendizaje de esta modalidad. Esta perspectiva permite comprender las relaciones entre emociones, su gestión y el aprendizaje resultante en estos entornos educativos.

2.3. Recursos Tecnológicos para el Aprendizaje

Las últimas investigaciones realizadas en entornos virtuales de enseñanza – aprendizaje muestran la importancia de tener en cuenta tanto las habilidades y capacidades cognitivas y afectivas que los estudiantes poseen o deben adquirir en dichos procesos; profundizar en nuevas formas de interacción que emulan y mejoran las habilidades de comunicación humana y estimulan el pensamiento crítico, mejorando el aprendizaje y de desarrollar entornos gráficos facultados por agentes virtuales que funcionan como tutores virtuales y que son capaces de interactuar con el alumno, siguiendo el modelo cara a cara humano, facilitando la comunicación.

Los avances realizados en el área, tanto de la inteligencia artificial como de la robótica, en la interacción hombre-máquina, se reflejan en el desarrollo de entornos gráficos, facultados por agentes virtuales que funcionan como tutores virtuales o profesores y son capaces de interactuar con el alumno siguiendo el modelo cara a cara humano con el fin de hacer frente a la comunicación (Beale and Creed, 2009; Frasson and Chalfoun, 2010). Lo cual refleja, el papel que puede jugar un tutor virtual afectivo resolviendo problemas, proporcionando consejos y explicaciones, dando soporte afectivo en la interacción con el alumno, favoreciendo el aprendizaje y exhibiendo contextualidad, continuidad y temporalidad.

Estudios recientes se centran en el desarrollo de aplicaciones en entornos gráficos habitados por agentes virtuales que, a modo de tutores o profesores virtuales, son capaces de interactuar con el alumno siguiendo el modelo de comunicación «*face to face*» humano. Para que una computadora sea capaz de interactuar con personas de forma natural, debe adquirir habilidades como inteligencia cognitiva, capacidades afectivas y de comunicación en lenguaje natural.

El tutor virtual debe mostrar ***inteligencia cognitiva*** respecto a los contenidos educativos. Estos no deben ser mostrados de una forma lineal y predeterminada, sino que el agente debe ser capaz de proporcionar la respuesta más adecuada para cada momento de la interacción y adaptar la transmisión de conocimientos a cada alumno, en función de su progresión durante la actividad. Los modelos basados en el conocimiento, permiten modelar tanto de forma supervisada como no-supervisada, el comportamiento del agente virtual, empleando algoritmos y métodos que emulan el funcionamiento de los sistemas cognitivos y emocionales humanos (como redes neuronales, lógica difusa o redes bayesianas).

El tutor debe ***responder al estado afectivo del usuario*** de la forma más empática y pedagógica, teniendo en cuenta el contexto emocional en cada instante. Un sistema capaz de percibir eventos afectivos en el usuario; de establecer una comunicación afectiva, que motive y acompañe al alumno durante el proceso de aprendizaje, presenta un gran potencial e interés para el desarrollo de nuevas aplicaciones educativas. Para ser completa, la comunicación afectiva debe ser bidireccional. Por una parte, el tutor virtual debe reconocer eventos afectivos en el usuario y reaccionar consecuentemente (por ejemplo, el tutor ofrecerá ayuda al usuario si detecta que está frustrado tras haber fallado muchas preguntas seguidas en un test; o el tutor puede dar una pista si el usuario está atascado en un ejercicio concreto; etc.). Por otra parte, el tutor virtual debe ser capaz de mostrar afecto. En particular, se deben modelar de forma especialmente cuidadosa, las expresiones faciales del agente virtual ya que, según estudios psicológicos, las expresiones faciales son el medio más potente, natural y directo que empleamos los seres humanos para comunicar nuestras emociones, valoraciones e intenciones. De acuerdo con Mehrabian (1972), las expresiones faciales contribuyen en un 55 % al efecto global del mensaje transmitido, por encima de la propia parte verbal del mismo, esta tan solo representa un 7 %. De este modo, aunque la modelización del cuerpo y las posturas del personaje virtual puedan ayudar a la comunicación, la correcta modelización del rostro determinará, en un altísimo grado, las capacidades afectivas finales del tutor virtual.

Por último, el tutor virtual debe estar dotado de ***capacidades de comunicación en lenguaje natural***. Para que el usuario se sienta cómodo interactuando con el agente virtual, es necesario permitirle una comunicación con él a través de lenguaje natural. El agente virtual debe de ser capaz de procesar el contenido del mensaje del usuario (a través de técnicas de Procesado del Lenguaje Natural (NPL)) computar una respuesta adecuada y responderle también a través de lenguaje natural.

Pero además, debemos tener en cuenta los efectos ya conocidos que estos entornos provocan en los alumnos a nivel afectivo y cognitivo. Un aprendiz experimenta una variedad de emociones al interactuar con un tutor virtual, de la misma manera que en el contexto del aprendizaje tradicional, un tutor humano puede influir en las emociones alumno con el objetivo de mejorar su eficiencia en el aprendizaje (Hargreaves, 2002). De manera similar, un tutor virtual puede ser visto como un participante emocional capaz de provocar emociones en el alumno. Por otra parte, éstas influirán fuertemente en sus capacidades cognitivas (Isen, 2000). Un agente virtual autónomo puede ser de incalculable valor cuando los estudiantes no reconocen que sus acciones no son óptimas o no son las apropiadas; en cuyo caso un agente virtual puede intervenir con consejos apropiados. Otras veces pueden encontrarse con situaciones que no son familiares y debido a la insuficiencia de conocimiento para afrontar la situación, se podrían ver beneficiados si tuvieran alguien que les guiara, contestara sus dudas o mostrara el procedimiento. De los estudiados hasta el momento tres son los efectos más característicos:

- *Effect Person* (Lester et al, 1997): La presencia de un agente en un entorno interactivo puede tener un efecto positivo en la percepción de la experiencia educativa de los estudiantes. Ejemplos: *Herman the Bug* (Lester et al, 1997); *Steve* (Johnson and Rickel, 2000); *AutoTutor* (Graesser et al, 2008).

- *Effect Proteo* (Yee and Bailenson, 2007): Los estudiantes pueden aprender porque están motivados por las características de sus avatares y quieren ser como ellos. En este caso, el papel del agente no es autoritario, sino fundamentalmente de apoyo emocional / social. La investigación de este efecto está más centrada en la inmersión en entornos 3D de juegos educativos. Ejemplos: *Troublemaker*

(Aimeur and Frasson, 1996); *Jake and Jane* (Arroyo et al, 2009).

- *Effect Protégé* (Chase et al, 2009): Los estudiantes hacen un mayor esfuerzo para aprender al tener que enseñar a su avatar lo que ellos han aprendido. El objetivo de estos agentes se basa en el paradigma «Aprender a Enseñar», esto significa que el estudiante aprende a enseñar al Agente los temas o conceptos que él ha aprendido. Ejemplos: *Betty* (Biswas et al, 2009)

En resumen, en este aspecto se trata de conocer las características de los entornos de aprendizaje, en los cuales, los avatares y los mundos virtuales son eficaces y apropiados, así como las características que tales entornos y herramientas necesitan tener para poder optimizar el proceso de enseñanza-aprendizaje.

Capítulo 3

Objetivos de la tesis

Basándonos en lo anteriormente expuesto, y desde un enfoque constructivista, los objetivos de esta tesis son mostrar las emociones que los alumnos sienten durante su proceso de aprendizaje colaborativo en entornos virtuales y cómo estas emociones influyen en su aprendizaje. Evaluando las emociones obtenidas, clasificándolas y observando su evolución dentro del periodo de tiempo que dure la acción formativa. Estudiando, además, para qué situaciones formativas, los tutores virtuales afectivos pueden resultar efectivos y apropiados. Determinando, finalmente, qué capacidades o habilidades deben tener los tutores virtuales para optimizar los procesos de aprendizaje de los alumnos. El resultado muestra que un enfoque integrado que incluye soluciones y estrategias metodológicas constructivistas para la detección e interpretación de la emoción se puede desarrollar y aplicar.

Tras un análisis detallado de los trabajos de investigación en curso en este campo, se puede concluir que las nuevas perspectivas y tendencias actuales para la mejora de la Inteligencia Emocional se articulan alrededor de dos grandes temas, «*Emotion Awareness in elearning*» y «*Emotional Feedback in elearning*» (Daradoumis et al, 2013a).

El problema de investigación que se ha desarrollado en esta tesis ha pretendido dar respuesta a algunas de las preguntas abiertas actualmente en torno a estos dos grandes temas, proponiendo un modelo conceptual de análisis de la emoción en un entorno CSCL y, en particular, en el discurso educacional (en concreto, en textos Wiki y en conversaciones síncronas como chats y asíncronas como foros) que tiene lugar en estos entornos. En esta línea:

- ***Problema de investigación 1:*** con respecto al «***Emotion Awareness in elearning***», nuestra investigación propone varias soluciones para identificar, por un lado, las emociones de los estudiantes en el discurso de forma no intrusiva y, por otro lado, proporcionar una representación gráfica del discurso que incluye las emociones de los estudiantes. Eso nos ha permitido desarrollar un medio importante para poder analizar como el conocimiento y compresión de los estados emocionales afecta al procesamiento de la información, a la calidad de la colaboración y a los resultados (rendimiento de aprendizaje del grupo).
- ***Problema de investigación 2:*** con respecto al «***Emotional Feedback in elearning***», se ha diseñado un prototipo que, basado en las conclusiones extraídas del problema anterior, facilite al profesor proporcionar «affective feedback» a los alumnos, guiarlos, orientarlos, ayudarlos, siempre de acuerdo con las necesidades y los sentimientos detectados.

A continuación se concretan los objetivos de esta tesis con respecto a los problemas de investigación anteriormente expuestos:

- **Objetivos en «Emotion Awareness in elearning»**
  - Detectar automáticamente, representar gráficamente emociones experimentadas por los estudiantes en procesos de aprendizaje colaborativo virtual (conversaciones, debates y wikis) y desarrollar una conciencia de grupo efectiva dinámica y con mayor rendimiento.
  - Analizar e interpretar las emociones individuales y grupales objetivamente en su contexto. Identificando causas emocionales e investigando el impacto de las emociones en su comportamiento, rendimiento, y experiencia de aprendizaje.
- **Objetivos en «Emotional Feedback in elearning»**
  - Descubrir en qué situaciones de aprendizaje un APT puede ser eficaz y apropiado, examinando el papel que juega en el diseño de contextos CSCL centrado en el estudiante.

- Permitir la autorregulación de la conducta individual y el desarrollo de actividades socio-cognitivas y socio-emocionales, en profesores y alumnos, proporcionando información contextualizada y personalizada, cognitiva y afectiva en el momento adecuado y en respuesta a la situación problemática.

Capítulo 4

Contribuciones al ámbito de investigación y limitaciones

Para dar una respuesta a los problemas de investigación planteados anteriormente, así como desarrollar los objetivos expuestos, a continuación se presentan las contribucciones de esta tesis entorno a los dos ámbitos de investigación en los que se enmarca esta tesis de acuerdo con las áreas de investigación del doctorado en Educación y TIC (elearning).

En el ÁMBITO DE LOS PROCESOS DE ENSEÑANZA-APRENDIZAJE, a nivel teórico-conceptual, ha sido necesario construir una base teórica sólida integrando y ampliando ideas y propuestas hacia una aproximación innovadora, a la vez que una aproximación innovadora que ha dado lugar a un modelo conceptual de análisis de la emoción. Dicho modelo centrado en contextos CSCL (Computer-Supported Collaborative Learning), aplica una extensión de la **Teoría de la Actividad** (AT) (Engeström et al., 1999) a un escenario que consiste en hacer que varios participantes (profesores y estudiantes) colaboren e interactúen con objetos específicos (texto y diálogo) mediante el uso de herramientas específicas de análisis de la emoción, para llevar a cabo actividades (creación de wiki, foros de debate y chats) de orientación específica. Dicho modelo incluye, además, el **factor tiempo** como una herramienta, para proporcionar al profesor y a los alumnos más control y flexibilidad en el desarrollo de sus respectivas tareas (Barber, 2010). Esta contribución se explica detalladamente en el artículo (Arguedas and Daradoumis, 2013) y constituye la **primera**

contribución de esta investigación al aprendizaje virtual.

Las herramientas específicas de análisis de la emoción, se utilizan dentro de este modelo extendido para diseñar escenarios de la AT en cada uno de los experimentos llevados a cabo (que incluye la información emocional y factor de tiempo) para el desarrollo de programas formativos basados en métodos tales como «Project-based Learning», «Problem-based Learning» or «Case-based Learning». Los escenarios se han configurado en un contexto «**blended learning**», con alumnos que participan tanto en clases presenciales como también en actividades de aprendizaje online en una plataforma de e-learning, como es el Moodle. El diseño y desarrollo de las actividades se ha llevado a cabo con la aplicación de una combinación novedosa de estrategias constructivistas como son la estrategia colaborativa «***JIGSAW***»para diseñar la solución de un problema planteado por etapas, respecto a la parte cognitiva de la actividad, así como la «***Disonancia Cognitiva***», para despertar y detectar emociones en las interacciones entre los diferentes usuarios (estudiante-profesor o alumno-alumno) durante las situaciones de intercambio de conocimientos que tienen lugar en las conversaciones en el aula virtual, respecto a la parte emocional del proceso de aprendizaje. Al provocar mediante conflictos cognitivos, la expresión de los posibles conflictos emocionales o estados afectivos de los estudiantes, que hemos dado en llamar «***Disonancia Emocional***». Esta contribución se explica detalladamente en el artículo (Arguedas and Daradoumis, 2013) y constituye la **segunda contribución** de esta investigación al aprendizaje virtual.

Además, se utilizan cuestionarios al inicio de la actividad de aprendizaje con el fin de construir un modelo emocional personalizado de cada uno de los alumnos. Esta contribución se explica detalladamente en el artículo (Arguedas and Daradoumis, 2013) y constituye la **tercera contribución** de esta investigación al aprendizaje virtual.

En el Ámbito de los Recursos Tecnológicos para el aprendizaje, ha sido necesario traducir este modelo conceptual en el diseño e implementación de un sistema computacional robusto, que capture e integre todas las ideas teóricas. Además ha servido como medio importante para testear y evaluar todo el proceso en situaciones reales de aprendizaje virtual, que integre una serie de herramientas con la intención de conseguir los objetivos de investigación propuestos.

Con respecto al primer tema objeto de nuestra investigación «***Emotion Awareness en elearning***», se ha desarrollado una herramienta de Análisis de Sentimientos para textos en español que nos permite extraer del discurso educativo los datos emocionales del proceso de enseñanza-aprendizaje llevado a cabo. Se han realizado dos versiones de dicha herramienta una de ellas basada en redes neuronales y la otra basada en lógica difusa integrando modelos categóricos y dimensionales de emoción así como un sistema Evento–Condición–Acción de reglas en base a la identificación de emociones realizada para extraer posibles estados emocionales. Esta contribución se explica detalladamente en el artículo artículo (Arguedas, Casillas, Xhafa, Daradoumis, Peña and Caballé, 2016) que constituyen la **cuarta contribución** de esta tesis. El análisis del estado emocional ha tenido en cuenta el contexto donde el aprendizaje se produce. Entendemos como contexto de aprendizaje toda la información pertinente relacionada con un grupo de alumnos que ha participado en la actividad de aprendizaje.

Además se ha proporcionado una representación gráfica de la estructura emocional del discurso en entornos de aprendizaje virtual y semipresencial, en cualquier espacio donde surgen las emociones (debates, chats, trabajo en equipo — por ejemplo, la creación de un wiki, una tarea de evaluación, etc—. Con este fin, se aplicará una extensión de la RST (Rhetorical Structure Theory), que fue aplicada originalmente en el Procesado del Lenguaje Natural y que se basa en el uso de relaciones coherentes entre dos unidades de texto adyacentes para analizar el discurso (texto y dialogo), cuyo proceso se ha automatizado mediante una Excel. Dicha representación ha sido presentada posteriormente tanto a alumnos como profesores para hacerles tomar conciencia de las emociones experimentadas durante la tarea. Esta contribución se explica detalladamente en el artículo (Arguedas, Daradoumis and Xhafa, 2016b) y que constituyen la ***quinta contribución*** de esta tesis.

Y con respecto al segundo tema objeto de nuestra investigación: «***Emotional Feedback in elearning***», se ha integrado nuestro modelo de clasificación emocional basado en lógica difusa (Fuzzy based classification model — FBCM) y el LMS Moodle donde se ha diseñado y desarrollado la actividad de aprendizaje en una aplicación web cliente–servidor con un avatar que se configuro con información cognitiva y emocional referente a la actividad que los alumnos llevaron a cabo sobre la plataforma Moodle integrada y a la que se aplicó el FBCM desarrollado en esta tesis El estudiante trabaja en el LMS, lleva a cabo su / sus tareas, colabora con sus compañeros mientras que, al mismo tiempo que él / ella puede interactuar con la APT de manera textual a través de la caja de edición situada en la parte inferior de la pantalla. El tutor pedagógico afectivo responde al estudiante con señales audibles y gestuales que han sido configuradas previamente, al tiempo que proporciona al estudiante la información que él / ella solicitado anteriormente. Esta contribución se explica detalladamente en el artículo (Arguedas, Xhafa, Casillas, Daradoumis, Peña and Caballé, 2016) y constituye la ***sexta contribución***.

Con respecto a las ***limitaciones*** detectadas en el desarrollo de esta investigación cabe destacar que en primer lugar, los experimentos llevados a cabo han dependido en gran medida de la disposición de los alumnos a involucrarse en las demandas del experimento, como por ejemplo, su voluntad de expresar sus emociones, aunque esto se haga de forma implícita a través de sus textos y conversaciones, o en otros casos, teniendo en cuenta el *feedback* del APT o la intervención misma del tutor humano.

En segundo lugar, respecto a la aplicación de las herramientas, por un lado, «*Sentiment Analysis*» en la mayoría de las aproximaciones no tiene en cuenta el significado emocional de las palabras ni construcciones lingüísticas que pueden afectar a la detección de la subjetividad, simplemente se basan en la aparición y la frecuencia de los términos; y por otro lado, la RST no se había aplicado nunca para el estudio/análisis de las emociones y hemos podido constatar que su representación solo tiene impacto y significación para el profesor.

Finalmente, hay que tener en cuenta el «ruido» de los datos producidos puesto que nuestro método no tiene porqué funcionar bien para cada estudiante y/o grupo, ya que depende de otros factores como por ejemplo, en el caso del grupo, de la configuración del mismo, de su estructura, perfil de sus miembros, intereses, etc.

En resumen, la aplicación de las herramientas descritas anteriormente proporciona conocimientos importantes acerca de cuándo determinados estados afectivos surgen y qué los causa. Por consiguiente, en respuesta a la detección de los estudiantes del estado afectivo y la presencia del tiempo, el tutor es capaz de proporcionar información adecuada a los estudiantes, hacerlos reaccionar a tiempo, guiarlos y dirigirlos de una manera apropiada. De esta manera, queremos ayudar a los estudiantes a mejorar su percepción del tiempo, su seguridad emocional y una participación más efectiva y fructífera en la experiencia de aprendizaje. Esto es más evidente cuando los alumnos llegan a ser capaces de salir de un estado afectivo negativo y entrar en uno más positivo en un momento particular de su proceso de aprendizaje.

Capítulo 5

Coherencia Contribución-Objeto de Investigación

En este apartado explicamos la evolución histórica de las contribuciones que han sido producto de este trabajo de tesis, lo que demuestra la coherencia entre las contribuciones y el objeto de investigación de la tesis. En primer lugar, se comenzó realizando una revisión crítica del estado del arte, de las investigaciones realizadas sobre la influencia de las emociones en el aprendizaje online y el tratamiento que se había realizado del tema hasta el momento. Dicha revisión fue desarrollada en el siguiente capítulo de libro:

Daradoumis, T. and Arguedas, M. (2013a). Studying the Suitability of Discourse Analysis Methods for Emotion Detection and Interpretation in Computer–mediated Educational Discourse. Innovative Methods and Technologies for Electronic Discourse Analysis. IGI Global Publishing, 2014, Hershey, Pennsylvania, USA, Ling, H. and Sudweeks, F. (Eds.), ISBN: 978-1-4666-4426-7, accessed May 09, 2013, pp. 119-143.

Durante la realización de la revisión del estado del arte, la doctoranda solicitó la participación al «Workshop on Tools and Technologies for Emotion Awareness in Computer–Mediated Collaboration and Learning (ARV 2013)». Dicho Workshop, de alto nivel y especializado en el tema de esta investigación de esta tesis, aprobó su asistencia tras la presentación del paper que detallamos a continuación.

Daradoumis, T. and Arguedas, M. (2013b). Paying attention to the learner's emotions in virtual collaborative learning. Alpine Rendez-Vous (ARV) Workshop on

Tools and Technologies for Emotion Awareness in Computer-Mediated Collaboration and Learning (ARV 2013). Villard-de-Lans, Vercors, France. January 28 - February 1, 2013. TELEARC & EATEL associations. $http://www.affective-sciences.org/$ $/system/files/webpage/Daradoumis\_Lafuente\_ARV2013.pdf$

Las conclusiones extraídas de la asistencia al mencionado Workshop donde se dieron cita investigadores pertenecientes a las últimas y más punteras investigaciones realizadas en el ámbito de investigación de esta tesis, se detallaron en un artículo presentado en el CISIS–2013 mostrando las últimas tendencias en Inteligencia Emocional hasta el momento, así como los dos campos de actuación en este tema «Emotion Awareness in elearning» y «Affective Feedback in elearning».

Daradoumis, T., Arguedas, M. and Xhafa, F. (2013a). Current Trends in Emotional elearning: New Perspectives for Enhancing Emotional Intelligence. In proceedings of the 7.th International Conference on Complex, Intelligent and Software Intensive Systems (CISIS–2013), Taichung, Taiwan, July 3-5, 2013, IEEE Computer Society, Los Alamitos, CA, USA. DOI: 10.1109/CISIS.2013.16, ISBN: 978-0-7695-4992-7, pp. 34-39.

En paralelo, y tras la realización del seminario «Time Factor in elearning» se propone un modelo conceptual de análisis de emocional para tratar los objetivos antes expuestos.

Este modelo conceptual aplica un escenario extendido de la Teoría de la Actividad que consiste en hacer que varios participantes (docentes y estudiantes) cooperen e interactúen con objetos específicos (tales como texto y el diálogo) a través del uso de herramientas específicas (APT, herramientas de análisis de la emoción) para llevar a cabo actividades de orientación específica. Dicho modelo se plasmó en la siguiente publicación:

Arguedas, M. and Daradoumis, T. (2013). Exploring learners$'$ emotions over time in virtual learning. eLC Research Paper Series, Issue 6. eLearn Center, Open University of Catalonia (UOC), Barcelona, Spain. ISSN: 2013-7966, pp. 29-39. $http://elcrps.uoc.edu/ojs/index.php/elcrps/article/view/1869/n6-arguedas$

Nuestro primer objetivo, con respecto a este modelo, fue el desarrollo y uso de un método de análisis del discurso para analizar las actividades de aprendizaje en colaboración con el objetivo de extraer las relaciones emocionales entre unidades del discurso y proporcionar una representación gráfica de la estructura emocional del discurso. Con todo lo anteriormente expuesto, en 2013 se comenzó a desarrollar un modelo de etiquetado de emociones en los textos del discurso educativo de los estudiantes mientras realizan sus tareas de aprendizaje en un entorno virtual. Para probar su efectividad se llevó a cabo un pequeño experimento que fue descrito en el artículo que detallamos a continuación y presentado al INCOS 2O13.

Daradoumis, T., Arguedas, M. and Xhafa, F. (2013b). Building Intelligent Emotion Awareness for Improving Collaborative elearning. In proceedings of the 5.th International Conference on Intelligent Networking and Collaborative Systems (INCoS 2013), September 9-11, 2013, Xi′an, China, IEEE Computer Society, Los Alamitos, CA, USA. DOI: 10.1109/INCoS.2013.49, ISBN: 978-0-7695-4988-0. pp. 281 - 288.

De igual manera, se desarrolló el plan de investigación, que fue presentado a la comisión académica, en marzo del mismo año. Durante el verano se diseño un caso de estudio que fue llevado a cabo en un instituto de secundaria de Zaragoza (España), para poner a prueba todo lo anteriormente expuesto con respecto al primer objetivo de la tesis, «Emotion Awareness in elearning». Toda la labor realizada se plasmó en el siguiente artículo, así como los resultados y las conclusiones encontradas.

Arguedas, M., Daradoumis, T. and Xhafa, F. (2014). Towards an Emotion Labeling Model to Detect Emotions in Educational Discourse. In proceedings of the 8.th International Conference on Complex, Intelligent and Software Intensive Systems (CISIS-2014), Birmingham, UK, July 2-4, 2014, IEEE Computer Society, Los Alamitos, CA, USA. DOI 10.1109/CISIS.2014.36, ISBN: 978-1-4799-4325-8, pp. 72-78.

Con las conclusiones y limitaciones obtenidas en el experimento anterior, se desarrolló a nivel conceptual una ontología que describiera los conceptos y procesos llevados a cabo biológicamente por nuestro sistema nervioso emocionalmente. Dicha ontología fue desarrollada en el siguiente paper:

Arguedas, M., Xhafa, F., Daradoumis, T. and Caballé, S. (2015). An Ontology about Emotion Awareness and Affective Feedback in elearning. In proceedings of the 7.th International Conference on Intelligent Networking and Collaborative Systems (INCoS 2015), Taipei, Taiwan. September 2-4, 2015. IEEE Computer Society, Los Alamitos, CA, USA. DOI 10.1109/INCoS.2015.78, ISBN: 978-1-4673-7695-2, pp. 156-163.

Asímismo, se desarrolló un nuevo caso de estudio con respecto al informe obtenido de nuestro caso de estudio anterior y que dio lugar no solo a la ontología sino al diseño de un nuevo caso de estudio cuyos resultados se han plasmado en las dos publicaciones que se mencionan a continuación:

Arguedas, M., Daradoumis, T. and Xhafa, F. (2016a). Analyzing how emotion awareness influences students motivation, engagement, self-regulation and learning outcome. Educational Technology and Society, Special Issue on «Intelligent and Affective Learning Environments: New Trends and Challenges», ISSN: 1176-3647, 19 (2), 87-103. [indexed in ISI SCI, 2015 IF = 1.104, Q2 in EDUCATION and EDUCATIONAL RESEARCH area].

Arguedas, M., Daradoumis, T. and Xhafa, F. (2016b). Analyzing the effects of emotion management on time and self-management in computer-based learning. Computers in Human Behavior (CHB), 63, 517-529. ISSN: 0747-5632. Elsevier, doi: 10.1016/j.chb.2016.05.068, October 2016. [indexed in ISI/SSCI, 2015 IF = 2.880, Q1 (21/129) in PSYCHOLOGY, MULTIDISCIPLINARY areas].

Además, se planteó una estancia de investigación en la Universidad de Guadalajara México con el Dr. Luis A. Casillas para el inicio del desarrollo de la ontología mencionada anteriormente y que dio lugar a dos patentes internacionales, de las cuales una de ellas fue puesta a prueba y los resultados iniciales así como el modelo de lógica difusa que se configuró dio lugar a la siguiente publicación:

Arguedas, M., Casillas, L., Xhafa, F., Daradoumis, T., Peña, A. and Caballé, S. (2016). A Fuzzy-based Approach for Classifying Students′ Emotional States in Online Collaborative Work. In proceedings of the 10.th International Conference on Complex, Intelligent and Software Intensive Systems (CISIS-2016), Fukuoka, Japan, July 6-8, 2016, IEEE Computer Society, Los Alamitos, CA, USA. DOI 10.1109/CISIS.2016.141, ISBN: 978-1-5090-0987-9, pp. 61-68.

Posteriormente, con las conclusiones extraídas de este trabajo y de los anteriores se llevó a cabo un nuevo experimento, en el que nuestro modelo ha sido puesto a prueba incluyendo tanto la herramienta de lógica difusa desarrollada anteriormente como un primer prototipo de un Affective Pedagogical Tutor (APT) y que ha sido descrito en el siguiente artículo, publicado en la revista SoftComputing.

Arguedas, M., Xhafa, F., Casillas, L., Daradoumis, T., Peña, A. and Caballé,

S. (2016). A model for providing emotion awareness and feedback using fuzzy logic in online learning. Soft Computing. ISSN: 1432-7643. Springer. Published online, 20 October 2016.[indexed in ISI SCI, 2015 IF = 1.630, Q2 in COMPUTER SCIENCE, ARTIFICIAL INTELLIGENCE and INTERDISCIPLINARY APPLICATIONS areas].

Capítulo 6

Resultados obtenidos, Discusión y Conclusiones Finales

El trabajo de esta tesis destaca por la definición de un marco conceptual bien fundado y argumentado que ha conducido en la implementación de un sistema completo para proporcionar conciencia y retroalimentación emocional utilizando lógica difusa en un entorno que incluye aprendizaje en línea.

6.1. Resultados Obtenidos

Entre los resultados obtenidos más destacados apuntamos:

- La capacidad del sistema de proporcionar ***conciencia emocional*** y analizar los efectos de este tipo de conciencia en varios aspectos relacionados con el aprendizaje. En particular, se analizó:
    - a) cómo la conciencia emocional puede influir en la *motivación*, el *compromiso*, la *autorregulación* y los *resultados* del aprendizaje de los estudiantes.
    - b) qué tipo de efectos puede tener la gestión de las emociones sobre la *gestión del tiempo* (time management) y la *autogestión* (self-management) en el aprendizaje por ordenador, en particular, sobre competencias como la *implicación conductual y cognitiva*, la *autorregulación* y el *rendimiento*

de los estudiantes, así como sobre la *reducción de la carga de trabajo* de los estudiantes.

- La capacidad del sistema de proporcionar ***retroalimentación emocional*** y analizar cómo ésta puede:
  - a) estar influida por el mecanismo de conciencia emocional la cual puede cambiar la actitud del maestro así como su retroalimentación (identificando, al mismo tiempo, las competencias que los profesores tienen que tener a fin de lograr un resultado positivo para cambiar el estado afectivo y cognitivo de los estudiantes) en una modalidad «blended learning» a largo plazo.
  - b) influir la gestión del tiempo (time management) y la gestión de uno mismo (self-management) en términos de implicación conductual y cognitiva, autorregulación y rendimiento de los estudiantes.

La importancia de estos dos resultados se demuestra por el hecho que han sido publicados en dos revistas con factor de impacto alto (pertenecientes en los cuadriles Q1 y Q2).

La ***estancia de investigación*** que la doctoranda realizó en la Universidad de Guadalajara México, dio lugar a ***dos patentes internacionales***, de las cuales una de ellas fue puesta a prueba, dando lugar a un modelo para el control de las emociones de los estudiantes utilizando la lógica difusa en un entorno de elearning, con el objetivo de proporcionar tanto conciencia de la emoción como retroalimentación afectiva a los estudiantes a través de un tutor pedagógico afectivo en línea (APT). Para probar y validar nuestro modelo se llevo a cabo un experimento en una situación real de aprendizaje virtual colaborativa.

Este resultado dio lugar a una publicación que fue enviada a otra revista de factor de impacto Q2.

6.2. Discusión

A continuación presentamos un análisis de los resultados obtenidos mediante una breve descripción de los experimentos que se han llevado a cabo para poder conseguir y justificar estos resultados. En todos los experimentos, hemos separado los estudiantes que participaron en dos grandes grupos: el grupo de control (CG) donde no se utilizó nuestro sistema y el grupo experimental (EG) en que se aplicó nuestro método y se utilizó nuestro sistema, con el fin de ver las diferencias en los resultados que podrían haber entre los dos grupos.

6.2.1. Primer Experimento

En este trabajo de investigación se trataron los resultados 1a) y 2a).

Esta investigación se llevo a cabo con la hipótesis y preguntas de investigación que se detallan a continuación.

6.2.1.1. *Hipótesis:*

«Aumentando la conciencia de la emoción de los alumnos, sus resultados de aprendizaje mejoran en relación con su motivación, el compromiso y la autorregulación. Además, mediante el aumento de la conciencia de la emoción de los profesores, su actitud y la retroalimentación se hacen más eficaces y oportunas».

6.2.1.2. *Preguntas de Investigación:*

- (1) ¿Hay alguna correlación significativa entre la conciencia de emoción de los estudiantes y su motivación y compromiso con su aprendizaje?

- (2) ¿Hay alguna correlación significativa entre la conciencia de emoción de los estudiantes y su autorregulación y sus resultados de aprendizaje?

- (3) ¿Hay alguna correlación significativa entre el conocimiento del profesor sobre las emociones de sus estudiantes y su actitud y su retroalimentación?

Todo el análisis y las respuestas a estas preguntas de investigación se encuentran detallados en el artículo Arguedas, Daradoumis and Xhafa (2016a) que está publicado en la revista con factor de impacto Educational Technology and Society ISI SCI, 2015 IF = 1.104, Q2. De forma breve, hacemos aquí una especial mención en los siguientes aspectos:

Respecto a la ***primera pregunta de la investigación***, los estudiantes de ambos grupos mostraron altos niveles de motivación en virtud de la existencia de emociones positivas como la alegría, así como fuerte concentración en la tarea y hacia la solidaridad con sus compañeros. Sin embargo, en presencia de emociones no tan positivas (como tristeza/vergenza, miedo/ansiedad y enojo/frustración), los estudiantes de Grupo de Control (CG) sintieron una alta tendencia al aburrimiento y al enfrentamiento, lo que les llevó a perder la motivación para continuar sus actividades, mostrando baja solidaridad con sus compañeros y una falta de confianza en sí mismos.

Por el contrario, los estudiantes del Grupo Experimental (EG) cuando sintieron emociones negativas como la ansiedad o la frustración, poco más de la mitad de ellos se sentían inseguros, pero fueron capaces de mantener al menos un mínimo de interés en la actividad. Esto fue aún más evidente cuando el sentimiento fue la tristeza. Por otra parte, cuando estos estudiantes que se sintieron tristes, fueron capaces de recibir y proporcionar sugerencias y opiniones de una manera constructiva, de este modo buscaron la manera de mantener su participación durante el desarrollo de la actividad.

Como consecuencia de lo anterior, concluimos que existe una ***correlación positiva significativa*** entre la ***conciencia emoción*** y la ***motivación*** de los estudiantes y su ***participación*** en el aprendizaje.

En lo que se refiere a la ***segunda pregunta de investigación,*** los estudiantes del CG obtuvieron las puntuaciones más bajas en la auto-regulación de todos los aspectos explorados, es decir, en una participación más oportuna en la actividad, en los cambios necesarios que podrían conducir hacia un comportamiento más positivo más rápido, en una participación más oportuna para crear y compartir conocimiento, en un mejor rendimiento antes de que sea demasiado tarde, y en una distribución más equilibrada de la carga de trabajo.

Por el contrario, los estudiantes del EG consiguieron unos resultados mucho mejores en la auto-regulación de todos estos aspectos, diferenciándose en las habilidades de autorregulación como la participación oportuna y gestión eficaz de los conocimientos que obtuvieron una puntuación por encima del 90 % y que han contribuido a mejorar el trabajo en equipo y un desarrollo más eficaz de la actividad.

Teniendo en cuenta los resultados de aprendizaje, los estudiantes del EG obtuvieron mejores resultados que los estudiantes CG. Una de las razones para la consecución de un mejor resultado del aprendizaje se basa en la construcción de alto grado de solidaridad y cohesión en el grupo, lo que favorece la confianza y el compromiso entre los miembros del grupo. ésto posee un gran potencial en la sensibilización de las emociones que experimentan por sí mismos y con respecto a sus compañeros durante toda la actividad, proporcionando a los estudiantes una herramienta importante para el desarrollo de la competencia emocional intragrupal y así construir un equipo emocionalmente inteligente.

En consecuencia, podemos afirmar que existe una ***correlación positiva significativa*** entre la ***conciencia de la emoción*** y la ***autorregulación*** de los estudiantes y sus ***resultados*** del aprendizaje.

En lo que se refiere a la ***tercera pregunta de investigación***, el profesor tuvo la capacidad de ser consciente de las emociones de los estudiantes tanto en CG y EG. De los resultados anteriores, se observa que el maestro interviene y es compatible con ambos grupos en casi todos los aspectos que hemos explorado. En cuanto al CG, ya que los estudiantes de este grupo no eran conscientes de sus emociones, necesitaron mucho más apoyo y retroalimentación afectiva de su maestro. Por esta razón, la actitud de los maestros se ha considerado crucial en todos los aspectos.

Especialmente, la retroalimentación afectiva del maestro ha consistido principalmente en metodologías dinámicas para motivar a los estudiantes a aprender, alentando el trabajo individual y a compartirlo con el equipo a la vez que se motiva a los estudiantes a ofrecer consejos y sugerencias a sus compañeros. En un segundo nivel, el profesor ha facilitado la discusión de grupo para manejar las emociones y los sentimientos de los alumnos cuando había un conflicto en el grupo. En cuanto al EG, ya que los estudiantes eran conscientes de sus emociones todo el tiempo, enfatizaron más su necesidad de pedir apoyo emocional por parte del profesor cuando había un conflicto en el grupo.

El resultado de la intervención del maestro hizo que estos estudiantes se sintieran felices, motivados, concentrados, seguros, mostrando una mayor solidaridad con sus compañeros, se alentó a los estudiantes a que dieran más sugerencias y opiniones, así fue más capaz de resolver los conflictos.

En conjunto, este análisis demuestra que existe una ***correlación positiva y significativa*** entre la ***conciencia de la emoción*** y la ***actitud del maestro y su retroalimentación***.

6.2.2. Segundo Experimento

El propósito de este estudio fue conseguir los resultados 1b) y 2b).
La hipótesis planteada para este estudio fue:

6.2.2.1. *Hipótesis:*

«Aumentar la capacidad de los alumnos para gestionar las emociones mejor y más eficazmente influirá positivamente en sus competencias en el tiempo y su autogestión en un contexto de aprendizaje basado en ordenador y, más concretamente, en su capacidad de aprendizaje en términos de compromiso conductual y cognitivo, su autorregulación y sus logros».

6.2.2.2. *Preguntas de Investigación:*

- (1) ¿Cómo está relacionada la conciencia emocional con el tiempo y la autogestión y con ello el rendimiento de los estudiantes en términos de implicación conductual y cognitiva, de autorregulación y de sus logros?
- (2) ¿Cómo está relacionada la retroalimentación emocional con el tiempo y la autogestión y con ello el rendimiento de los estudiantes en términos de

implicación conductual y cognitiva, de autorregulación y de sus logros?

- (3) ¿Reduce la gestión emocional y del tiempo la carga de trabajo de los estudiantes?

Todo el análisis y las respuestas a estas preguntas de investigación se encuentran detallados en el artículo Arguedas, Daradoumis and Xhafa (2016b) que está publicado en la revista con factor de impacto Computers in Human Behavior ISI/SSCI, 2015 IF = 2.880, Q1. De forma breve, hacemos aquí una especial mención en los siguientes aspectos:

Respecto a la ***primera pregunta de la investigación***, todos los estudiantes (en ambos grupos control y experimental) estaban contentos con las actividades de aprendizaje que tenían que llevar a cabo, ya que experimentaron altas emociones positivas, estados mentales y comportamientos durante la ejecución de estas actividades.

Nuestros resultados muestran que la relación entre la conciencia de la emoción (EA) y la autogestión del tiempo (TM) se refiere a las competencias de orientación conductual y los logros. Los estudiantes en el grupo experimental (EG), que están dotados de la capacidad de EA, tienden a cambiar su comportamiento hacia uno más positivo, así como a establecer metas para alcanzar y medir su progreso en mayor medida que los estudiantes en el grupo control (CG).

Sin embargo, los estudiantes del EG solo muestran un desempeño ligeramente mejor en competencias tales como la participación cognitiva (involucrarse para crear y compartir conocimientos) y la autorregulación (de su participación en la actividad) que los estudiantes CG.

Esto puede ser debido a varios factores que deben ser más investigados y analizados y que puede estar relacionados con un perfil propio de los alumnos: los estilos de aprendizaje, nivel de inteligencia emocional, así como sus habilidades innatas de autocontrol tiempo. Otros factores que pueden estar relacionados con la maduración, el temperamento y el aprendizaje de estrategias específicas para la regulación del comportamiento y de las emociones, entre otros.

Las emociones positivas (como felicidad/satisfacción), los estados mentales (como la motivación y la concentración) y comportamientos (como ser de apoyo y útiles) tuvieron efectos positivos significativos sobre el compromiso conductual y los logros. En cuanto a las otras dos competencias («compromiso cognitivo» y «autorregulación»), sin duda tuvieron un efecto más positivo sobre la participación cognitiva, aunque «ser útil» (Dar Sugerencias / Opiniones) tuvo un impacto más positivo en la autorregulación.

Por el contrario, las emociones negativas (como la tristeza/vergenza, el miedo/ansiedad y la ira/frustración) tuvieron un efecto negativo en la autorregulación, especialmente en el caso de la ira/frustración. De hecho, este último tuvo un efecto negativo en todas las demás competencias (de compromiso conductual y cognitivo y logro). Aquí, es notable observar que el miedo/ansiedad tuvo un impacto muy positivo en el rendimiento, ya que los estudiantes en esta situación fueron «empujados» para aumentar los esfuerzos con el fin de lograr sus objetivos.

En cuanto a los estados emocionales negativos (tales como inseguro y aburrido), el primero de ellos tuvo un impacto más positivo en todas las competencias, en especial por sus logros, mientras que el segundo tuvo un impacto bastante negativo en todas las competencias, siendo más desfavorable para el logro.

Por último, los comportamientos negativos (tales como hacer oposición) tuvieron un impacto más negativo en todas las competencias, a excepción de la autorregulación, lo que significa que la autorregulación puede estar ligeramente favorecida por enfrentar situaciones. Hemos observado que esto era especialmente evidente en los estudiantes del EG (que eran conscientes de su comportamiento).

En lo que se refiere a la ***segunda pregunta de investigación***, nuestros resultados muestran que la retroalimentación afectiva del maestro (TAF) añade un nuevo elemento a las competencias de autogestión del tiempo (TM) y en particular, TAF contribuye al rendimiento de los estudiantes en términos de compromiso conductual y cognitivo, así como en términos de sus logros. De hecho, los estudiantes en el grupo experimental (EG), que recibieron retroalimentación afectiva del maestro, estaban involucrados en crear y compartir conocimientos sobre el tiempo en un grado mayor que los estudiantes en el grupo control (GC).

En cuanto a la última competencia, la autorregulación, se observó que TAF sin duda ayudó a los estudiantes del EG más que a los estudiantes del CG en auto-regular su participación en la actividad, sin embargo, la diferencia entre los dos grupos no era digna de mención. Esto significa que TAF debería ir acompañado de otras capacidades de los maestros, como el hecho de que los profesores deben estar familiarizados con los factores que influyen en la capacidad del alumno para auto-regularse.

En el primer caso, la promoción de la auto-regulación en las aulas, los maestros deben enseñar a los estudiantes los procesos auto-regulación que facilitan el aprendizaje. Del mismo modo, los profesores deben proporcionar estrategias efectivas de instrucción para fomentar la auto-regulación en el aula.

Asimismo, se ha demostrado que la motivación puede tener un impacto fundamental en los resultados académicos de los estudiantes y que sin motivación, la autorregulación es mucho más difícil de lograr. En este sentido, el profesor en nuestro experimento, exploró de qué forma la motivación está relacionada con la autoregulación. Como se ha demostrado, el hecho de que el maestro fuera estimulante para los estudiantes en sus trabajos individuales, para que compartan dichos trabajos con sus equipos, tuvo un efecto positivo en la auto-regulación de los estudiantes.

Esta conclusión se ve reforzada aún más por el hecho de que cuando los estudiantes estaban motivados eran más receptivos a auto-regular su participación en la actividad. Otras intervenciones de los maestros que tuvieron un efecto significativo en el desempeño de los estudiantes en términos de compromiso conductual y cognitivo, así como los logros, fueron la asistencia emocional a los estudiantes cuando había un conflicto en el grupo y la resolución de preguntas a los estudiantes, ofreciendo consejos y sugerencias.

En cuanto a la ***tercera pregunta de la investigación***, los resultados mostraron que esta pregunta tuvo una respuesta positiva en todos los aspectos. Más concretamente, en cuanto a la gestión emocional (que incluye tanto la conciencia emoción y la retroalimentación emocional), nuestro estudio demostró que las emociones positivas (como la felicidad/satisfacción), los estados mentales (como la motivación y la concentración) y comportamientos (como ser de apoyo y útiles) tuvieron efectos positivos significativos sobre aligerar la carga de trabajo de los estudiantes.

Además, se demostró que la retroalimentación afectiva del maestro también ha contribuido a aligerar la carga de trabajo de los estudiantes. Esto incluye todo tipo de retroalimentación que utiliza el maestro, aunque una mención especial se debe hacer con respecto a la retroalimentación dada al trabajo individual de cada estudiante animándoles y motivándoles para compartirlo con su grupo, presentando los resultados más destacados.

Esto significa que la motivación puede ser considerada como un medio importante para reducir la carga de trabajo del estudiante. En cuanto a gestión del tiempo, nuestro trabajo ha demostrado que los estudiantes del EG fueron capaces de hacer un mejor manejo de su carga de trabajo que los estudiantes del CG.

6.2.3. Tercer Experimento

En este trabajo se consiguió el objetivo 3.

6.2.3.1. ***Hipótesis:***

«Proporcionando una conciencia de la emoción, así como una retroalimentación tutorial afectiva en línea automática a los estudiantes, estos mejoran sus resultados de aprendizaje a tiempo».

6.2.3.2. *Pregunta de Investigación:*

- (1) ¿Hay alguna correlación significativa entre la conciencia emoción de los estudiantes, la retroalimentación del tutor virtual afectivo y sus resultados de aprendizaje?

Todo el análisis y la respuesta a esta pregunta de investigación se encuentran detallados en el artículo Arguedas, Xhafa, Casillas, Daradoumis, Peña and Caballé (2016) que ha sido publicado en la revista con factor de impacto Soft Computing ISI SCI, 2015 IF = 1.630, Q2 y que actualmente se encuentra bajo revisión. De forma breve, hacemos aquí una especial mención en los siguientes aspectos:

Este trabajo demostró que esta pregunta tuvo una respuesta positiva en todos los aspectos en el grupo experimental en el que, a los estudiantes se les facilitó tanto representaciones gráficas para la toma de conciencia de sus emociones, como retroalimentaciones emocionales. En particular, demostramos que todas las *características dimensionales* de la emoción, tales como la satisfacción, la intensidad y el control emocional. Además de las y *características categóricas* de la emoción, como la alegría, la tristeza, la confianza y la anticipación, así como los estados emocionales derivados de dichas características categóricas como el amor, el optimismo y el fatalismo, tuvieron efectos positivos significativos en un mejor el rendimiento del aprendizaje en el EG.

En particular, el experimento mostró que la conciencia emocional de las características dimensionales tuvo un gran impacto positivo en los resultados de la actividad de aprendizaje de los estudiantes en el EG, mientras que en el grupo de control sólo la característica dimensional intensidad se comprobó que tenía una relación positiva implícita con el resultado obtenido de los estudiantes.

Además, las características categóricas (como la alegría, la tristeza, la confianza y la anticipación) tuvieron efectos positivos significativos sobre el rendimiento de actividad para los estudiantes del EG. Así mismo se informó que no hay correlación significativa a los estudiantes CG.

Por último, una vez nuestro tutor pedagógico afectivo (APT) entró en juego, se obtuvieron estados emocionales tales como el amor, el optimismo y el fatalismo que tuvieron efectos positivos significativos sobre el rendimiento de los estudiantes del EG. En contraste, se informó que no hubo ninguna correlación significativa para los estudiantes CG.

6.3. Conclusiones Finales

Los resultados de este trabajo mostraron que, siendo conscientes de sus emociones, los estudiantes llegan a ser más conscientes de su situación, lo que les impulsa a cambiar y adaptar su comportamiento para el beneficio de su grupo.

Por otra parte, se observó que su capacidad de aprendizaje también mejoró en relación con su motivación, su compromiso y su autorregulación.

También, fue explorada la actitud los profesores cuando estos son conscientes del estado emocional de sus estudiantes. Se observó que el maestro intervinió para apoyar a todos los estudiantes de manera consciente y a tiempo. En el caso de los estudiantes del grupo experimental, la retroalimentación afectiva del maestro llegó a ser más focalizada, cuando se sabía que los estudiantes eran conscientes de una situación emocional difícil o se encontraban en un caso de conflicto socio-cognitivo.

Además, nuestros resultados mostraron que «***la conciencia emocional***» está bastante relacionada con «***el tiempo y la autogestión***» en el sentido de que, cuando los estudiantes son conscientes de sus emociones, pueden mejorar su capacidad de aprendizaje en términos de implicación conductual y de logros de aprendizaje y, en parte, en términos de implicación cognitiva y auto-regulación.

Así mismo, «***la retroalimentación emocional***» está más estrechamente relacionada con «***el tiempo y la autogestión***», lo que significa que, cuando un maestro proporciona información afectiva explícita a los estudiantes, esta puede mejorar su rendimiento de aprendizaje en términos de implicación conductual y cognitiva, así como de los logros de aprendizaje y, en parte, en términos de auto-regulación, ejerciendo mayor ponderación sobre la motivación como un factor crucial, siendo esta un factor para mejorar la auto-regulación.

En esta misma línea, se demostró también que una gestión emocional y del factor tiempo, explicita y eficaz puede reducir la carga de trabajo de los estudiantes.

Aplicando nuestro nuevo modelo basado en la lógica difusa, se ha visto de forma muy clara que una representación gráfica más visual, explícita y enfocada de las emociones dimensionales y categóricas presentada a los estudiantes del grupo experimental (EG) después de cada tarea produjo resultados de aprendizaje mucho mejores que los del grupo control (GC).

De hecho, las nubes de palabras generadas ayudaron a los estudiantes a ser conscientes de sus emociones, a superar posibles situaciones de tristeza, a mejorar la anticipación y la confianza y a cumplir con su tarea con éxito.

En cuanto a la función y la influencia del APT, los resultados mostraron que la retroalimentación afectiva tenía realmente un efecto muy positivo en los estudiantes de EG.

De hecho, el apoyo ofrecido por la APT, a través de expresiones emocionales y consejos, ayudó a los estudiantes a superar por ejemplo, estados emocionales tales como el fatalismo y a aumentar su optimismo, lo que les llevó a realizar sus actividades con éxito.

Por último, nuestro trabajo reveló también algunas ***preguntas abiertas*** dignas de una investigación adicional. En cuanto al ***primer eje de nuestra investigación***, la conciencia emocional, una pregunta abierta importante es *¿en qué forma la conciencia de la emoción puede ser reforzada con el fin de lograr una implicación cognitiva eficaz y auto-regulación? ¿Qué otras competencias en «el factor tiempo y la* *autogestión» puede fortalecer la conciencia de la emoción y mejorar el rendimiento de los estudiantes?*

En cuanto al ***segundo eje de nuestra investigación***, la retroalimentación emocional, *¿cómo «la gestión del tiempo y la autogestión» pueden ser combinadas con otros factores que pueden mejorar la auto-regulación?* Además, *¿qué otras competencias en «el factor tiempo y la autogestión» pueden proporcionar retroalimentación emocional y por lo tanto mejorar el rendimiento de los estudiantes?* También, se necesita una investigación más profunda para corroborar la relación positiva entre la «gestión emocional y del tiempo» con la carga de trabajo del estudiante, examinando cómo esto está afectando también a la carga de trabajo del profesorado.

En cuanto al diseño de un tutor virtual pedagógico afectivo (APT) que pueda proporcionar retroalimentación a los estudiantes de forma automática o semiautomática, se pueden plantear cuestiones importantes acerca de:

- (1) el tipo de APT que es más apropiado y eficaz a varias situaciones de aprendizaje colaborativo centradas en el estudiante;
- (2) la comprensión de los factores que llevan a los estudiantes a permanecer en el mismo estado afectivo negativo para un determinado período de tiempo (lo que les puede conducir a un deterioro de su capacidad de aprendizaje, fracaso, e incluso la retirada de los estudios);
- (3) el establecimiento de criterios que indicaran cual es el momento más adecuado en el que APT pudiera intervenir y controlar la situación afectiva de los estudiantes;
- (4) el tipo de retroalimentación afectiva que mejor se adapta a las necesidades de los estudiantes y a su estado afectivo.

En este sentido, la investigación se puede centrar en la ***mejora de nuestro sistema de reglas difusas*** con el fin de lograr tres objetivos importantes en los entornos virtuales de aprendizaje: *aumentar su precisión*, *incluir más estados emocionales* en sus capacidades de observación, y *procesar y analizar* los estados emocionales de los estudiantes *en tiempo real*.

Capítulo 7

Contribuciones Presentadas

7.1. Autores

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7.3. Artículos en Revistas JCR

7.3.1. (1) Referencia

1. Arguedas, M., Daradoumis, T. and Xhafa, F. (2016a). Analyzing how emotion awareness influences students" motivation, engagement, self-regulation and learning outcome. Educational Technology and Society, Special Issue on «Intelligent and Affective Learning Environments: New Trends and Challenges», ISSN: 1176-3647, 19 (2), 87-103. [indexed in ISI SCI, 2015 IF = 1.104, Q2 in EDUCATION and EDUCATIONAL RESEARCH area].

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Analyzing How Emotion Awareness Influences Students' Motivation, Engagement, Self-Regulation and Learning Outcome

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ABSTRACT

Considering social and emotional competence in learning, *emotion awareness* aims to detect the emotions that students show during their learning interactions and make these emotions explicit to them. Being aware of their emotions, students become more conscious of their situation, what may prompt them to behavioral change. The main goal of this work is to analyze the effects of emotion awareness, supported by specific teaching strategies, on students' motivation, engagement, self-regulation and learning outcome in long-term blended collaborative learning practices. A bilateral goal also involves an initial study that explores the way emotion awareness affects teacher's attitude and feedback as well as the competencies that teachers need to have in order to achieve a positive change on students' affective and cognitive state. To this end a quasi-experimental study was designed with high school students. The results of this study show that when students are aware of their emotions and guided by specific teaching strategies, their learning performance improves in relation to their motivation, engagement and self-regulation. Likewise, when teachers are conscious of students' emotional state their attitude and feedback become more effective and timely.

Keywords

Emotion awareness, Affective feedback, Affective learning, Motivation, Engagement, Self-regulation and learning outcome

Introduction

Emotion awareness and *affective feedback* emerge as important factors that influence learning process and learners' performance (Calvo & D'Mello, 2010; Feidakis et al., 2013). To foster effective learning, teachers employ a student-centered constructivist approach, involving different cognitive and collaborative learning strategies (Rosenshine, 1997; Daradoumis & Kordaki, 2011). The combination of all these four elements leads to an integrated framework that aims to improve students' motivation, engagement and self-regulation, and ultimately students' learning outcome and skills during their collaborative learning processes (see Figure 1).

Figure 1. Key factors that lead to effective learning outcome and skills

Among cognitive strategies, cognitive dissonance is the perception of incompatibility between two cognitions, which can be defined as any element of knowledge, including attitude, emotion, belief, or behavior (Pintrich et al., 1993). The cognitive dissonance strategy holds that contradicting cognitions serve as a driving force that compels the mind to acquire or invent new thoughts or beliefs, or to modify existing beliefs, in order to reduce the amount of dissonance (conflict) between cognitions (Aïmer, 1998; Lee et al., 2003). According to Piaget's theory (1967; 1980), when a child recognizes cognitive conflict (disequilibrium), this recognition motivates him or her to attempt to resolve the conflict and thus change his/her cognition, attitude, or behavior. Piaget called the process of resolving conflict "equilibration." According to him, equilibration refers to the process of self-regulation that maintains a balance between "assimilation" and "accommodation." Several educational interventions have been designed to foster dissonance in students by increasing their awareness of conflicts between prior beliefs and new information (e.g., by requiring students to defend prior beliefs) (Guzzetti et al., 1993). Moreover, according to Aronson (1995) and Graesser et al., (1996), creating and resolving cognitive dissonance can have a powerful impact on students' motivation for learning. In our case-study, we use cognitive dissonance to increase ***motivation*** for learning as well as foster students' inner ***self-regulation***.

Among collaborative learning strategies, Jigsaw is a popular and extensively used strategy in which the members of the class are organized into "jigsaw" groups (Aronson & Patnoe, 2011; Perkins & Saris, 2001; Bratt, 2008). Students are then reorganized into "expert" groups containing one member from each jigsaw group. The members of the expert group work together to learn the material or solve the problem, then return to their "jigsaw" groups to share their learning. This process helps students improve their listening, communication, and problem-solving skills. In addition, the teacher's role in the jigsaw is to facilitate learning and support students by encouraging them to help each other and to ensure that everyone in their group understands the material and will be confident presenting it to his/her group. Jigsaw strategy is an efficient way for students to become ***engaged*** in their learning, be individually accountable for their learning and achieve more ***self-regulation*** in their performance (DiDonato, 2013). This strategy maximizes interaction and establishes an atmosphere of cooperation and respect for other students.

Regarding emotion awareness, the main objectives of emotional education can be summarized as: gaining a better understanding of emotions and identifying the emotions of others (Pekrun, 2005); developing the ability to identify and control our own emotions (Goleman, 1995; Kort & Reilly, 2002); developing the ability to self-motivate and change negative emotions into positive (Gardner, 2006); and, managing conflict in a positive way (D'Mello et al., 2007; Baker et al., 2007). Consequently, the ability of students to perceive emotion was positively related to peer bonding (Han & Johnson, 2012), whereas empathy with the learner's emotion would increase their motivation in learning (Pérez-Marín & Pascual-Nieto, 2013).

Based on emotion awareness information, the teacher can provide affective feedback ensuring in that way students' emotional safety and their engagement or persistence in the learning experience (Feidakis et al., 2014). An adequate (timely, situation-aware and personal) affective feedback can cause a change in the students' emotional state, which can redirect their focus of attention and can induce a change in the way they think, act and interact with others, as well as it can regulate their behavior in a learning situation (Shen et al., 2009; Bahreini et al., 2012). In this sense, it is also important to know the emotional competencies that teachers should have in order to provide the most adequate affective feedback to their students (Jennings, 2011). There are also specific types of affective feedback that use emotional reactions, such as applause, to reduce negative emotional states especially in male university students in specific educational situations such as computerized self-assessment testing (Liu et al., 2015).

In the recent years, research in *emotion awareness* in learning situations has focused on several issues that include: capturing the sentiments and the emotional states enclosed in textual information so that opinions and emotions embedded in them could play a key role in decision-making processes (Loia & Senatore, 2014); examining the impact of the so-called academic emotions (enjoyment, anxiety, pride, anger, hope, shame/fault, relief, boredom, hopelessness) on students' ways of thinking and information processing (Pekrun et al., 2011); embedding emotion awareness into e-learning environments "ecologically," by avoiding introducing obtrusiveness or invasiveness in the learning process (Feidakis et al., 2014); identifying patterns of emotional behavior by observing motor-behavioral activity (facial expressions, voice intonation, mouse movements, log files, sentiment analysis, etc.) (Heylen et al., 2005; Davis et al., 2008); using affect grid to measure emotions in software requirements engineering (Colomo-Palacios et al., 2011); studying motivation in work environments in the IT field (Sinha et al., 2014).

As discussed above, previous literature emphasizes the need of both emotion awareness and teacher's affective feedback as two important elements in students' learning process. However, there is not yet an extensive analysis of the relationship between emotion awareness and students' motivation, engagement, self-regulation and learning outcome as well as emotion awareness and teacher's attitude and feedback. The significance of this study is to bridge this gap and provide a detailed analysis on the way emotion awareness affects students' motivation, engagement, self-regulation and learning outcome if it is coupled with cognitive and collaborative learning strategies (such as cognitive dissonance and Jigsaw strategy respectively) which play an important role in reinforcing students' motivation for learning, engagement and self-regulation. So far, no other study has conducted such an integrated analysis of all these key factors that lead to effective learning outcome and skills, as it is depicted in Figure 1. To this end, we first set our research goal, hypothesis and questions. Then, we present our case study description, and we explain how we address these questions through a real experiment with high school students. Next, we present the results of the experiment, we discuss the obtained results concerning the research questions set and we check the validity of our research hypothesis. Finally, we provide our conclusions with suggestions for future research.

Research hypothesis and aims

Goal: The main goal of this work is to analyze the effects of emotion awareness on students' motivation, engagement, self-regulation and learning outcome in long-term blended collaborative learning practices. A bilateral goal also involves an initial study that explores the way emotion awareness affects teacher's attitude and feedback as well as the competencies that teachers need to have in order to achieve a positive change on students' affective and cognitive state.

Hypothesis: "Increasing the emotion awareness of learners, their learning outcomes improve in relation to their motivation, engagement and self-regulation. Besides, by increasing the emotion awareness of teachers, their attitude and feedback become more effective and timely."

Independent Variable: X = emotion awareness

Dependent Variables: Y = students' motivation in learning
Z = students' engagement in learning
H = students' self-regulation
J = learning outcome
K = affective feedback

Research questions

(1) Is there a significant correlation between students' emotion awareness and their motivation and engagement in learning?
(2) Is there any significant correlation between students' emotion awareness and their self-regulation and learning outcome?
(3) Is there any significant correlation between teacher's awareness about students' emotions and his/her attitude and feedback?

Methodology

Case study description

In this work, we were based on an emotion analysis model (Arguedas & Daradoumis, 2013) that integrates the four concepts mentioned before, that is, emotion awareness, affective feedback, cognitive strategies and collaborative learning strategies within an Activity Theory Framework (Engeström et al., 1999). This framework describes a problem based learning scenario where participants interact with learning objects by means of a specific cognitive strategy, such as cognitive dissonance, and a specific collaborative learning strategy, such as Jigsaw, in order to carry out goal-oriented activities.

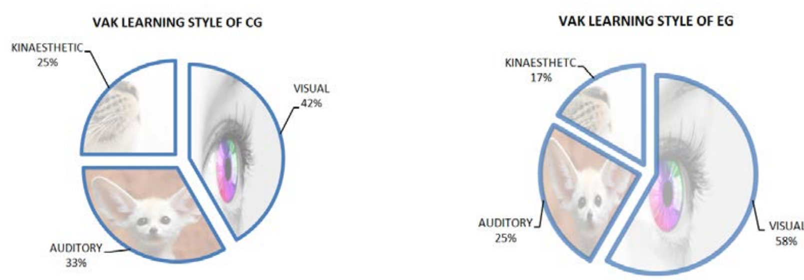
In parallel, we also employed a discourse analysis method, based on the work of Arguedas et al. (2014), to analyze text and conversation generated by students collaboratively in order to identify and represent the students' emotions that take place during these activities in a non-intrusive way. This information is shown to both teacher and students. This provides the teacher with the necessary emotion awareness in regard of the way students' emotions appear and evolve over time, which enables him/her to offer students cognitive and affective feedback.

Participants

This experiment was carried out with a class of twenty-four fourth-year high school students, taking an introductory Computer Science course, using the Moodle platform. We divided students in six groups of 4 members and we chose three of these groups as the experimental group (EG) and the rest as the control group (CG). All students worked in a collaborative activity based on the Jigsaw strategy for 15 class sessions (5 weeks). All students (18 girls (75%) and 6 boys (25%)) had the same characteristics and background, and the election of CG and EG was done completely randomly. Students in the EG were informed for the emotions they experimented during the activity, so they were emotion aware all the time. In contrast, students in the CG had not any emotion awareness facilities.

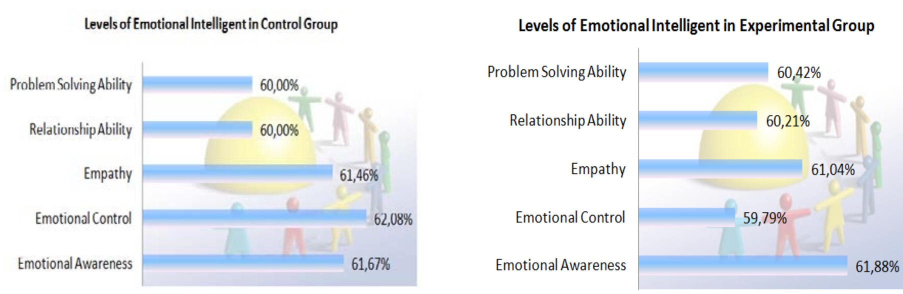
At course presentation, all students were informed of their preferred learning style and their emotional intelligence level by having them take specific tests at the beginning of the activity. At the beginning of the activity, to acquire students' learning styles, students answered a questionnaire based on VAK Learning Styles' Questionnaire of Lynn O'Brien (1990). In addition, to measure the initial level of students' emotional intelligence we used a questionnaire based on PEYDE's Questionnaire (Gallego & Gallego, 2004).

As regards students' learning styles, in the EG, 58% of them were visual, 25% auditory and 17% kinesthetic (Figure 2 (b)), whereas in the CG, 42% of the students were visual, 33% auditory and 25% kinesthetic as shown in Figure 2 (a).



(a) (b)

Figure 2. Graphical representation of students' VAK Learning Style in (a) CG and (b) EG



(a) (b)

Figure 3. Graphical representation of students' Emotional Intelligent Levels in (a) CG and (b) EG

Towards the levels of students' emotional intelligence, in the EG the results were a 60.42% in Problem Solving Ability, 60.21% in Relationship Ability, 61.04% in Empathy, 59.79% in Emotional Control and 61.88% in Emotional Awareness (Figure 3 (b)). While in the CG, the results were a 60.00% in Problem Solving Ability, 60.00% in Relationship Ability, 61.46% in Empathy, 62.08% in Emotional Control and 61.67% in Emotional Awareness as shown in Figure 3 (a).

Procedure and data collection

The scenario included a collaborative learning activity which was implemented following the Problem-Based Learning method and the Jigsaw collaborative strategy. The topic of the activity was “Introduction to Internet” and it was carried out in the Moodle environment.

Based on the Jigsaw collaborative strategy, the learning activity was divided in ten stages which in turn were grouped around five tasks to facilitate their implementation as shown in Figure 4. For each task, the teacher provided all the necessary resources (documents and tools). Data was collected in the texts and dialogues produced by students during their group work. The teacher guided and gave support to the learning activity, by providing appropriate affective and cognitive feedback and encouraged the students to participate actively in building their knowledge.

Figure 4. Tasks of the learning activity design

To extract emotions from discourse created by students in virtual spaces (Wiki, chats and forum debates), we first used a sentiment analysis tool developed by Jurado and Rodriguez (2015). Then, we applied an extension of the Rhetorical Structure Theory (RST) tool (Arguedas et al., 2014) in order to obtain a graphical representation of the emotional structure of discourse. Through this, we managed to provide both teacher and students with means to be aware of the students’ emotions and their evolution over time in a non-intrusive way. In the end of the learning activity, we used a questionnaire that has been designed with both open-ended and closed-ended questions, taking our research hypothesis and questions into account.

More specifically, discourse (text and conversation) has been divided into segments which were analyzed in order to discover and show all the emotions that appear in them. With regard to Wiki text, division was carried out according to the intentional structure of the text (Grosz & Sidner, 1986); that is, each segment conveys a specific goal which is the result of the contribution issued by each group member. In regard of dialogue, divisions were carried out at two levels, first at the exchange level and then at the move level inside each exchange. Doing so, we created a clear association between the intentional and the emotional structure of discourse in both modes (text and dialogue). All segments were numbered sequentially and we refer to them as units of analysis. Both Wiki text and conversation were analyzed segment by segment by applying first Sentiment Analysis and then the extended RST. The obtained outcomes are displayed graphically, as shown in an example of a Wiki text in Figures 5 and 6.

1. ACTIVITY: Explain and document the subject "Introduction to Internet"

2. TASKS ASSIGNMENT

(2.1) "First, our group has to establish the color codes that each of its members will use. Second, we have to split up in pairs and each couple will be in charge of two topics of the assigned activity, so we will manage to equally share the theoretical and practical parts. Let's go boys!!!", said Cristina.

(2.2) Cristina and Pedro– "We take care of the task *What is internet?* and of the task *Technical elements and how Internet works*" "I choose red" said Cristina. "I choose blue" said Pedro.

(2.3) Antonio and Pablo – "We take care of the task *Historic evolution of Internet* and of the task *The digital world: What services does Internet provide?*" "I choose orange!!!" said Antonio "then I choose green!!!☺"said Pablo.

(2.4) "Planning is ready, let's do this!" – Pablo says.

3. TASK 1: What is internet?

(3.1.) "Internet is a global system of interconnected computer networks that use the Internet protocol suite (TCP/IP) to link several billion devices worldwide. It is a network of networks that consists of millions of private, public, academic, business, and government networks of local to global scope, linked by a broad array of electronic, wireless, and optical networking technologies." – Pedro says.

(3.2.) "Don't forget to write down the source, Pedro!" – Cristina says.

(3.3.) "Oh! You're right Cristina. https://en.wikipedia.org/wiki/Internet" – Pedro says

4. TASK 2: "Historic evolution of Internet"

(4.1)"Here we have a timeline: http://www.w3.org/2005/01/timelines/timeline-2500x998.png" - Pablo says

(4.2) "Wow! That's cool Pablo! : D" – Antonio says

5. TASK 3: "Technical elements and how internet works"

(5.1) "This video explains how internet works and which are its technical elements: https://www.youtube.com/watch?v=7_LPdttKXPc" – Cristina says.

(5.2) "Easy peasy! :P" – Pedro says

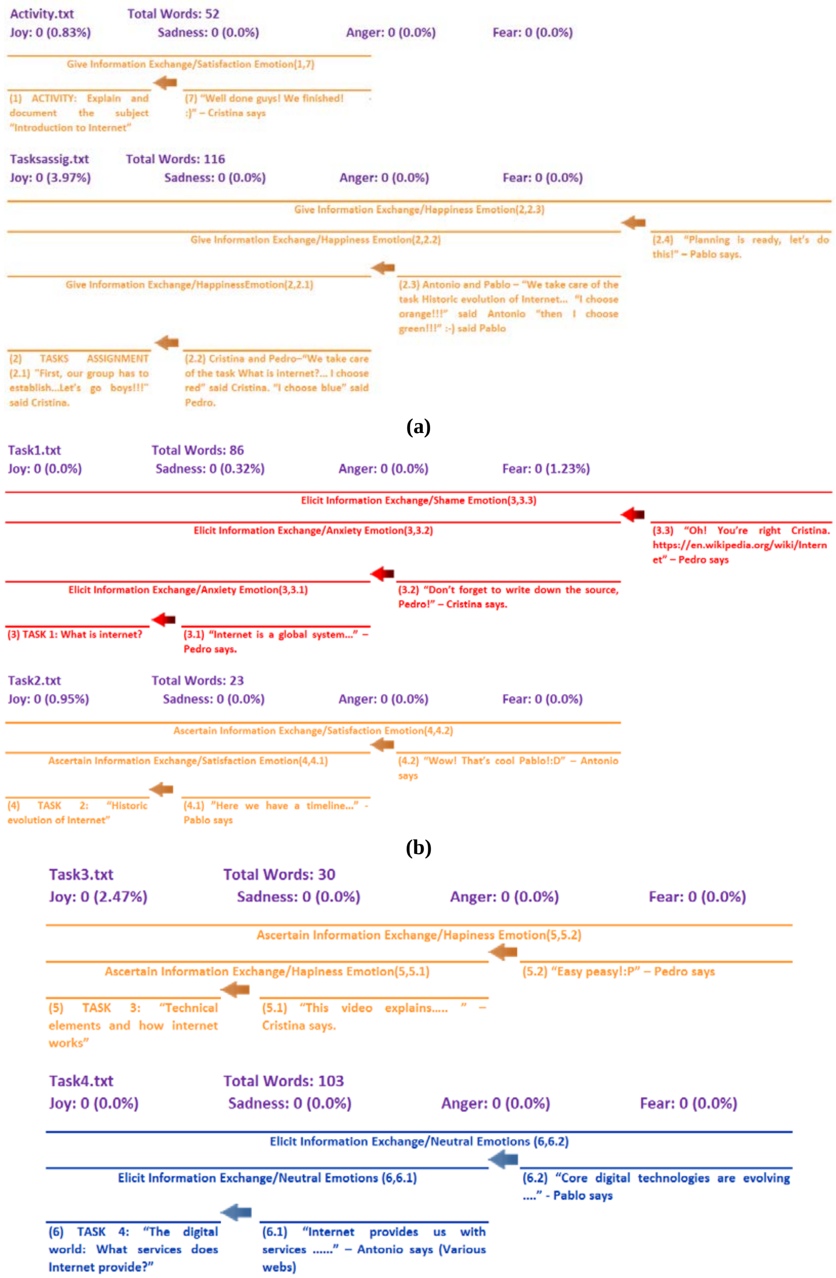
6. TASK 4: "The digital world: What services does Internet provide?"

(6.1) "Internet provides us with services such as: Electronic mail (e-mail), world wide web, file transfer protocol (ftp), chat rooms, mailing lists, instant messaging, chats, news groups, remote access, file sharing, streaming media, internet telephony (VoIP), online gaming, etc." – Antonio says (Various webs)

(6.2) "Core digital technologies are evolving and converging rapidly, fueled by real-time, real-world data, driving us toward a Knowing Society and creating the foundation for an avalanche of innovative software platforms and other digital tools available and affordable to anybody and everybody, everywhere, virtually for any purpose" - Pablo says (https://www.eifonline.org/digitalworld2030.html)

7. "Well done guys! We finished! ☺" – Cristina says

Figure 5. Text of wiki



(c)

Figure 6. Emotions detected in the text (wiki) and graphical representation of the emotional structure of the text (wiki)

Let's explain both Figures in more detail. Initially, a "give-information" exchange is initiated by move 1 and presents the activity topic. This exchange can be considered as successfully completed only when a final supporting move (move 7) is provided at the end. In this exchange, the predominant emotion is *joy* (*happiness/satisfaction*). In order to implement the activity, in segment 2, a group member (Cristina) initiates a "give-information" exchange with move 2.1 in which she explains how the task topics will be assigned and organized within the group. The exchange is completed by three consequent supporting moves (2.2, 2.3 and 2.4) contributed by the other group members. Here again, the predominant emotion is *joy* (*happiness/satisfaction*). Next, each pair of students works on its task.

The first task is initiated through a question in segment 3 in the form of an "elicit-information" exchange. This exchange is completed by three supporting moves (3.1, 3.2 and 3.3), contributed by both members of the pair. Here, the predominant emotion is *anxiety* expressed by one of the members (move 3.2), followed by *shame* expressed by the other member (in the beginning of move 3.3). The second task is set up as a problem in segment 4 in the form of an "ascertain-information" exchange and is resolved by one of the members of the pair (move 4.1), whereas the other member (move 4.2) confirms the given solution. Here, the predominant emotion is *joy* (*happiness/ satisfaction*). Task 3 is again set as a problem ("ascertain-information" exchange) in segment 5 and is resolved as before (through moves 5.1 and 5.2). Here again, the predominant emotion is *joy* (*happiness/satisfaction*). Finally, task 4 is presented as a question in segment 6 in the form of an "elicit-information" exchange. Here, both members of the pair provide complementary answers (moves 6.1 and 6.2) which complete the exchange goal successfully. In this case, no obvious emotions are expressed by either member; so, their emotional behavior here is characterized as neutral.

Data analysis

Our goal was to obtain both quantitative and qualitative data in order to measure and evaluate learners' emotional state concerning the following units of analysis:

- Emotion Awareness (EA)
- Affective Feedback (AF)

As regards EA, the questionnaire was composed of four questions that included 16 items classified into four categories, using a five-point Likert-type scale ranging from 1 (Almost never) to 5 (Almost always) and two open-ended questions requiring qualitative answer. As concerns AF, the questionnaire was composed of two questions that included 5 items, using a five-point Likert-type scale ranging from 1 (Almost never) to 5 (Almost always) and one open-ended question requiring qualitative answer. All the questionnaire items are shown in Figure 7.

Labels	Item
	EMOTION AWARENESS
4.1.EA	Happiness/Satisfaction
4.2.EA	Sadness/Shame
4.3.EA	Fear/Anxiety
4.4.EA	Anger/Frustration
5.1.EA	Motivated
5.2.EA	Concentrated
5.3.EA	Unsafe
5.4.EA	Bored
6.1.EA	Student has shown Solidarity
6.2.EA	Student has given Suggestions/Opinions
6.3.EA	Student was in Opposition to
10.1.EA	Student self-regulates his participation in the activity on time
10.2.EA	Student changes her behavior (towards more positive) faster
10.3.EA	Student gets involved to create and share knowledge on time
10.4.EA	Student improves his performance before it's too late
10.5.EA	Student lightens her workload
	AFFECTIVE FEEDBACK
8.1.AF	Teacher has used dynamic methodologies that have motivated me to learn
8.2.AF	Teacher has attended my feelings and emotions when there was a conflict in the group
8.3.AF	Teacher has facilitated group discussion to manage emotions
8.4.AF	Teacher has encouraged and motivated my individual work, sharing it with the team
8.5.AF	Teacher has resolved my questions and offered advice and suggestions

Figure 7. The questionnaire items

Regarding the statistical techniques employed in the analysis of the questionnaire data, we used descriptive statistics, calculating relative frequencies (%), as well as graphics to represent reality objectively. We also used bivariate correlation and analysis of variance to find relationships between the variables under study for each of the questions of our study.

Results

Reliability statistics

To ensure the reliability of data collection, we applied the Cronbach's alpha coefficient as well as the skewness and kurtosis for each variable that was examined in order to check for multivariate normality. In this sense, the absolute values of skewness and the absolute values of kurtosis did not exceed a univariate skewness of 2.0 and a univariate of kurtosis of 7.0; as such, we assumed that there was no critical problem regarding multivariate normality. Finally, the results of descriptive statistics obtained are shown in Table 1.

Cronbach's alpha is considered to be a coefficient of reliability (or consistency). A reliability coefficient of .70 or higher is considered "acceptable" in most social science research situations. All values of Cronbach's alpha in Table 1 are higher than .70, which reinforces the reliability of our test scores.

Table 1. The Cronbach's alpha coefficient and descriptive statistics of EA and AF, in CG and EG

	CG						EG					
	Cronbach's alpha coefficient (EA)			Cronbach's alpha coefficient (AF)			Cronbach's alpha coefficient (EA)			Cronbach's alpha coefficient (AF)		
	.720			.743			.771			.835		
	Emotion awareness (EA)											
	Mean	*SD*	Variance	Skewness	Kurtosis	CA(*)	Mean	*SD*	Variance	Skewness	Kurtosis	CA(*)
4.1.EA	3.55	1.126	1.269	-.276	-.767	.697	3.58	.962	.925	-.363	-.273	.667
4.2.EA	1.65	.971	.943	1.570	1.988	.733	1.65	.860	.740	1.086	.173	.660
4.3.EA	1.37	.758	.575	2.883	10.022	.712	1.62	.825	.681	1.391	1.560	.666
4.4.EA	2.27	.936	.877	.202	-.828	.751	2.20	1.054	1.112	.930	.703	.671
5.1.EA	3.43	1.015	1.029	-.165	-.281	.673	3.70	1.020	1.041	.190	-.149	.645
5.2.EA	3.35	1.087	1.181	-.256	-.209	.711	3.42	.944	.891	-.689	-.004	.624
5.3.EA	1.53	.873	.762	1.240	1.506	.719	1.10	.911	.829	.829	-.109	.665
5.4.EA	2.82	1.112	1.237	.070	-.605	.726	2.40	1.108	1.227	.687	.102	.814
6.1.EA	3.32	1.000	1.000	.264	-.496	.701	3.57	.890	.792	-.357	.141	.645
6.2.EA	3.25	1.159	1.343	-.173	-.575	.682	3.64	.986	.973	.013	.296	.665
6.3.EA	2.23	1.212	1.470	.772	-.240	.708	2.60	1.153	1.329	.297	-.559	.825
10.1.EA	3.10	.969	.939	.025	-.006	.701	3.18	.792	.627	.293	.919	.627
10.2.EA	3.03	.956	.914	-.068	-.327	.696	3.42	.962	.925	-.346	-.010	.627
10.3.EA	3.13	.892	.795	.175	-.217	.707	3.18	.892	.796	.217	-.052	.622
10.4.EA	3.33	1.036	1.073	-.245	-.231	.665	3.35	.954	.909	-.402	-.151	.630
10.5.EA	3.17	1.181	1.395	.112	-.815	.700	3.25	1.052	1.106	-.073	-.379	.613
	Affective feedback (AF)											
	Mean	*SD*	Variance	Skewness	Kurtosis	CA(*)	Mean	*SD*	Variance	Skewness	Kurtosis	CA(*)
8.1.AF	3.13	.833	.694	.288	.449	.558	3.32	.854	.729	.177	-.521	.821
8.2.AF	2.97	1.057	1.118	-.199	-.578	.760	3.28	1.180	1.393	-.130	-.829	.794
8.3.AF	2.75	1.002	1.004	-.203	-.611	.621	2.92	1.154	1.332	.031	-.571	.809
8.4.AF	3.70	.889	.790	.189	-1.011	.547	3.88	1.156	1.336	-.078	-1.213	.798
8.5.AF	3.70	1.109	1.231	-.527	-.766	.556	3.77	1.198	1.436	-.570	-.794	.785

Note. CA(*): Cronbach's alpha if element is deleted.

The values obtained from the descriptive statistics performed are described as follows:

With regard to Emotion Awareness (EA):

- Students' Emotions (4.1.EA – 4.4.EA): The mean exceeded the value of three (3.0) in the items 4.1.EA (Happiness/Satisfaction), obtaining the values 3.55 in the CG and 3.58 in the EG.
- Students' Mental States (Motivation) (5.1.EA - 5.4.EA): The mean exceeded the value of three (3.0) in the following items: 5.1.EA.-Motivation (CG 3.43 – EG 3.70) and 5.2.EA.-Concentration (CG 3.35 – EG 3.42).
- Students' Behaviors (Engagement) (6.1.EA – 6.3.EA): The mean exceeded the value of three (3.0) in the following items: 6.1.EA-Solidarity (CG 3.32 – EG 3.57) and 6.2.EA-Provide Suggestions (CG 3.25 – EG 3.64).
- Attitude changes experienced by students (self-regulation skills) (10.1.EA – 10.5.EA): The mean exceeded the value of three (3.0) in all items in both groups; however, all item values in EG are higher than the ones in CG.
- From these results, at first glance EG students experienced higher mental states, behaviors and attitude changes than CG students. This indicates that Emotion Awareness, supported by specific teaching strategies, is strongly related to students' motivation, engagement and self-regulation.

With regard to Affective Feedback (8.1.AF – 8.5.AF):

- The mean exceeded the value of three (3.0) in the items 8.1.AF (3.13), 8.4.AF (3.70) and 8.5.AF (3.70) in the CG and in the items 8.1.AF (3.32), 8.2.AF (3.28), 8.4.AF (3.88) and 8.5.EA (3.77) in the EG.

Here, we see that EG students benefited more from teacher's attitude and affective feedback than CG students did.

Pearson's correlations

Once we gathered the data obtained in the questionnaires, we calculated the *Pearson correlation coefficient* for the different variables to answer our research questions.

Regarding the first research question. We have correlated EA (X) with students' motivation in learning (Y) and students' engagement in learning (Z). To this end, we have used the data gathered in items 4, 5 and 6. The results obtained are shown in Table 2 and are presented graphically in Figures 8 and 9.

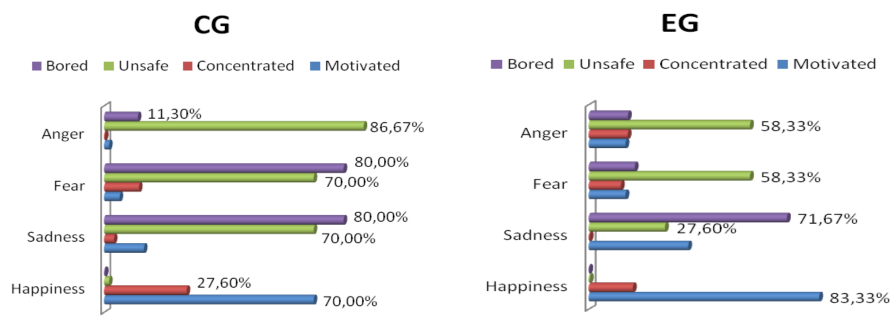
Table 2. Pearson correlation coefficient (n = 60) for research question 1

	CG				EG			
	4.1.EA	4.2.EA	4.3.EA	4.4.EA	4.1.EA	4.2.EA	4.3.EA	4.4.EA
				Motivation				
5.1.EA	.215*	-.033	.275*	-.213	.285*	.080	.107	-.003
5.2.EA	.212*	-.235	-.117	-.227	.228*	.241	.078	.017
5.3.EA	.059	.404**	.340**	-.260*	-.026	.221	.322**	.-228*
5.4.EA	-.243	.473**	.222	.227	-.191	.256*	-.182	.133
				Engagement				
6.1.EA	.490**	-.320*	-.267*	-.110	.561**	-.069	.093	.040
6.2.EA	.230	-.041	.202	.000	.245	.302*	-.144	-.101
6.3.EA	.140	.344**	.606**	.138	.114	-.058	-.253	-.086

Note. $^{*}p$ = .05; $^{**}p$ = .01.

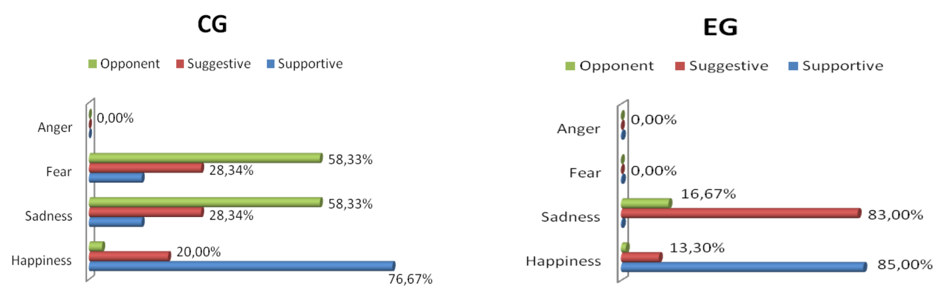
As regards motivation, in the EG, taking into account that students had EA, when they felt joy (happiness), they were highly motivated (83.33%). However, when they experienced sadness they were bored (71.67%), but at the same time they tried to maintain their motivation to work. As concerns fear/anxiety and anger/frustration, these emotions led them to an unsafe/uncertainty mood (58.33%). In the CG, taking into account that students had no EA, when they experienced joy, they were motivated (70.00%) in the task. However, when emotions such as sadness and fear/anxiety appeared, they felt unsafe (70.00%) and bored (80.00%), whereas they showed a high tendency to opposition and disagreement, thus losing interest to continue developing their activities. In the case of experiencing anger or frustration, students of the CG felt unsafe (86.67%), i.e., they had a strong lack of self-confidence.

As regards engagement, in the EG, when students experienced joy, they had a supportive behavior (85.00%) with peers. When they experienced sadness, they made suggestions and gave their opinion (83.33%) to their peers. Fear and anger did not present any correlation. In the CG, when students experienced joy they maintained a supportive behavior - solidarity (76.67%) with peers. But when they felt sadness and fear, they showed low solidarity as well as opposition (58.33%) to the suggestions of their peers.



(a) (b)

Figure 8. Correlation between students' emotions and their motivation in learning in (a) CG and (b) EG



(a) (b)

Figure 9. Correlation between students' emotions and their engagement in learning in (a) CG and (b) EG

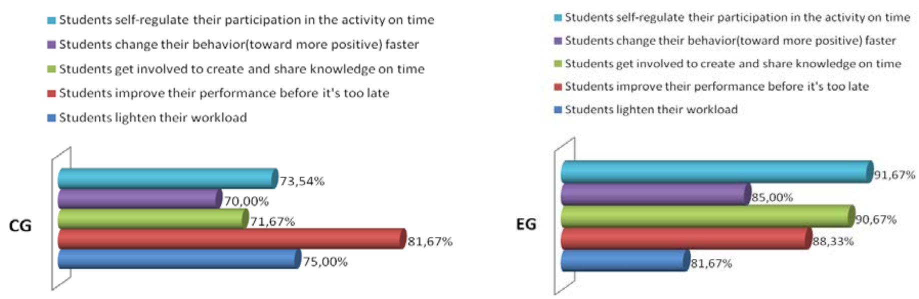
Regarding the second research question. We have correlated EA (X) with students' self-regulation (H) and learning outcome (J). To this end, as concerns H, we have used the data gathered in items 4, 5, 6 and 10. The results obtained are shown in Table 3 and are presented graphically in Figure 10. In relation to J, we have employed the final mark assigned to each task and the final mark obtained at the end of the activity.

Table 3. Pearson correlation coefficient (*n* = 60) for research question 2

	4.1.EA	4.2.EA	4.3.EA	4.4.EA	5.1.EA	5.2.EA	5.3.EA	5.4.EA	6.1.EA	6.2.EA	6.3.EA
						CG					
10.1.EA	.399**	-.070	-.212	-.329*	.300*	.143	.176	-.014	.492**	.174	-.136
10.2.EA	.235	-.078	.006	-.010	.299*	.005	.121	.074	.432**	.191	.139
10.3.EA	.213	-.082	.002	-.124	.310*	.213	.125	-.026	.275*	.180	-.108
10.4.EA	.537**	-.067	.316*	-.320*	.315*	.437**	.194	.010	.338**	.466**	.207
10.5.EA	.236	-.199	-.164	.128	.278*	.271*	.071	.037	.471**	.266*	.055
						EG					
10.1.EA	.191	.046	-.124	-.045	.355**	.372**	-.013	-.143	.583*	.345**	-.193
10.2.EA	-.029	.077	-.052	.000	.325*	.478**	.045	.060	.453*	.194	-.290*
10.3.EA	.288*	.151	.074	-.076	.426**	.511**	.114	-.007	.290*	.225	-.257*
10.4.EA	.014	.069	.216	.098	.399**	.481**	.094	-.279*	.352**	.488**	-.271*
10.5.EA	.004	.173	.308*	.199	.295*	.457**	.042	.000	.496**	.288**	-.308*

Note. $^{*}p$ = .05; $^{**}p$ = .01.

As regards "students' self-regulation," EG students felt more motivated (86.33%) as well as more concentrated to the task (90.00%). Moreover, they showed more solidarity (85.00%) to their peers as well as more willingness to making suggestions (83.33%). All this allowed students to self-regulate their participation in the activity on time (91.67%) as well as to change to a more positive behavior faster (85.00%), a fact that allowed them to be constructive and cooperative when they were facing socio-cognitive conflicts that occurred among the members of the group, due to the application of the cognitive dissonance strategy, and thus achieve the desired conceptual change more effectively. Furthermore, when students experienced joy (81.67%) they felt more involved to create and share knowledge on time (90.67%). As students were feeling more motivated and concentrated on the task, they felt less boredom (71.67%) or anger (68.33%), which led them to continuously try and thus improve their performance before it was too late (88.33%). Finally, high concentration combined with anxiety and opposed points of view seemed to influence positively a more balanced distribution of work among the group members, which achieved to lighten students' workload (81.67%) during the development of the activity.



(a) (b)

Figure 10. Correlation between students' emotion awareness and self-regulation in (a) CG and (b) EG

CG students experienced less joy (71.67%), motivation (80.00%), concentration in the task (76.67%) and solidarity to peers (81.67%) than EG students. Under these circumstances, students managed to self-regulate their participation in the activity on time at a rate of 73.54%, whereas they had difficulty to show better ability to change to a more positive behavior faster (70.00%) as well as better skills to get involved to create and share knowledge on time (71.67%). Moreover, low performance in motivation, concentration and solidarity had negative effect in lightening students' workload (75.00%), whereas when they felt emotions such as anxiety and anger, combined with low motivation, concentration, joy and solidarity, acted rather as a barrier to the students' efforts to improve their performance before it was too late (81.67%).

As regards "learning outcome," we were based on the data gathered in items 4, 5, and 6 of Figure 7 (X) and on the mark that students obtained in each task as well as on final mark awarded at the end of activity (J). The results obtained are shown in Tables 4, 5 and 6.

Table 4. Descriptive statistics of learning outcome

	CG (n = 60)				EG (n = 60)			
	Mean	*SD*	Skewness	Kurtosis	Mean	*SD*	Skewness	Kurtosis
Marks	7.5744	1.47604	-.240	-1.534	8.5778	1.08839	-.673	-.175

Table 4 shows that the average score of EG students has been higher than the one of CG students. In Table 5, when we examine all marks obtained by EG students, we see that there is a significant relationship between learning outcome and student's supportive behavior with peers, which means that good learning outcome is achieved through solidarity among group members. Instead, examining all the marks obtained by CG students, we see that there is a significant relationship between the result obtained in the activity and a variety of emotions that students have experienced, ranging from joy to sadness or fear, and passing from concentration and solidarity with peers to opposition in case of disagreement. This oscillation in students' emotions certainly influences their learning outcome in a positive or negative manner. Finally, our analysis obtained an interesting result that concerns the marks that were higher than or equal to 9 (Table 6). In the EG it was found again that there is a strong correlation between learning outcome and solidarity with peers. In the CG it was found that there is a strong correlation between learning outcome and opposition in case of disagreement. In this case, it is shown that strong oppositions among group members, without letting them have an explicit awareness of this situation, have prevented them from achieving a very good learning outcome.

Table 5. Pearson correlation coefficient and learning outcome with all the marks

	CG (n = 60)						EG (n = 60)					
	4.1.EA	4.2.EA	4.3.EA	5.2.EA	6.1.EA	6.3.EA	4.1.EA	4.2.EA	4.3.EA	5.2.EA	6.1.EA	6.3.EA
All the marks	.328*	-.387**	-.255*	.546**	.284*	-.285*	.343*	-.008	-.070	.581**	.292*	-,113

Note. $^{*}p$ = .05; $^{**}p$ = .01.

Table 6. Pearson correlation coefficient and learning outcome with marks greater than or equal to 9

	CG (n = 14)	EG (n = 27)
	6.3.EA	6.1.EA
Marks >= 9	-.616*	.276*

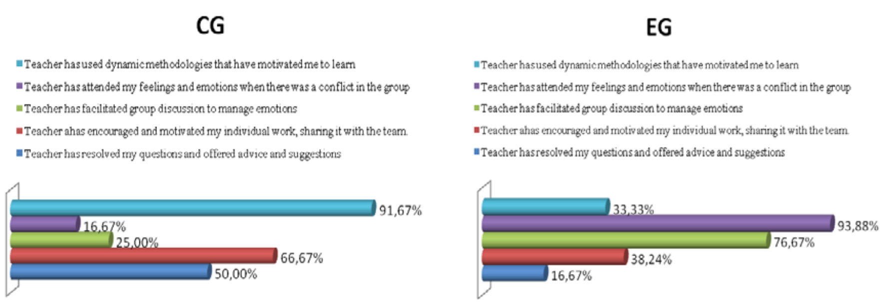
Note. $^{*}p$ = .05.

Regarding the third research question. We have correlated EA (X) with affective feedback (K). To this end, we have used the data gathered in items 4, 5, 6 and 8 of Figure 7. Table 7 shows the results obtained for items: 8.1.AF, 8.2.AF, 8.3.AF, 8.4.AF and 8.5.AF, whereas Figure 11 shows these results graphically. In fact, these items represent the competencies that teachers need to have in order to achieve a positive change on students' affective and cognitive state.

Table 7. Pearson correlation coefficient for research question 3

	CG (n = 60)					EG (n = 60)				
	8.1.AF	8.2.AF	8.3.AF	8.4.AF	8.5.AF	8.1.AF	8.2.AF	8.3.AF	8.4.AF	8.5.AF
4.1.EA	.444**	.243	.409**	.439**	.270*	.391**	.285*	.151	.202	.032
4.2.EA	-.235	.054	-.248	-.045	-.351**	-.008	-.001	-.013	.059	-.081
4.3.EA	-.186	.142	-.167	.367**	.012	.296*	.079	-.070	.024	-.229
4.4.EA	-.264*	-.196	-.217	-.106	-.215	.192	.131	.028	.189	-.016
5.1.EA	.352**	.409**	.292*	.635**	.313*	.411**	.469**	.137	.320*	.006
5.2.EA	.378**	.232	.424**	.269*	.496**	.128	.288*	.017	.214	.012
5.3.EA	.087	.148	-.078	.079	-.252	.099	.288*	.038	.090	-.013
5.4.EA	-.046	.038	-.118	.012	-.265*	-.208	.029	.106	.241	.225
6.1.EA	.559**	.074	.402**	.319*	.408**	.161	.280*	.311*	.275*	-.192
6.2.EA	.281*	.311*	.069	.469**	.389**	-.179	-.083	.261*	.123	.034
6.3.EA	-.031	.138	-.133	.459**	.066	.010	.022	.319*	-.003	-.007

Note. $^{*}p$ = .05; $^{**}p$ = .01.



(a) (b)

Figure 11. Correlation between teacher's awareness about students' emotions and his/her attitude and feedback in (a) CG and (b) EG

As regards item 8.1.AF, the teacher has extensively used dynamic methodologies to motivate students to learn (91.67%). As shown in the correlations in Table 7, this helped more CG students in several aspects (provided them more satisfaction, alleviated their frustration, supported more motivation, enhanced their concentration to the activity and solidarity with others as well as encouraged their involvement to the activity through suggestions and opinions). As concerns item 8.2.AF, the teacher had to attend more the feelings and emotions of EG students, when there was a conflict in the group. Regarding 8.3.AF, the teacher has facilitated group discussion to manage emotions at 76.67%.

This action has helped EG students mainly in three aspects: increasing their solidarity, encouraging them to provide more suggestions and opinions, and mediating to resolve conflicts. Instead, CG students were mainly benefited in basic emotional aspects, since they felt happier, more motivated, concentrated and more sympathetic. Finally, exploring the other two items (8.4.AF and 8.5.AF), in which the teacher has encouraged and motivated students' individual work sharing it with the team, as well as the teacher has resolved students' questions offering advice and suggestions, these actions have helped much more CG students in many aspects as seen in Table 7. Regarding EG students, they do not seem to have very significant correlations (except from two aspects related to students' motivation and solidarity which are encouraged by teacher's action 8.4.AF).

Discussion

Given the three research questions we set in this work (for the sake of convenience we repeat them here), we analyze the results presented above and obtain the following conclusions:

(1) Is there a significant correlation between students' emotion awareness and their motivation and engagement in learning?
(2) Is there any significant correlation between students' emotion awareness and their self-regulation and learning outcome?
(3) Is there any significant correlation between teacher's awareness about students' emotions and his/her attitude and feedback?

In regard of the first research question, students in both groups showed high levels of motivation under the existence of positive emotions such as joy, as well as strong concentration to the task and solidarity to their peers. However, in the presence of not so positive emotions (such as sadness/shame, fear/anxiety, and anger/frustration), CG students felt very bored and high tendency to dispute, which led them to lose motivation to continue their activities. Moreover, they showed low solidarity to their peers. Finally, when they felt anger or frustration, they had a strong lack of self-confidence. In contrast, EG students when they felt negative emotions such as anxiety or frustration, little more than half of them felt unsafe, but they were able to maintain at least a minimum interest on the activity. This was even more obvious when they were feeling sad. Moreover, when these students felt sad, they were able to receive and provide suggestions and opinions in a constructive way, thus they managed to maintain their engagement during the development of the activity. As a consequence of the above, we draw the conclusion that there is a significant positive correlation between emotion awareness and students' motivation and engagement in learning.

In regard of the second research question, CG students definitively obtain lower scores in self-regulating all explored aspects, that is, a more timely participation in the activity, the necessary changes that could lead towards a more positive behavior faster, a more timely involvement to create and share knowledge, a better performance before it's too late, and a more balanced distribution of their workload. In contrast, EG students achieved much better results in self-regulating all these aspects, distinguishing self-regulation skills such as timely participation and effective knowledge management that scored above 90% and which contributed to enhance teamwork and a more effective development of the activity. Considering learning outcome, EG students performed better than CG students. One of the reasons for achieving better learning outcome is grounded in building high degree of group solidarity and cohesion, which favours trust and engagement among the members of the group. Having the potential of emotion awareness of themselves and their peers during the whole activity provides students with an important tool to develop emotional competence for the group and thus build an emotionally intelligent team. As a result, we can claim that there is a significant positive correlation between emotion awareness and students' self-regulation and learning outcome.

In regard of the third research question, the teacher had the capability to be aware of students' emotions both in CG and EG. From the above results, we see that the teacher intervenes and supports both groups in almost all aspects that we explored. As regards the CG, since students in this group were not aware of their emotions, they needed much more support and affective feedback from their teacher, for this reason teachers' attitude has been considered crucial in all aspects. Especially, teacher's affective feedback has primarily involved dynamic methodologies to motivate students to learn, encouraged and motivated students' individual work, sharing it with the team and resolved students' questions offering advice and suggestions. At a second level, teacher has facilitated group discussion to manage emotions and attended students' feelings and emotions when there was a conflict in the group. Regarding the EG, since the students were aware of their emotions all the time, they emphasized more their need to ask for emotional support by the teacher when there was a conflict in the group. The result of the teacher intervention made these students feel happy, motivated, concentrated, safe, show more solidarity to their peers, encouraged to provide more suggestions and opinions, as well as more capable of resolving conflicts. All in all, this analysis proves that there is a significant positive correlation between emotion awareness and teacher's attitude and feedback.

Conclusions and future work

In this work we investigated the way emotion awareness influences students' motivation, engagement, self-regulation and learning outcome as well as teacher's attitude and feedback (identifying, at the same time, the competencies that teachers need to have in order to achieve a positive change on students' affective and cognitive state) in long-term blended learning practices. The results of our work showed that being aware of their emotions, students become more conscious of their situation, which prompts them to change and adapt their behavior for the benefit of their group. Moreover, it has been observed that their learning performance also improved in relation to their motivation, engagement and self-regulation. We also explored teachers' attitude when they are conscious of students' emotional state. We saw that teacher intervenes to support all students consciously and on time. In the case of Experimental Group students, teacher's affective feedback becomes even more focused, knowing that students were aware of a difficult emotional situation they encountered in case of socio-cognitive conflict.

Our future work now turns to investigate more on the nature and impact of affective feedback on students' learning process. This represents a first step toward the long-term objective of designing a virtual Affective Pedagogical Tutor (APT) that provides (semi)-automated feedback to students. This raises important issues about: the type of APT that is most appropriate and effective to student-centered collaborative learning situations; the understanding of the factors that have led students to remain in the same negative affective state for a certain period of time (which can lead them to deterioration of their learning performance, failure, and even withdrawal from studies); the establishment of criteria that indicates the most adequate moment that APT can intervene and monitor students' affective situation; and, the type of affective feedback that best fits the students' needs and affective state.

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Analyzing the effects of emotion management on time and self-management in computer-based learning

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A B S T R A C T

Emotional learning involves the acquisition of skills to recognize and manage emotions, develop care and concern for others, make responsible decisions, establish positive relationships, and handle challenging situations effectively. *Time* is an important variable in learning context and especially in the analysis of teaching-learning processes that take place in collaborative learning, whereas *time management* is crucial for effective learning. The aim of this work has been to analyze the effects of emotion management on time and self-management in e-learning and identify *the competencies in time and* self-management *that are mostly influenced when students strive to achieve effective learning*. To this end, we run an experiment with a class of high school students, which showed that increasing their ability to manage emotions better and more effectively enhances their competency to manage the time allocated to the learning practice more productively, and consequently their learning performance in terms of behavioral engagement and achievement and partly, in terms of cognitive engagement and self-regulation. Teacher affective feedback was proved to be a crucial factor to enhance cognitive engagement.

1. Introduction

Learning is the process of acquiring knowledge, skills, values and attitudes, through study, education or experience. This process produces a change in the behavior of a person from the result of experience by the association between a stimulus and its corresponding response. Nowadays, from a socio-constructivist view, learning depends on the context and the social negotiation and interaction with others. Moreover, computer-based learning has become a usual way of learning since the expansion of internet and the enormous facilities it offers in online and blended learning. Under this frame, computer-based learning environments have to foster learning that is self-regulated, constructive, context-sensitive and often collaborative.

Many studies have focused on the consequences of emotion management on computer-based learning. Brave and Nass (2002) show that a great variety of emotions play important role in every computer-related situation. Negative emotions require mental or behavioral adjustment, whereas positive emotions urge students to explore the computer-based environment and direct the actions that they take in it. Vuorela and Nummenmaa (2004) also argue that emotion regulation is important to effective functioning in web-based learning environments, whereas effective emotion regulation can enhance social interactions in a virtual environment (Gross & John, 2003; Tu & McIsaac, 2002). More recently, a detailed review of emotion regulation in Intelligent Tutoring Systems showed that emotion management during computer-based learning may produce more optimistic emotions as well as better learning gain (Malekzadeh, Mustafa, & Lahsasna, 2015).

According to Bach and Forés (2007), this has significant implications for teaching and learning. Therefore, teacher expectations have a significant impact on student outcomes, which shows why these expectations need to be positive as well as realistic. Teachers should provide the necessary time, space and support to students in order to make them reflect on the learning strategies that were used and on the way these strategies have influenced students' learning. If students' experiences have been negative, teacher should follow a scaffolding approach that moves students progressively to attenuate the impact that those negative experiences

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have had in their motivation to learning (Belland, Kim, & Hannafin, 2013). In general, a learning environment should provide the means to identify and nurture personal interests and intrinsic motivation of students. Emotions have a diagnostic value for teachers, because they reveal underlying cognitions, commitments and concerns. Teachers who are aware of what motivates their students and are sensitive to their emotions may use this information in a useful way to improve their learning process. Moreover, teachers' own behavior, teaching practices and evaluation may trigger specific emotions in students, which in turn affect the quality of learning that takes place (Boekaerts, 2010). Fortunately, emotional regulation can reduce the negative responses and serves as a containment mechanism (Niven, Totterdell, & Holman, 2009). Several strategies have been developed to regulate emotions (Moyal, Henik, & Anholt, 2014).

Taking all the above into account, we use the term "emotional management" to include the methods and tools to handle two very important tasks in affective learning: emotion awareness and emotional feedback (Feidakis, Caballé, Daradoumis, Gañán, & Conesa, 2014). Moreover, we use the term "time management" – which really means 'self-management' since we manage ourselves to make the most of time – as a key element for student learning development (Garrison, 1997). Time and self-management competencies are key factors for improving students' self-regulating learning and thus for enhancing learning performance in web-based courses (Cobb, 2003). That goes back to Bandura (1982) social learning theory where self-efficacy is considered a key element for learning success. Self-management is the main factor for students' self-efficacy, stimulation of motivation and insurance of balanced social life (Ivanova, 2011). Self-efficacy arises from the gradual acquisition of complex *cognitive* and *behavioral* skills (Bandura, 1982) whereas other researchers, such as Locke, Frederick, Lee, and Bobko (1984), found that the magnitude of self-efficacy was positively related to *goal setting*. Moreover, a key skill in self-management is *self-regulation* which concerns the ability of a student to organize, manage and address several elements of their learning for themselves (Zimmerman, 2008). As a consequence, among the competencies that affect students' performance, this research mainly considers these four competencies: behavioral and cognitive engagement, self-regulation, and achievement orientation.

In fact, students' performance is enhanced when motivation is translated into behavioral, emotional, and cognitive engagement (Fredricks, Blumenfeld, & Paris, 2004; Reeve, 2013). In a school context, positive behavioral engagement means actively participating in academic activities according to classroom norms; positive emotional engagement means exhibiting interest and happiness during academic activities; positive cognitive engagement means actively deploying strategies to understand content, solve problems, or otherwise use information (Fredricks et al., 2004).

Moreover, motivation, engagement, and self-regulation are the primary determinants of students' learning outcomes, and whether or not they will persist through challenging tasks (Harris, Graham, Mason, & Sadler, 2002). In particular, self-regulation is essential to the learning process and is recognized as an important predictor of student academic achievement (Jarvela & Jarvenoja, 2011). Finally, the achievement goal theory, which is developed within a social-cognitive framework, proposes that students' motivation and achievement-related behaviors can be understood by considering the reasons or purposes they adopt while engaged in academic work (Ames, 1992). As such, achievement orientation focuses on how students think about themselves, their tasks, their performance, and their well-being (Ryan & Deci, 2000).

From all the above, we see that the concepts of emotion management as well as time and self-management are crucial for increasing learning performance. However, the relationship between emotion management and time and self-management in computer-based learning has not been sufficiently investigated yet by the research community.

The aim of this work is to analyze the effects of emotional management on time management in computer-based learning and identify *which are the competencies in time and self-management that are mostly influenced when students strive to achieve effective learning*. To achieve this, we focus our work on competencies that affect students' learning and development, such as behavioral and cognitive engagement, self-regulation, and achievement orientation.

In order to achieve this goal, Section 2 sets the base of our work by carrying out a comprehensive and critical analysis of the literature that deals with emotion and time management in learning. Then in Section 3, we present our approach at a conceptual design level, we set our research hypothesis and questions, and we explain how we address these questions through a real experiment in a class of high school students. Section 4 presents the results of the experiment. Next in Section 5, we discuss and analyze the obtained results with regard to the research questions set and we check the validity of our research hypothesis. Finally, we provide our conclusions and possible future work.

2. Theoretical background in emotion and time management in learning

2.1. Emotion awareness

Emotions are defined as subjective experiences which are dependent on the context in which they arise. They are experienced in various situations and serve a variety of functions in the academic environment including promoting or undermining behavioral and cognitive engagement, self-regulation of learning activities and achievement (Linnenbrink-Garcia & Pekrun, 2011). *Learning* involves three particular cognitive processes, attention, memory and reasoning; with respect to each of them, students' cognitive ability depends on their emotions (Frasson & Chalfoun, 2010). According to them, emotions can be used in the learning context to increase students' attention as well as to improve memory and reasoning. As a consequence, relationships between objects or ideas are made more easily while they promote efficiency and rigor in decision making and problem solving (Isen, 2000). Therefore, *emotional learning* involves the acquisition of skills to recognize and manage emotions, develop care and concern for others, make responsible decisions, establish positive relationships, and handle challenging situations effectively (Durlak, Weissberg, Dymnicki, Taylor, & Schellinger, 2011).

In the recent years, research in *emotion awareness* in learning situations has focused on several issues that include: analysis of learning interactions to detect emotions through the application of a variety of methods, such as discourse analysis, sentiment analysis or opinion mining that allows non-intrusive automatic detection and extraction of emotions from student-created texts and dialogues (Daradoumis, Arguedas, & Xhafa, 2013a, 2013b); capturing the sentiments and the emotional states enclosed in textual information so that opinions and emotions embedded in them could play a key role in decision-making processes (Loia & Senatore, 2014); examining the impact of the so-called academic emotions (enjoyment, anxiety, pride, anger, hope, shame/fault, relief, boredom, hopelessness) on students' ways of thinking and information processing (Pekrun, Goetz, Frenzel, & Perry, 2011); embedding emotion awareness into e-learning environments "ecologically", by avoiding introducing obtrusiveness or invasiveness in the learning process (Feidakis et al., 2014); identifying patterns of emotional behavior by observing motor-behavioral activity (facial expressions, voice intonation, mouse movements, log files, sentiment analysis, etc.) (Arroyo, du Boulay, Eligio, Luckin, & Porayska-Pomsta, 2011; D'Mello et al., 2008; Heylen, Nijholt, & op den Akker, 2005; Mao & Li, 2009; Woolf, Burelson, & Arroyo, 2007).

However, there is a gap in investigating the way emotion awareness is related to students' performance from the perspective of "time and self-management", that is, taking into account very important competencies which are related to successful learning, such as behavioral and cognitive engagement, self-regulation, and achievement. Limited research attempted to explore some aspect of this relationship, whereas there are virtually no empirical data on when or why relations exist (or do not exist). In one of these works, Subic-Wrana et al. (2014) examines the way emotion awareness influences emotion regulation strategies and self-reports of negative emotions. Their first findings suggested that conscious awareness of emotions may be a precondition for the use of reappraisal as an adaptive emotion regulation strategy. Few studies of emotion and achievement have largely focused on anxiety, but there has been little theoretical and empirical attention devoted to the treatment of other emotions (Valiente, Swanson, & Eisenberg, 2012). In another work, You and Kang (2014) examined the role of academic emotions (enjoyment, anxiety, and boredom) in the relationship between perceived academic control and self-regulated learning in online learning. Moreover, while the concepts of cognitive and behavioral engagement are well understood in the context of previous research (Fredricks et al., 2004), and it is evident that there is a strict interrelationship of emotion and cognition in learning situations (Robinson, 2013), there is a scarcity of research in the relationship between emotion awareness and behavioral and cognitive engagement. As a consequence, our work presents an initial effort to fill this gap.

2.2. *Emotional feedback*

Once the learners' affective state is recognized, they need to see some reaction from the teacher; an adaptation to their cognitive performance as well as to their feelings. The main objective of affective feedback is to motivate the respondent, to facilitate their learning process and, to some extent, to improve their mood (Mao & Li, 2009).

In particular, the teacher should be able to encourage active learning and collaborative knowledge construction, monitor and provide appropriate models of expression especially when it comes to negative emotions that are often more difficult to communicate in an appropriate manner. An effective emotional feedback allows the design of modular and reusable activities, adapted to the student learning style, thus providing a more grounded activity planning. As a consequence, the teacher should be equipped with the necessary emotional skills for helping students react on time, especially in the case of negative emotions (e.g., anxiety), handle the time they have to carry out their learning activities more effectively either they work individually or in group, and know how to choose among a variety of technology resources and tools, and decide how and when to use them.

Despite the importance of emotional feedback, the number of scientific experiments reporting on successfully affective feedback strategies is quite limited. A reference work was published by D'Mello, Lehman, and Graesser (2011) presenting Autotutor, an ITS able to hold conversations with humans in natural language taking to account the learner's both cognitive and affective states. In another project, Sensitive Artificial Listener-SAL (Bevacqua et al., 2012) sustains an emotionally-colored interaction with users by collecting users' verbal and non-verbal behaviors and reacting appropriately pulling them towards specific emotional states.

Robison, McQuiggan, and Lester (2009) have reported on the results of two studies that were conducted with students interacting with affect-informed virtual agents, evaluating somehow the agents' response to both positive and negative affective states. They classify affective feedback strategies into parallel-empathetic (exhibit an emotion similar to that of the target), reactive-empathetic (focus on the target's affective state, in addition to his/her situation) or task-based (change task sequence – supplementary to empathetic strategies).

In contrast, there is a fair amount of research on social support and feedback that includes information about what students did well (Labuhn, Zimmerman, & Hasselhorn, 2010), what they need to improve, and steps they can take to improve their work (Hattie & Timperley, 2007). This type of feedback can assist students in improving their academic achievement (Brookhart, 2011), it also can promote student motivation (Wigfield, Klauda, & Cambria, 2011) and self-regulation (Labuhn et al., 2010).

Taking into account that there are few studies that exploit computer mediated affective feedback strategies and their impact on students' performance or affective state, whereas the number of tools and strategies to design expressive avatars in response to learner's emotion detection is quite limited, the need for further research in this area is far from evident, especially concerning the relationship between emotional feedback and behavioral and cognitive engagement, self-regulation, and achievement.

2.3. *Time and self-management*

Time management is one of the crucial components which are helpful in students' online learning (Song, Singleton, Hill, & Koh, 2004). Research in time management in learning context has been reported long ago (Britton & Tesser, 1991; Macan, Shahani, Dipboye, & Phillips, 1990). Most of the studies investigated the correlations of time management with academic performance (grades) and, especially, stress. Misra and McKean (2000) found that time management behaviors had a greater buffering effect on academic stress than leisure satisfaction activities. In fact, anxiety, time management, and leisure satisfaction were all predictors of academic stress in their multivariate analysis. Their results showed that anxiety reduction and time management in conjunction with leisure activities may be an effective strategy for reducing academic stress in college students.

In other studies, Connolly et al. (2003) suggested that time management is one of the factors that might encourage students to participate to a greater extent in online discussions. Other researchers (e.g., Reimann, 2009) examine the concept of time regulation, which is considered as part of learning regulation and is determined by productivity. In this context, Franco-Casamitjana, Barberà, and Romero (2013) defined a methodological design for analyzing time regulation patterns and learning efficiency in collaborative learning contexts in online education. In addition, faculty also needs development and support in time management (Alexander, 2001). An adequate time management is a necessary factor in facilitating and enhancing the teaching-learning processes and to improve *teacher workload* (Barberà, 2010).

Nevertheless, there are no clear research works that explore the relationship between emotion management and time and self-management in education, an issue that this study comes to explore and provide some answers.

2.4. Behavioral engagement, cognitive engagement, self-regulation and achievement orientation

Behavioral and cognitive engagement in education has been extensively investigated. In fact, Fredricks et al. (2004) proposed that school engagement is a multidimensional construct composed of behavioral, emotional, and cognitive components. Archambault, Janosz, Morizot, and Pagani (2009) assessed these three distinct dimensions of student engagement in high school and examined the relationships between the nature and course of such experiences and later dropout. Also, Wang & Eccles (2011) explored these three trajectories in school and their differential relations to educational success. Another study provides a thorough examination of the relationship among affective, cognitive, behavioral, and academic factors of student engagement of 9th Grade students (Burrows, 2010). Students' engagement and learning has been also linked to motivational factors, such as self-efficacy (Linnenbrinka & Pintrich, 2003; Walker, Greene, & Mansell, 2006). Regarding emotional factors, Reschly, Huebner, Appleton, and Antaramian (2008) found that frequent positive emotions during school were associated with higher levels of student engagement and negative emotions with lower levels of engagement. In addition, Tsai and Bagozzi (2014) examined the way cognitive, emotional and social factors influence students' contribution behavior in virtual communities which tend to be goal directed and specifically linked to the so called we-intentions.

Yet, student engagement is also related with another important component: achievement. Martin and Dowson (2009) examined the role of interpersonal relationships in students' academic motivation, engagement, and achievement. Knowledge sharing processes also affect students' achievement. Zhang, Ordóñez De Pablos, and Zhou (2013), Zhang, Ordóñez De Pablos, and Xu (2014) show how cultural values effect on explicit and implicit knowledge sharing within a multi-national virtual class and how knowledge sharing visibility impacts on incentive-based relationship in IT-based knowledge management systems. Further research investigated the associations between affective qualities of teacher–student relationships and students' school engagement and achievement (Roorda, Koomen, Spilt, & Oort, 2011). In fact, it has been shown that emotion is closely related to academic achievement (Gil-Olarte Márquez, Palomera Martín, & Brackett, 2006; Nelson, Benner, Lane, & Smith, 2004; Parker et al., 2004; Reyes, Brackett, Rivers, White, & Salovey, 2012). Kim, Park, and Cozart (2014) used motivation, emotion, and learning strategies, as predictors for achievement. They also found that emotions such as boredom, enjoyment, and anger significantly predicted students' achievement in a self-paced online mathematics course.

Finally, self-regulation and learning constitutes a very important research topic. Research shows that self-regulated students are more engaged in their learning (Labuhn et al., 2010). Self-regulated learners also perform better on academic tests and measures of student performance and achievement (Schunk & Zimmerman, 2007; Zimmerman, 2008). Often, self-regulated learning (SRL) is explained with motivation, emotion, and learning strategies (Abar & Loken, 2010). Several studies have demonstrated the role of emotion in SRL. Pekrun, Goetz, Daniels, Stupnisky, and Perry (2010) have shown that self-regulated learners have positive emotions, including hope, enjoyment, and pride in learning, whereas they control and regulate negative emotions, such as anger, anxiety, boredom, and frustration. Cho and Heron (2015) showed that significant differences in motivation and emotion were found in passing and non-passing students. Students who passed the course reported significantly higher task value and self-efficacy for learning.

This work aims at giving a new insight in the research of relationships that exist between emotion and time and self-management, especially as concerns the competencies *behavioral and cognitive engagement, self-regulation*, as well as *achievement* which are directly linked to students' performance in a computer-based learning context. This is explained in detail in the following sections.

2.5. Research hypothesis and goals

2.5.1. Goal

The goal of this work is to analyze the effects of emotional management on time and self-management in e-learning and identify *which are the competencies in time and self-management that are mostly influenced when students strive to achieve effective learning*.

2.5.2. Hypothesis

"Increasing the ability of learners to manage emotions better and more effectively will positively influence their competencies in time and self-management in a computer-based learning context and, more specifically, their learning performance in terms of behavioral and cognitive engagement, self-regulation and achievement".

2.5.3. Research questions

(1) How is "emotion awareness" related to "time and self-management" and thereby to "students' performance" in terms of behavioral and cognitive engagement, self-regulation, and achievement?
(2) How is "emotional feedback" related to "time and self-management" and thereby to "students' performance" in terms of behavioral and cognitive engagement, self-regulation, and achievement?
(3) Does "emotional and time management" reduce student workload?

3. Design and methodology

3.1. Models and tools

Nowadays, learning environments are built from a constructivist point of view, where students take more control over their learning processes which are developed gradually over time, whereas teachers' work is highly demanding since it requires continuous monitoring, scaffolding and assessment of students' performance. Taking emotions into account, we need to provide teachers with different methods and tools to let them understand and analyze the emotional phenomenon and how it evolves over time.

To that end, we are based on an emotion analysis model (Arguedas & Daradoumis, 2013) which has its roots in the Activity Theory (AT) (Engeström, Miettinen, & Punamäki, 1999). Our approach describes an AT scenario where participants (teacher and students) work together and interact with specific objects to carry out goal-oriented activities, as shown in Fig. 1.

Given this AT scenario, our first step was to develop a discourse analysis method to analyze collaborative learning activities (that included written text and dialogues) in a non-intrusive way in order to identify and represent the students' emotions that take place during these activities. To achieve this, we employed a combination of tools such as Sentiment Analysis and Rhetorical Structure Theory (RST) (Daradoumis et al., 2013a). This endeavor has been complemented through a study of the role that Time Factor plays in the whole process and has been also supported by the design of specific questionnaires at the beginning and the end of the process. The

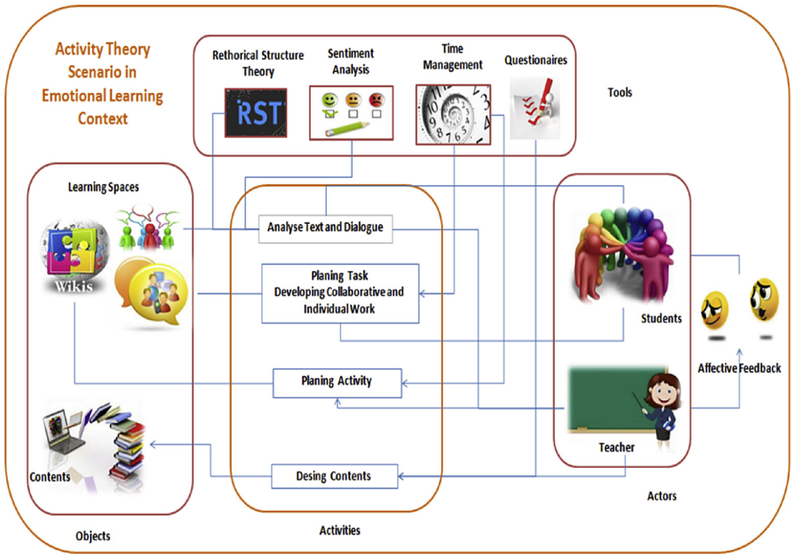

Fig. 1. An activity theory scenario in an emotional learning context.

result of this approach has been the identification of the emotional relations held between discourse units and a graphical representation of the emotional structure of discourse (as shown in Fig. 2, Section 3.2). This provides the teacher with the necessary emotion awareness in regard of the way students' emotions appear and evolve over time, which enables him/her to offer students cognitive and affective feedback. Both emotion awareness and affective feedback can be closely related to the time factor and more specifically to the way emotion awareness and affective feedback can influence time and self-management and consequently student's performance in computer-based learning. This is an important issue that this work seeks to investigate as it is analyzed in the following sections.

3.2. Emotion awareness

In order to provide emotion awareness among participants in the experimental group, we applied our Emotion Labeling Model at all conversations that took place in the group during the learning activity. The graphical representation of the emotional structure of the conversations produced was shown to both teacher and students of the experimental group. The conversation was split in different exchange types. In this way, the teacher was aware of students' emotions during their interactions in the virtual learning space (chat and forum), s/he could observe how students' emotions were changing and evolving in all exchange types and could intervene on time. And students were aware of their own emotions and their peers. In contrast, the students of the control group were not supported by this facility and carried out their activity in a conventional way.

Fig. 2 (a1, a2 and a3) shows the emotional structure of three conversation segments as it is depicted by the RST tool. It shows three emotion types (Happiness/Satisfaction, Shame, and Anger) that appear as the conversation evolves through exchange types (such as ascertain-information, elicit-information and give-information) produced by the participants. As we can also observe in these examples, emotion and cognition are closely linked (Frasson & Chalfoun, 2010).

3.3. Participants and procedure

Participants were a sample of 124 fourth-year high school students attending the subject "Introduction to computer science". Among students, 93 were girls (75%) and 31 were boys (25%). We divided students in 31 teams of four members and we chose 16 of these teams as the experimental group and the rest as the control group. Thus, the control group consisted of 60 students and the experimental group of 64 students. The number of teachers that participated in the experiment was two (2), one for the experimental and one for the control group. Each teacher provided and managed the same learning activity and tasks for both groups so that both groups had the same task characteristics in the experiment. The experiment was conducted for five weeks with a total of 15 sessions.

The procedure we followed was to design a scenario which is shown in Fig. 3. First, the scenario included a collaborative learning activity which was implemented following the Problem-Based Learning method and the Jigsaw collaborative strategy. And then, the scenario provided several questionnaire types to both teachers and students, which are described in detail in the following section. The topic of the activity was "Introduction to Internet" and was carried out in the Moodle environment.

The activity designed by the teachers was arranged in several synchronous and asynchronous tasks such as wiki creation, forum debate and chat realization, where students were encouraged to participate actively in building their knowledge. In this way, the teacher's role was reduced to guide and give support to the learning activity, by providing appropriate affective and cognitive feedback.

Based on the Jigsaw collaborative strategy, the learning activity was divided in ten stages which in turn were grouped around five tasks to facilitate their implementation as we show below. For each task, the teacher provided all the necessary resources (documents

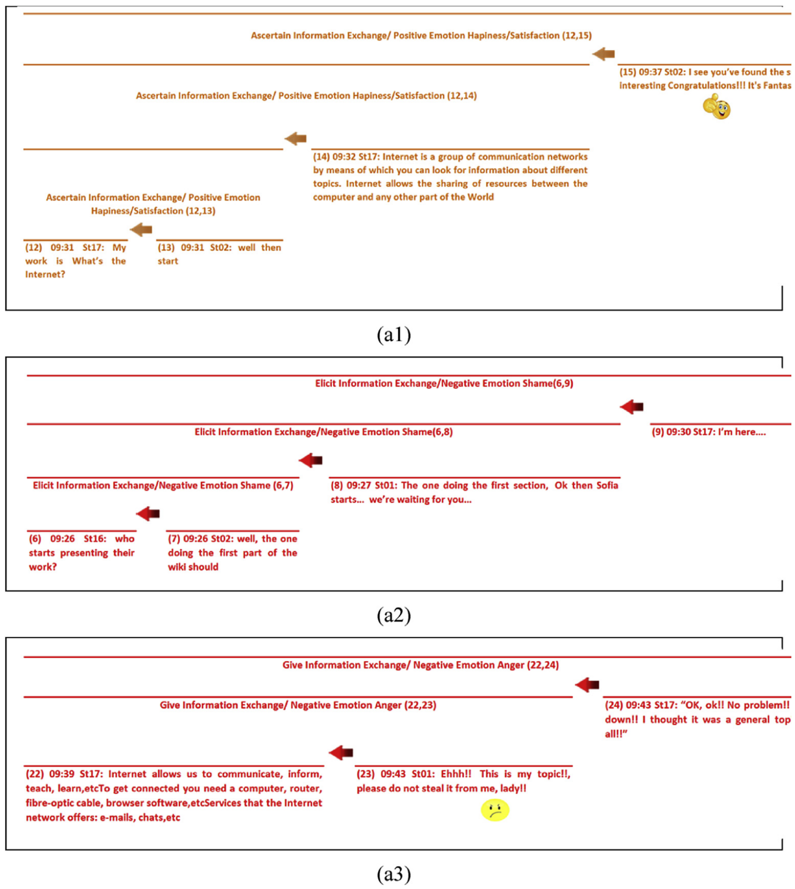

Fig. 2. Representation of the Emotional Structure of conversation segments through RST during a chat carried out by students of the experimental group (a1, a2 and a3).

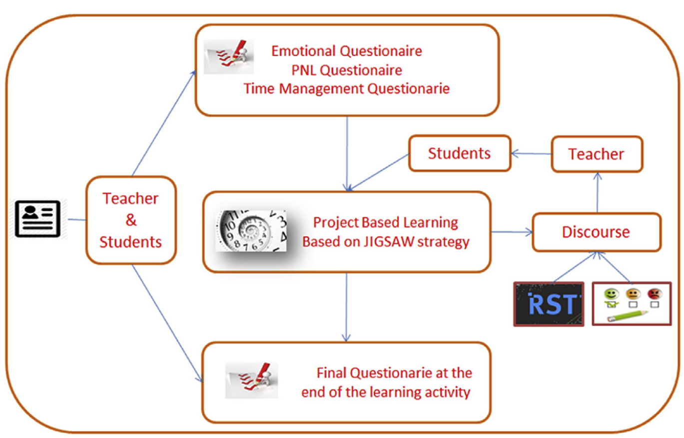

Fig. 3. Our scenario based on PBL & Jigsaw strategy and supported by different questionnaire types.

and tools).

a) *First Task*: Division of the activity on topics and organization of groups (Initial chat)
b) *Second Task*: Individual development of each topic (Creation of the wiki)
c) *Third Task*: Meeting of "experts". Using the cognitive dissonance strategy, the teacher sets three questions about each topic of the activity to urge students to reflect upon specific issues of the activity (Use of an asynchronous forum)
d) *Fourth Task*: Meeting of the groups to determine how they will carry out the preparation and presentation of the final report. (Final chat)
e) *Fifth Task*: Preparation and presentation of the final report.

3.4. Research instruments and data collection

At the beginning of the activity, we used three different questionnaire types: a VAK Learning Styles' Questionnaire of Lynn O'Brien (1990) to acquire participants' learning styles; a PEYDE's Questionnaire (Gallego & Gallego, 2004) to measure the initial level of participants' emotional intelligence; and, finally a questionnaire to measure how participants are managing time and self through organization, prioritizing, scheduling, etc. All participants, teachers and students, answered the three questionnaires. The data collected was used to set the teaching/learning profiles of the participants.

At the end of the learning activity of the experiment, we elaborated specific questionnaires aiming to obtain quantitative and qualitative data to measure and evaluate our research questions and hypothesis. We asked students from both groups (control and experimental) to fill in a specific questionnaire with closed and open-ended questions, with the aim of obtaining quantitative and qualitative data in order to respond the three research questions set. For the closed-ended questions we used a five-point Likert-type scale ranging from 1 (Almost never) to 5 (Almost always).

To this end, we defined specific indicators related to Emotion Awareness (EA) and Teacher Affective Feedback (TAF) – that concern the issue of Emotional Management – and Time and Self-Management (TM). Indeed, these are the three axes that are bound to our research questions. Emotion Awareness includes indicators that concern positive and negative emotions, emotional states and behaviors that students experiment while performing their tasks both in the classroom and in the virtual environment. Teacher Affective Feedback involves indicators that concern the way teacher's attitude and interventions influence students' behavior and emotional states as well as the evolution of their learning process. Time and Self-Management indicators are connected to both EA and TAF and, for the sake of consistency, are the same for both axes. The three axes and their indicators that underlie the questionnaire are shown in Table 1.

Regarding the statistical techniques employed in the analysis of the questionnaire data, we used descriptive statistics, calculating relative frequencies (%), as well as graphics to represent reality objectively. We also used bivariate correlation and analysis of variance to find relationships between the variables under study for each of the questions of our study.

4. Results

4.1. Setting the participants' profile

We first present the data obtained from the three initial questionnaires, which concerned participants' (teachers and students) learning styles, level of emotional intelligence, as well as time and self-management skills. The skills explored were the abilities to plan, delegate, organize, direct and control.

a) Teachers

Regarding the teachers, the VAK style was 41.33% visual, 32.33% auditory and 26.33% kinesthetic (Fig. 4). The levels of emotional intelligence showed an 87.50% in Problem Solving Ability, 90.00% in Relationship Ability, 92.50% in Empathy, 90.00% in Emotional Control and 90.00% in Emotional Awareness (Fig. 5). Finally, the level of time and self-management was at a Good Level 87.50% (Fig. 6).

b) Students.

First, with regard to the learning style of students that participated in the experimental group, 58% of them were visual, 25% auditory and 17% kinesthetic. In the control group, 42% of the students were visual, 33% auditory and 25% kinesthetic, as shown in Fig. 4.

Second, with regard to the levels of emotional intelligence of the Experimental Group students, the results showed a 60.42% in Problem Solving Ability, 60.21% in Relationship Ability, 61.04% in Empathy, 59.79% in Emotional Control and 61.88% in Emotional Awareness. In the Control Group, the results showed a 60.00% in Problem Solving Ability, 60.00% in Relationship Ability, 61.46% in Empathy, 62.08% in Emotional Control and 61.67% in Emotional Awareness, as shown in Fig. 5. No significant differences were shown in this aspect for both groups.

Finally, as concerns time and self-management skills in the experimental group, the results we obtained were: Middle Level 66.67% and Good Level 33.33%, as shown in Fig. 6. In the Control Group we had Bad Level 8.33%, Middle Level 33.33% and Good Level 58.33%. As such, it will be interesting to see how "emotion and feedback awareness" will improve or not students' time and self-management skills in the experimental group, as it is sought by our research questions.

4.2. Descriptive statistics and the Cronbach's alpha coefficient

We applied a descriptive statics method that also examined the skewness and kurtosis of each variable in order to check for multivariate normality. The absolute values of skewness and the absolute values of kurtosis did not exceed a univariate skewness of 2.0 and a univariate of kurtosis of 7.0; it was assumed that there was no critical problem regarding multivariate normality. The only case where the values of skewness and kurtosis have exceeded a univariate skewness of 2.0 (2883) and a univariate of kurtosis of 7.0 (10.022) occurred for the item of EA.3 (fear) in the control group.

Table 2 shows the results of the descriptive statistics obtained by both control and experimental groups ($n = 60$ and $n = 64$). The Cronbach's alpha coefficients of the scale used were 0.793, 0.767 and 0.779 with regard to EA questionnaire items (Table 2(a)), TAF questionnaire items (Table 2(b)) and TM questionnaire items (Table 2(c)), respectively.

The values obtained from the descriptive statistics performed convey the following information:

The mean of EA exceeded the value three (3.0) for the following items: EA.1-Happiness/Satisfaction (which concerns students' emotion): 3.55 in the Control Group (CG) and 3.58 in the Experimental Group (EG); EA.5-Motivation (CG 3.43 – EG 3.10) and EA.6-Concentration (CG 3.35 – EG 3.42), which concern mental states; and, EA.9-Solidarity (CG 3.32 – EG 3.57) and EA.10-provide suggestions (CG 3.25 – EG 3.10), which concern behaviors. This

Table 1
Indicators of the questionnaire and their tags used in statistical calculations.

Tag	Axes/Indicators
Emotion Awareness (EA)	
EA.1	Happiness/Satisfaction
EA.2	Sadness/Shame
EA.3	Fear/Anxiety
EA.4	Anger/Frustration
EA.5	Motivated
EA.6	Concentrated
EA.7	Unsafe
EA.8	Bored
EA.9	Showing Solidarity
EA.10	Giving Suggestions/Opinions
EA.11	Making Opposition
Teacher Affective Feedback (TAF)	
TAF.1	Using dynamic methodologies that motivate students to learn
TAF.2	Attending students' feelings and emotions when there is a conflict in the group
TAF.3	Facilitating group discussion to manage emotions
TAF.4	Encouraging and motivating students' individual work, sharing it with the team
TAF.5	Solving students' questions and offering advice and suggestions
Time and Self Management (TM) wrt EA & TAF	
TM.1.EA	Self-regulating participation in the activity on time
TM.2.EA	Changing behavior (towards more positive) faster
TM.3.EA	Getting involved to create and share knowledge on time
TM.4.EA	Setting goals to achieve and measuring one's progress in reaching them
TM.5.EA	Lightening workload
TM.1.TAF	Self-regulating participation in the activity on time
TM.2.TAF	Changing behavior (towards more positive) faster
TM.3.TAF	Getting involved to create and share knowledge on time
TM.4.TAF	Setting goals to achieve and measuring one's progress in reaching them
TM.5.TAF	Lightening workload

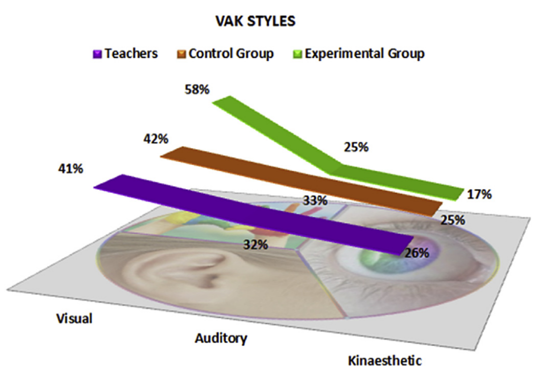

Fig. 4. Graphical representation of VAK learning style in Experimental Group, Control Group and Teachers.

indicates that students had experienced high positive emotions, mental states and behaviors both in the experimental and control group.

The mean of TAF exceeded the value three (3.0) in the Control Group (CG) for the following items: TAF.1 (3.13), TAF.4 (3.70) and TAF.5 (3.70), whereas in the Experimental Group (EG) this happened for the items: TAF.1 (3.32), TAF.2 (3.28), TAF.4 (3.45) and TAF.5 (3.77). This indicates that students in both groups had perceived that the teachers have used dynamic methodologies that motivated them to learn, has encouraged and motivated them in their individual work sharing it with the team, and has solved their questions offering advice and suggestions. However, unlike CG students, EG students had perceived that the teacher has attended their feelings and emotions when there was a conflict in the group (TAF.2). Moreover, as regards item TAF.3, students in EG had perceived in a greater degree (2.92) that the teacher has facilitated group discussion to manage emotions than students in CG (2.75).

The mean of TM exceeded the value three (3.0) in both CG and EG for all the items, as shown in Table 2. However, all item values in EG are higher than the ones in CG, especially for certain items that we need to make a specific mention. As regards Emotion Awareness (EA), these items are: TM.2.EA (Changing behavior towards more positive faster), TM.4.EA (Setting goals to achieve and measuring one's progress in reaching them) and TM.5.EA (Lightening workload). As regards Teacher Affective Feedback (TAF), the distinguishing items are: TM.2.TAF (Changing behavior towards more positive faster), TM.3.TAF (Getting involved to create and share knowledge on time), TM.4.TAF (Setting goals to achieve and measuring one's progress in reaching them) and TM.5.TAF (Lightening workload). This indicates that Emotion Awareness is to some extent related to "Time and Self-Management" and subsequently to "students' performance" in terms of behavior and achievement, whereas Teacher Affective Feedback is more closely related to "Time and Self-Management" and subsequently to "students' performance" in terms of behavioral and cognitive engagement as well as achievement. Moreover, both Emotional Management (EA and TAF) and Time and Self-Management (TM) are related to student workload.

Finally, we present the correlations between variables TM & EM (EA and TAF) that were found in the experimental group in Tables 3 and 4 respectively.

Firstly, a significant positive correlation was found between EA and TM. In particular, we found higher correlations between:

- Happiness/Satisfaction as emotion *caused* TM.2.EA (r 0.314, $p < 0.01$), TM.4.EA (r 0.307, $p < 0.01$) and TM.5.EA (r 0.236, $p < 0.01$)
- Motivation as mental state *caused* TM.1.EA (r 0.211, $p < 0.05$), TM.2.EA (r 0.359, $p < 0.01$), TM.4.EA (r 0.554, $p < 0.01$) and TM.5.EA (r 0.252, $p < 0.01$)

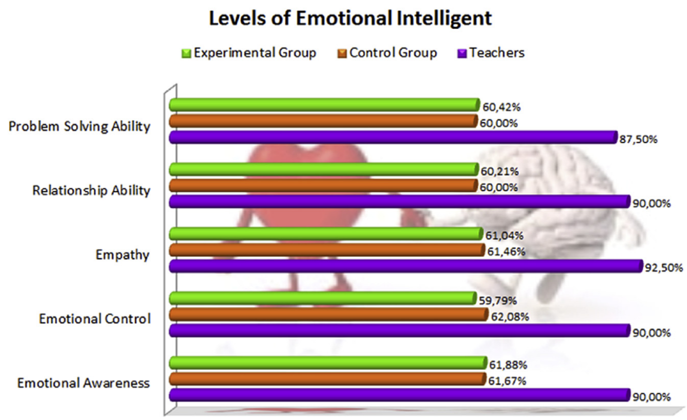

Fig. 5. Graphical representation of Levels of Emotional Intelligent in Experimental Group, Control Group and Teachers.

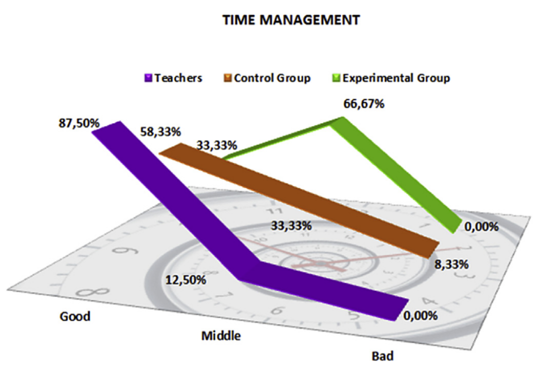

Fig. 6. Graphical representation of Time Management in Experimental Group, Control Group and Teachers.

- Concentration as mental state *caused* TM2.EA (r 0.352, $p < 0.01$), TM.4.EA (r 0.412, $p < 0.01$) and TM.5.EA (r 0.353, $p < 0.01$)
- Be supportive as behavior *caused* TM2.EA (r 0.391, $p < 0.01$), TM.4.EA (r 0.275, $p < 0.01$) and TM.5.EA (r 0.364, $p < 0.01$)
- Give feedback and suggestions as behavior *caused* TM.2.EA (r 0.240, $p < 0.01$), TM.4.EA (r 0.298, $p < 0.01$) and TM.5.EA (r 0.252, $p < 0.01$).

Secondly, a significant positive correlation was found between TAF and TM. In particular, we found higher correlations between:

- TAF.2 (Teacher attending students' feelings and emotions when there was a conflict in the group) *caused* TM.2.TAF (r 0.332, $p < 0.01$), TM.3.TAF (r 0.259, $p < 0.01$), TM.4.TAF (r 0.267, $p < 0.01$) and TM.5.TAF (r 0.228, $p < 0.05$),
- TAF.4 (Teacher encouraging and motivating students' individual work, sharing it with the team) *caused* TM.1.TAF (r 0.190, $p < 0.05$), TM.2.TAF (r 0.271, $p < 0.01$), TM.3.TAF (r 0.232, $p < 0.05$), TM.4.TAF (r 0.343, $p < 0.01$) and TM.5.TAF (r 0.246, $p < 0.01$),
- TAF.5 (Teacher solving students' questions and offering advice and suggestions) *caused* TM.2.TAF (r 0.278, $p < 0.01$), TM.3.TAF (r 0.215, $p < 0.05$), TM.4.TAF (r 0.224, $p < 0.05$) and TM.5.TAF (r 0.188, $p < 0.05$),
- TAF.3 (Teacher facilitating group discussion to manage emotions) *caused* TM.2.TAF (r 0.186, $p < 0.05$), and
- TAF.1 (Teacher using dynamic methodologies that motivated students to learn) *caused* TM.5.TAF (r 0.187, $p < 0.05$).

5. Discussion

The purpose of this study was to analyze the effects of emotion management on time and self-management in computer-based learning and identify *which are the competencies in time and self-management that are mostly influenced when students strive to achieve effective learning.*

To this end, based on the results we obtained in Section 4.2 above, we proceed to discuss and provide a response to the research questions we set in the beginning of our study. For the sake of convenience, we repeat each question below:

How is "emotion awareness" related to "time and self-management" and thereby to "students' performance" in terms of behavioral and cognitive engagement, self-regulation, and achievement?

First of all, all students (in both Control and Experimental groups) were happy with the learning activities they had to carry out since they experienced high positive emotions, mental states and behaviors during the implementation of these activities.

Our results show that the relationship between Emotion Awareness (EA) and Time and Self-Management (TM) mostly concerns behavioral and achievement orientation competencies. Students in Experimental Group (EG), who are endowed with EA capability, tend to change their behavior towards a more positive one, as well as to set goals to achieve and measure their progress in reaching them to a greater degree than students in Control Group (CG). However, EG students just show a slightly better performance in competencies such as cognitive engagement (getting involved to create and share knowledge) and self-regulation (of their participation in the activity) than CG students. This may be due to several factors that need to be further investigated and analyzed and which may be related to the students' own profile that we examined in the beginning of our study: learning styles, level of emotional intelligence, as well as their innate time self-management skills. Other factors may be related to maturation (Toga, Thompson, & Sowell, 2006), temperament (Fowles & Kochanska, 2000) and learning

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Table 2
Descriptive statistics of (a) Emotion Awareness – EA, (b) Teacher Affective Feedback – TAF and (c) Time and Self Management – TM (Data concern students both in Control and Experimental Group).

	Control Group (CG) (n = 60 students)						Experimental Group (EG) (n = 64 students)					
	Mean	SD.	Skewness	Kurtosis	Min.	Max.	Mean	SD.	Skewness	Kurtosis	Min.	Max
A) Descriptive statistics of Emotion Awareness – EA												
EA.1	3.55	1.126	−0.276	−0.767	1	5	3.58	0.962	−0.363	−0.273	1	5
EA.2	1.65	0.971	1.570	1.988	1	5	1.65	0.860	1.086	0.173	1	4
EA.3	1.37	0.758	2.883	10.022	1	5	1.62	0.825	1.391	1.560	1	4
EA.4	2.27	0.936	0.202	−0.828	1	4	2.20	1.054	0.930	0.703	1	5
EA.5	3.43	1.015	−0.165	−0.281	1	5	3.10	1.020	0.190	−0.149	1	5
EA.6	3.35	1.087	−0.256	−0.209	1	5	3.42	0.944	−0.689	−0.004	1	5
EA.7	1.53	0.873	1.240	1.506	0	4	1.87	0.911	0.829	−0.109	0	4
EA.8	2.82	1.112	0.070	−0.605	1	5	2.40	1.108	0.687	0.102	1	5
EA.9	3.32	1.000	0.264	−0.496	1	5	3.57	0.890	−0.357	0.141	1	5
EA.10	3.25	1.159	−0.173	−0.575	1	5	3.10	0.986	0.013	0.296	1	5
EA.11	2.23	1.212	0.772	−0.240	1	5	2.60	1.153	0.297	−0.559	1	5
B) Descriptive statistics of Teacher Affective Feedback – TAF												
TAF.1	3.13	0.833	0.288	0.449	1	5	3.32	0.854	0.177	−0.521	2	5
TAF.2	2.97	1.057	−0.199	−0.578	1	5	3.28	1.180	−0.130	−0.829	1	5
TAF.3	2.75	1.002	−0.203	−0.611	1	5	2.92	1.154	0.031	−0.571	1	5
TAF.4	3.70	0.889	0.189	−1.011	2	5	3.45	1.156	−0.078	−1.213	1	5
TAF.5	3.70	1.109	−0.527	−0.766	1	5	3.77	1.198	−0.570	−0.794	1	5
C) Descriptive statistics of Time and Self Management – TM												
TM.1.EA	3.10	0.969	0.025	−0.006	1	5	3.13	0.792	0.293	0.919	1	5
TM.2.EA	3.03	0.956	−0.068	−0.327	1	5	3.42	0.962	−0.346	−0.010	1	5
TM.3.EA	3.13	0.892	0.175	−0.217	1	5	3.18	0.892	0.217	−0.052	1	5
TM.4.EA	3.33	1.036	−0.245	−0.231	1	5	3.55	0.954	−0.402	−0.151	1	5
TM.5.EA	3.17	1.181	0.112	−0.815	1	5	3.32	1.052	−0.073	−0.379	1	5
TM.1.TAF	3.20	0.860	0.258	0.276	1	5	3.28	0.698	1.193	1.656	2	5
TM.2.TAF	3.32	0.854	−0.669	0.398	1	5	3.57	0.851	−1.069	0.655	1	5
TM.3.TAF	3.73	1.163	−0.458	−0.756	1	5	3.97	1.041	−0.491	−1.060	2	5
TM.4.TAF	3.08	0.962	0.065	−0.449	1	5	3.33	0.965	0.193	−1.149	2	5
TM.5.TAF	3.20	1.070	0.185	−0.653	1	5	3.43	1.041	0.305	−1.034	1	5

The grey shaded values in Table are used to highlight the most significant differences between individual values obtained in control and experimental groups.

Table 3
Correlations between Time and Self-Management & Emotion Awareness of Experimental Group students (n = 64).

Pearson correlations										
	EA.1	EA.2	EA.4	EA.5	EA.6	EA.7	EA.8	EA.9	EA.10	EA.11
TM.1.EA	0.113	−0.021	−0.191*	0.211*	0.139	0.096	−0.079	0.106	0.147	0.015
TM.2.EA	0.314**	−0.005	−0.011	0.359**	0.352**	0.115	−0.034	0.391**	0.240**	−0.038
TM.3.EA	0.127	0.027	−0.099	0.150	0.147	0.122	−0.022	0.155	0.129	−0.174
TM.4.EA	0.307**	−0.006	−0.107	0.554**	0.412**	0.143	−0.128	0.275**	0.298**	−0.015
TM.5.EA	0.236**	−0.035	0.161	0.252**	0.353**	0.038	0.012	0.364**	0.252**	−0.104

The grey shade is used to highlight the most significant correlation values obtained in certain variables in the experimental group.
*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

Table 4
Correlations between Time and Self-Management & Teacher Affective Feedback of Experimental Group students (n = 64).

Pearson correlations					
	TAF.1	TAF.2	TAF.3	TAF.4	TAF.5
TM.1.TAF	0.129	0.142	0.053	0.190*	0.140
TM.2.TAF	0.082	0.332**	0.186*	0.271**	0.278**
TM.3.TAF	0.000	0.259**	0.007	0.232*	0.215*
TM.4.TAF	0.146	0.267**	0.147	0.343**	0.224*
TM.5.TAF	0.187*	0.228*	0.195*	0.246**	0.188*

The grey shade is used to highlight the most significant correlation values obtained in certain variables in the experimental group.
*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

specific strategies for regulating behavior and emotions (Davis & Levine, 2013; Ochsner & Gross, 2005), among others.

Positive emotions (such as happiness/satisfaction), mental states (such as motivation and concentration) and behaviors (such as be supportive and helpful) had significant positive effects on behavioral engagement and achievement. As regards the other two competencies (cognitive engagement and self-regulation), they certainly had more positive effect on cognitive engagement, though "being helpful" (Giving Suggestions/Opinions) had a more positive impact on self-regulation (as shown in Table 3).

In contrast, negative emotions (such as sadness/shame, fear/anxiety and anger/frustration) had a negative effect on self-regulation, especially in the case of anger/frustration. In fact, the latter had a negative effect on all other competencies (behavioral and cognitive engagement, and achievement). Here, it is remarkable to observe that fear/anxiety had a very positive impact on achievement, since students in this situation were "pushed" to increase efforts in order to achieve their goals. As regards the negative emotional states (such as unsafe and bored), the first one had a rather positive impact on all competencies, especially for achievement, whereas the second one had a rather negative impact on all competencies, being more unfavorable to achievement. Finally, negative behaviors (such as making opposition) had a rather negative impact on all competencies, except self-regulation, which means that self-regulation may be slightly favored by confronting situations. We observed that this was especially evident in EG students (who were aware of their behavior).

- How is "emotional feedback" related to "time and self-management" and thereby to "students' performance" in terms of behavioral and cognitive engagement, self-regulation, and achievement?

Our results show that Teacher Affective Feedback (TAF) adds a new element to Time and Self-Management (TM) competencies. In particular, TAF contributes to students' performance in terms of behavioral and cognitive engagement as well as achievement. Indeed, Students in Experimental Group (EG), who explicitly received teacher's emotional feedback, were involved to create and share knowledge on time to a greater extent than students in Control Group (CG). As concerns the last competency, self-regulation, we observed that TAF certainly helped EG students more than CG students in self-regulating their participation in the activity; however, the difference between the two groups was not noteworthy. This means that TAF should be accompanied with further teacher capabilities, such as the fact that teachers should be familiar with the factors that influence a learner's ability to self-regulate (Wolters, 2011). In the first instance, to promote self-regulation in classrooms, teachers must teach students the self-regulated processes that facilitate learning. In a study of high school students, Labuhn et al. (2010) found that learners who were taught self-regulation learning skills through monitoring and imitation were more likely to elicit higher levels of academic self-efficacy (i.e., confidence) and perform higher on measures of academic achievement compared to students who did not receive such instruction. Likewise, teachers should provide effective instructional strategies for encouraging self-regulation in the classroom (Andreassen & Braten, 2011; Tonks & Taboada, 2011).

Moreover, it has been shown that motivation can have a pivotal impact on students' academic outcomes and without motivation, self-regulation is much more difficult to achieve (Zimmerman, 2008). In this sense, the teacher in our experiment explored the way motivation is related to self-regulation. As shown in Table 4, the fact that the teacher was encouraging and motivating students' individual work, sharing it with the team (TAF.4) had a positive effect on students' self-regulation (TM.1.TAF). This finding is further reinforced by the fact that when students were motivated (EA.5) they were more receptive to self-regulate their participation in the activity (TM.1.EA), as shown in Table 3.

Other teacher interventions that had a significant effect on students' performance in terms of behavioral and cognitive engagement as well as achievement (TM.2.TAF, TM.3.TAF and TM.4.TAF) were TAF.2 (Teacher attending students' feelings and emotions when there was a conflict in the group) and TAF.5 (Teacher solving students' questions and offering advice and suggestions). Instead, the other two types of affective feedback (TAF.3: Teacher facilitating group discussion to manage emotions and TAF.1: Teacher using dynamic methodologies that motivated students to learn) that teacher used had less or no significant effect respectively, as shown in Table 4. Indeed, TAF.3 had a notable positive impact on students' behavior only. This means, that teacher should revise and reconsider these two types of emotional feedback and explore alternative ways to apply them.

- Does "emotional and time management" reduce student workload?

Our results showed that this question had a positive answer in all aspects. More specifically, as regards emotional management (that includes both emotion awareness and emotional feedback), Table 3 shows that positive emotions (such as happiness/satisfaction), mental states (such as motivation and concentration) and behaviors (such as be supportive and helpful) had significant positive effects on lightening students' workload.

In addition, Table 4 shows that Teacher Affective Feedback has also contributed in lightening students' workload. This includes all kinds of feedback that teacher used, though a special mention should be made to feedback TAF.4 (Encouraging and motivating students' individual work, sharing it with the team) which presented more outstanding results. This means that motivation can be considered an important means for reducing student workload. As regards Time Management, Table 2(c) shows that EG students were able to make a better management of their workload than CG students.

6. Conclusion and future work

This work aimed to shed some light on the relationship between emotion management and time and self-management in computer-based learning. To tackle this issue, we explored the way some of the competencies in time and self-management may be affected when students are explicitly aware of their emotions and receive explicit emotional feedback by the teacher. The competencies examined were: behavioral and cognitive engagement, self-regulation, and achievement orientation.

The hypothesis set by our study *"Increasing the ability of learners to manage emotions better and more effectively will positively influence their ability to manage the time allocated to the learning practice more productively, and consequently their learning performance in terms of behavioral and cognitive engagement, self-regulation and achievement"*, indeed turns out to be fairly true. This is especially true for the case of behavioral engagement as well as achievement and partially true for cognitive engagement and self-regulation.

In particular, our study set two main research questions for testing emotion awareness and emotional feedback as two independent enquiries.

Our results showed that "emotion awareness" is fairly related to "time and self-management" in the sense that when students are aware of their emotions may enhance their learning performance in terms of behavioral engagement and achievement and, partly, in terms of cognitive engagement and self-regulation.

Besides, "emotional feedback" is more closely related to "time and self-management", meaning that when a teacher provides explicit affective feedback to students, this may enhance their learning performance in terms of behavioral and cognitive engagement as well as achievement and, partly, in terms of self-regulation, placing more weight on motivation as a critical factor for enhancing self-regulation.

In addition, we performed a basic exploration of a third research question that concerned the relationship between "emotional and time management" and student workload. At first sight, it was shown that an explicit and effective emotion and time management can reduce students' workload.

This research also revealed new interesting aspects and important issues that certainly need further investigation. Some of these aspects and issues concern the first axis of our research, emotion awareness. An important open question is how emotion awareness can be reinforced in order to achieve an effective cognitive engagement and self-regulation. What other competencies in "time and self-management" can emotion awareness strengthen and thus improve students' performance further? As regards the second axis of our research, emotional feedback, how this can be combined with other factors that can improve self-regulation? Also, what other competencies in "time and self-management" can emotional feedback nourish and thus improve students' performance further? Finally, deeper research is needed to corroborate the positive relationship between "emotional and time management" and student workload, as well as to examine how this is also affecting teacher workload.

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7.3.3. (3) Referencia

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A model for providing emotion awareness and feedback using fuzzy logic in online learning

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Abstract Monitoring users' emotive states and using that information for providing feedback and scaffolding is crucial. In the learning context, emotions can be used to increase students' attention as well as to improve memory and reasoning. In this context, tutors should be prepared to create affective learning situations and encourage collaborative knowledge construction as well as identify those students' feelings which hinder learning process. In this paper, we propose a novel approach to label affective behavior in educational discourse based on fuzzy logic, which enables a human or virtual tutor to capture students' emotions, make students aware of their own emotions, assess these emotions and provide appropriate affective feedback. To that end, we propose a fuzzy classifier that provides a priori qualitative assessment and fuzzy qualifiers bound to the amounts such as few, regular and many assigned by an affective dictionary to every word. The advantage of the statistical approach is to reduce the classical *pollution* problem of training and analyzing the scenario using the same dataset. Our approach has been tested in a real online learning environment and proved to have a very positive influence on students' learning performance.

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Keywords Fuzzy logic · Affective learning · Students' emotive states · (APT) Affective Pedagogical Tutor · Affective feedback

1 Introduction and motivation

Our research work aims at investigating the effectiveness of an emotion labeling model to detect emotions in educational discourse (text and conversation) in a nonintrusive way making emotion awareness explicit both at individual and at group level (Arguedas et al. 2014). Studies have shown that emotional experiences influence student's motivation, learning strategies and achievement, whereas such emotional experiences are influenced by personality and classroom characteristics (Frasson and Chalfoun 2010; Goetz et al. 2006).

Given that people are able to express a wide range of emotions, which vary in intensity, duration, context, etc., during activity time, our model is based on dimensional categories of emotions (Scherer 2005). It also makes use of affective dictionaries expressing the emotional weights of words as a function of affective dimensions (Pleasure, Arousal, etc.).

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Due to the nature of affective dimensions, which consists of aspects manifesting continuity, this means that dimensions show a wide range of high-precision alternatives; thus, every dimension requires a previous treatment. Therefore, each dimension must be preprocessed to obtain fuzzy values corresponding to the magnitudes of each emotional dimension. Such fuzzy values are the qualitative awareness that can be bound to such continuity. Actually this is an analog to discrete conversion.

Once the conversion into qualitative emotional awareness is performed, discrete affective states as well as knowledge regarding emotional performance become available to both teachers and students. Diverse academic and business scenarios could be supported and improved by emotional awareness, which would allow performing different micro-adjustments to discourse or behaviors every aspect of computer-mediated human interaction. Traditional human interaction allows participants to gather a whole range of inputs to build a rich image from reality. However, human interaction supported by digital channels would imply a loss of information, even though sophisticated digital channels are used. Hence, every additional mechanisms aimed at providing supplementary information would entail a further understanding of the new functionalities they offer.

Indeed, among the opportunities to add supplementary information is the possibility to provide emotional awareness from text. The reader may consider a virtual scenario in which different people are interacting, such as a virtual chat room. These people are mainly using text messages and emoticons to communicate. It would be interesting to both participants and the chat monitor person/system to be able to have a mechanism to analyze chat text in order to discover the emotions underlying conversation as well as to produce specific emotional feedback to support and monitor participants' needs.

The aim of this study is to present an effective approach to label affective behavior in educational discourse based on fuzzy logic, which will enable a human (or virtual) tutor to capture students' emotions, make students aware of their own emotions, assess these emotions and provide appropriate feedback to the involved actors. In order to address these challenges, this paper is organized as follows. In Sect. 2, we present a comprehensive analysis of the state of the art of approaches to modeling emotions, mainly in learning environments, focusing more on two important issues that concern affective dictionaries and fuzzy logic in sentiment analysis. Based on this analysis, in Sect. 3, we present the conceptual design of our model. Section 4 describes the context, the experiment and the data used for the analysis. In Sect. 5 we show how our model is implemented in a real case setting. Finally, in Sect. 6, we present the results obtained, whereas Sect. 7 provides a critical discussion of the results. Finally Sect. 8 concludes with the directions for future work.

2 Related work

Our goal is to classify and later label up the students' emotional state through the analysis of their educative discourse in a virtual learning environment. To that end, before starting the design of our model, we have extensively revised the literature related to three topics that concern its development.

First, we reviewed various existing models for the classification of the different emotional states. Secondly, we studied the different affective dictionaries that have been compiled so far, to identify how each one of them provides the use of information about the affective weights of words composing the educational discourse. Finally, we checked out the related works about the application of fuzzy logic in the sentiment analysis field.

2.1 Emotion models

In artificial intelligence, affective computing is the branch of studies and development systems that can recognize, interpret, process and simulate human affects, whereas its main goal is to simulate empathy. Regarding the approach proposed in this study, our aim is to make the machine capable of interpreting the emotional state of humans and adapting its behavior to them, giving an appropriate response to their emotions (Tao and Tan 2005; Leu et al. 2014).

There are two leading models describing how humans perceive and classify emotion, namely dimensional and categorical models (Feidakis et al. 2013; Daradoumis et al. 2013). Categorical models classify emotions into basic, secondary, tertiary, etc. (Ekman and Friesen 1971; Ortony et al. 1988; Pekrun 1992), while dimensional models specify gradual emotions as Arousal, valence, control, intensity, duration, frequency of occurrence, etc. (Rusell 1983; Kort and Reilly 2002; Scherer et al. 2013; Kuncheva 2000).

In the learning context, emotions can be used to increase student's attention as well as to improve memory and reasoning (Isen 2000). In this context, tutors must be prepared to create affective learning situations and encourage collaborative knowledge construction as well as identify those students' feelings which hinder learning process (Lorenzo and Ibarrola 2000).

According to Kort and Reilly (2002) emotion measurement tools and techniques fall into three main categories:

– Psychological (subjective report using verbal or pictorial scales or questionnaires, etc.). For instance, the PAD (Pleasure–Arousal–Dominance) emotional state model is a psychological model developed in Mehrabian and O'Reilly (1980) to describe and measure emotional states. PAD uses three numerical dimensions to represent all emotions. Its initial use was in a theory of environmental psychology, the core idea being that physical environments influence people through their emotional impact. The PA part of PAD was developed into a circumplex model of emotion experience, and those two dimensions were termed "core affect." The D part of PAD was re-conceptualized as part of the appraisal process in an emotional episode (a cold cognitive assessment of the situation eliciting the emotion). A more fully developed version of this approach is termed the psychological construction theory of emotion. The PAD model has been used to study nonverbal communication such as body language in psychology (Mehrabian 1972). It has also been applied to the construction of animated characters that express emotions in virtual worlds (Becker et al. 2007).

- Physiological (use of sensors to capture biometric signals). For instance, Goncalves et al. (2016) present a multimodal approach by using multiple sensors to collect and assess users' emotion at interaction time while interacting with a game.
- Behavioral (observation or capturing of motor-behavioral activity, e.g., facial expressions, sentiment analysis of text input, mouse and keyboard logs, etc.). Sentiment analysis tools have been used in this work to provide means for the identification of the attitude holder and the polarity of the attitude as well as for the description of the emotions and sentiments of the different actors involved in the text. Plutchik offers an integrative theory based on evolutionary principles (Plutchik 2001). Emotions are adaptive—in fact, they have a complexity born of a long evolutionary history—although we conceive emotions as feeling states. According to Plutchik (2001), the feeling state is part of a process involving both cognition and behavior and containing several feedback loops.

As mentioned before, our goal in this work is to develop tools that provide teachers with useful information about students' emotional state, so that they can assess these emotions, and eventually provide appropriate affective feedback to students. To this end, we choose a mixed model composed by three dimensions (Mehrabian and O'Reilly 1980) and eight emotional labels (Plutchik 2001).

2.2 Affective dictionaries

In the sentiment analysis field, textual information includes, among others, subjective expressions that describe people's sentiments, appraisals or feelings toward entities, events and their properties (Liu 2012).

The majority of studies apply classification algorithms to obtain the contextual polarity, and the frequent terms of a document, that is to say, are simply based on the appearance and frequency of terms or the text valence in order to determine whether it is a positive or negative critique (Li et al. 2016). A new trend in emotion research consists in performing lexical analysis of texts with the aim of identifying the words that can predict the affective states of the authors (Calvo and D'Mello 2010).

Within this area, some affective dictionaries have been developed and are widely used. These dictionaries provide a lexical repository in different languages. In particular, we have carried out a major review of affective dictionaries in Spanish language concerning both emotion models (dimensional and categorical).

SentiWordNet is a lexical resource for opinion mining (Baccianella et al. 2010). SentiWordNet assigns to each synset (i.e., synonyms which are grouped into unordered sets) of WordNet Affect [a linguistic resource for a lexical representation of affective knowledge (Strapparava and Valitutti 2004)] three sentiment scores: positivity, negativity and objectivity. The method used to develop SentiWordNet is an adaptation to synset classification of a previous method for deciding the PN-polarity (identifies whether a term that is a marker of opinionated content has a positive or a negative connotation) and SO-polarity (describes a given situation or event, without expressing a positive or a negative opinion on it) of terms (Esuli and Sebastiani 2006). The method relies on training a set of ternary classifiers, each of them capable of deciding whether a synset is positive, negative or objective. However, SentiWordNet is not available in Spanish.

The development of the framework Affective Norms for English Words (ANEW) (Bradley et al. 1999) is an instrument for the dimensional perspective of emotions based on works of Wundt (1896) and Osgood et al. (1957). From this perspective, three basic dimensions are proposed, through which the entire range of human emotions can be organized: valence (which ranges from pleasant to unpleasant), Arousal (which ranges from calm to excite) and Dominance or control (ranging from in control to out of control). The ANEW list provides normative values in these dimensions for 1,034 words, and there is a Spanish adaptation of the ANEW made by Redondo et al. (2007).

Whissell's Dictionary of Affect in Language, originally designed to quantify the pleasantness and activation of specifically emotional words, was revised to increase its applicability to samples of natural language. A third-rated dimension (imagery) was added, and normative scores were obtained for natural English. Evidence supports the reliability and validity of ratings. The revised Dictionary, which contains ratings for characteristic words of natural language, is a portable tool that can be applied in almost any situation involving language (Whissell 2009).

The NRC Emotion Lexicon (EmoLex) is a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy and disgust) and two sentiments (negative and positive) (Mohammad and Turney 2013). The annotations were manually done by crowd sourcing. Despite some cultural differences, it has been shown that a majority of affective norms are stable across languages. Given that three basic dimensions, namely valence, Arousal and Dominance, are commonly used by researchers, we decided to use the Spanish version of ANEW dictionary merged with the Spanish version of EmoLex. Our approach to manage word lists is inspired by the effort of Maas et al. (2011), so we can collect affective indicators for words.

2.3 Fuzzy logic applied to sentiment analysis

Regarding fuzzy logic supporting sentiment analysis, several studies have been carried out, however not all in virtual learning. For instance, Moharrer et al. (2015) proposed a novel two-phase methodology based on interval type-2 fuzzy sets (T2FSs) to model the human perceptions of the linguistic terms used to describe the online services satisfaction. The analysis is carried out by using well-established metrics and results from the social sciences context.

Andreevskaia and Bergler (2006) focus on the WordNet dictionary so that they can acquire some awareness from text mining based on the sentiment analysis approach. Ali et al. (2016) focused on sentiment analysis in the academic field and were able to capture average behaviors shown by words, based on regular statistics analysis. They managed to build a fuzzy logic scheme, aimed at producing a qualitative description for words, turning quantitative magnitudes into literal terms bound to qualitative perceptions, such as good, bad, etc. Another application field for sentiment analysis is the stock market, where one can build trading scenarios based on opinion mining from information extracted from technical analysis and trends shown by stock trading systems and the market. This is discussed in Wu et al. (2014), where features, predictions and trading are dealt using intelligent support.

Our proposal aims to produce a scheme for word treatment, similar to Andreevskaia and Bergler (2006). Nevertheless, our study focuses on the ANEW dictionary and fuzzy qualifiers bound to amounts such as few, regular and many. These qualifiers will be then crossed over throughout specific inference rules.

These inference rules can explain the amounts achieved by accumulating numeric data from indicators and express them in qualitative terms. Hence, high-level emotions could be inferred from plain numbers. Inspired by Kuncheva (2000), our proposal is a fuzzy classifier, more precisely, a statistical classifier, which provides a priori qualitative assessment to the amounts assigned by ANEW to every word. The advantage of the statistical approach is to reduce the classical *pollution* problem of training and analyzing the scenario using the same dataset. Affective dictionaries usually have a limited number of words. Our statistical classifier uses centrality and dispersion measures calculated from the ANEW analysis dimensions. These measures are used to build the fuzzy classifier, as explained later in this paper.

3 A fuzzy-based classification model for inferring affective states

3.1 Fuzzy sets and fuzzy rules

Before describing our conceptual fuzzy-based model for inferring emotional states, we briefly present the process for setting the different fuzzy sets as well as the way we match our emotional thesaurus and we build our fuzzy rules system.

Regarding our fuzzy sets, as we explained in Arguedas et al. (2016c), we developed our own fuzzy classifier. In order to calculate the curves of each group corresponding to each magnitude (Pleasure, Arousal and Dominance), we run our tool three times, one for each dimension. At each run we gave the tool the mean of the values for that channel, its standard deviation, a file with the complete group of values for that dimension and a file with the qualitative values for that channel. In fact we used the same qualitative values for the three channels, but we configured the tool to establish different qualitative values for each one of the channels. From these results, we built the curves of the three groups related to each magnitude (Pleasure, Arousal and Dominance). The final outcome of this process has been a text file where each line contains a word from the dictionary, its term in English, its term in Spanish, the values for Pleasure, Arousal and Dominance, and their corresponding numerical values. This process is described in detail in (Arguedas et al. 2016c).

The group of various rules constitutes a rule base or knowledge base. Our model contains 24 rules that result from combining eight qualitative values obtained for every emotional axis of the Plutchick's model as primary, secondary and tertiary dyads. These rules are propositions that allow us to express the available knowledge about the relationship between antecedents and consequents and make affirmations of the *If-Then* type. For more details see Arguedas et al. (2016c).

3.2 Our conceptual fuzzy-based model for inferring emotional states

This section presents our conceptual model which is built by a set of components depicted in Fig. 1. These components process the students' texts through various steps which are explained below in more detail. In fact, our conceptual fuzzy-based model for inferring emotional states is described in three layers as shown in Fig. 1.

First layer: *The Affective Grammatical Tagger (AGT)* takes the text of discourse created by one or more students and performs several processes: (1) The AGT checks the

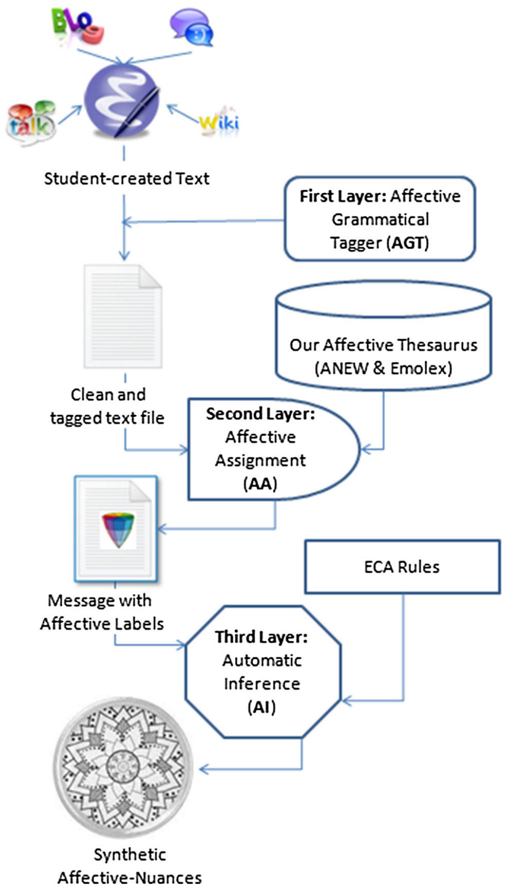


Fig. 1 A conceptual fuzzy-based model for inferring emotional states

messages word by word in order to solve typing problems that could have been in the text. (2) The AGT verifies that the words are in the dictionary. During this process, the AGT analyzes the text received as input. The output of this component will be two files, one of them with a clean and tagged text and the other with codes of "Complemented Language" (Etchevers 2006) that contains emoticons, onomatopoeia (haha, mua, m-mhmm), repetition of words (exceeeeeelent), etc., as shown in Fig. 2.

Second layer: The Affective Assignment (AA) takes each of the text files obtained previously, associates each word of them with the terms contained in our thesaurus and assigns to every word the dimensional and categorical emotional load.

The dimensional affective load is obtained using the information provided by ANEW dictionary, while the categorical affective load, as well as the valence (positive and negative) for each of the words, is obtained using the information provided by Emolex.

Once all the text has been processed, the mean of the obtained value for each characteristic is then calculated and the obtained mean values for Pleasure, Arousal and Dominance are fuzzified.

Finally, a new file is generated as shown in Fig. 3. This file contains a line with the obtained values for each of the authors of the discourse that is being analyzed every time.

Third layer: In this step, **the Automatic Inference (AI)** component takes the message with affective labels file as input. This file that contains the average affective information of each author both at dimensional and at categorical level is used to trigger our fuzzy rules system. The outcome of fuzzy rules system is to obtain the emotional states of each author during his/her learning process.

The output of this component is the synthetic opinion of the original message from the point of view of the emotional and affective state of the authors of the analyzed discourse, as shown in Fig. 4.

4 Implementation and extension of the model

Our fuzzy-based classification model (FBCM)[1] is built out of a set of tools implemented in Java. These tools process the students-created texts following the phases defined in the conceptual model.

Once the process has finished, we obtain the synthetic opinion of the original message that depicts author's emotional and affective state, which is then presented to the Affective Pedagogical Tutor (APT).

The APT can be human or virtual. In this work, we implemented and used a virtual APT for experimentation. It is a client–server Web application and constitutes an important extension of the model.

This application is installed in the computer of each student, connects to the server and displays the APT on the left side of the screen. In fact, we created an integrated learning environment that integrates the APT, the Moodle LMS embedded on the right side of the screen, a text edit box that allows the student to contact the APT textually, as well as the FBCM model that processes the emotional information.

The APT can be represented by two characters (masculine/feminine) so that each student can choose the character that is more comfortable for him/her. As such, the APT is characterized by a specific voice, the emotional expressions that can display and the dialogues that can be involved.

[1] The fuzzy-based classification model has been implemented and patented by Marta Arguedas with name FUZZYEMOSYS, on March 16, 2016, under registration number TXu 1-997-006.

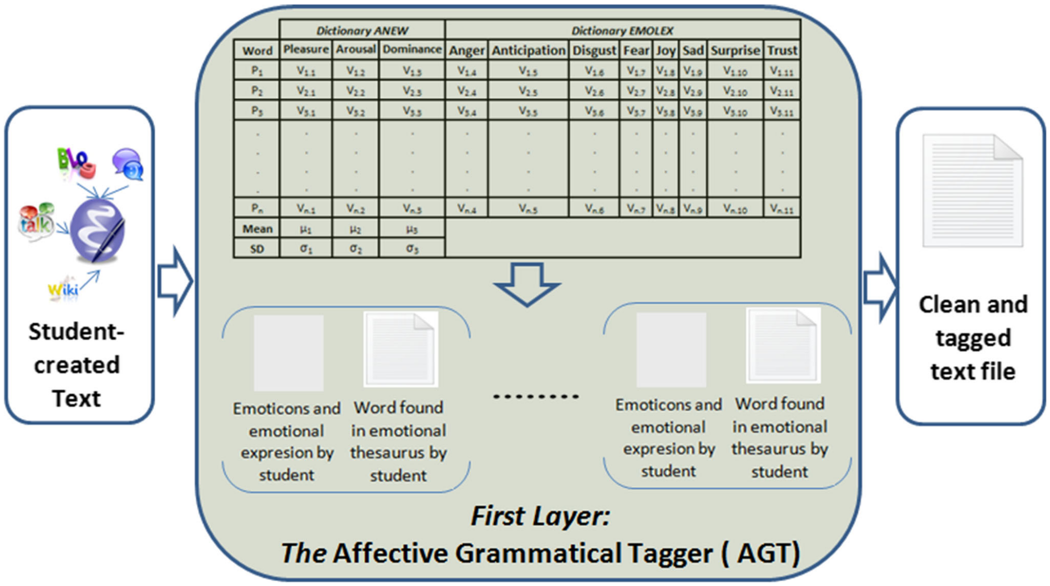


Fig. 2 First layer: the Affective Grammatical Tagger (AGT)

Students carry out the activity designed by the human teacher in the Moodle LMS. The interactive e-learning course is broadcasted to every user with the same contents. Depending on the student's academic and emotional evolution throughout the course, the human teacher can provide additional personalized material and exercises.

The student works on the LMS, carries out his/her tasks, collaborates with peers, whereas at the same time he/she can interact with the APT in a textual manner through the edit box located at the bottom of the screen. The Affective Pedagogical Tutor responds to student with audible and gestural signals that were scheduled in advance, while providing the student the information that he/she previously requested, as shown in Fig. 5.

When a student completes a task, the APT accesses the student-created texts and forwards them to be processed by the FBCM model. The FBCM stores the extracted emotional information in the web server. Finally, the APT can easily access every emotional log (sorted by student name, course name and task) through the Moodle platform, take it as input and create adequate affective feedback.

The *framework* used offers some predefined virtual agents to be used (if needed) as virtual tutors in the learning environment. Each available virtual agent has its own set of facial expressions and body animations that can be used as needed. The *goal* of these expressions and animations is to make the virtual agents able to express different emotional states, making their representation more believable. In order to increase the lifelikeness of the communication between the student and the virtual agent, bidirectional natural language conversation has been enabled.

The *virtual agent* is able to speak to the student and to understand what the student is saying. The student-virtual agent communication can be established via text, thanks to an integrated text box in which the student can chat, so text messages can be clearly displayed on the screen. Thanks to the use of an AIML[2]-based conversational engine and a fusion rule engine that processes questions in natural language, the student is allowed to use text and express him/herself in natural language as well as to ask questions to an ontology repository (like DBPEDIA[3]). to obtain the answer.

5 Datasets from a real learning context

5.1 Learning context

Nowadays computer-supported collaborative learning (CSCL) environments are viewed as an important electronic learning medium for distance education.

Working together, while accomplishing a task is seen as a characteristic of a powerful learning environment, aiming at active construction of knowledge. Through a process of

[2] AIML: Artificial Intelligence Markup Language (www.alicebot.org/aiml.html).

[3] DBpedia is a crowd-sourced community effort to extract structured information from Wikipedia and make this information available on the Web (http://wiki.dbpedia.org/about).

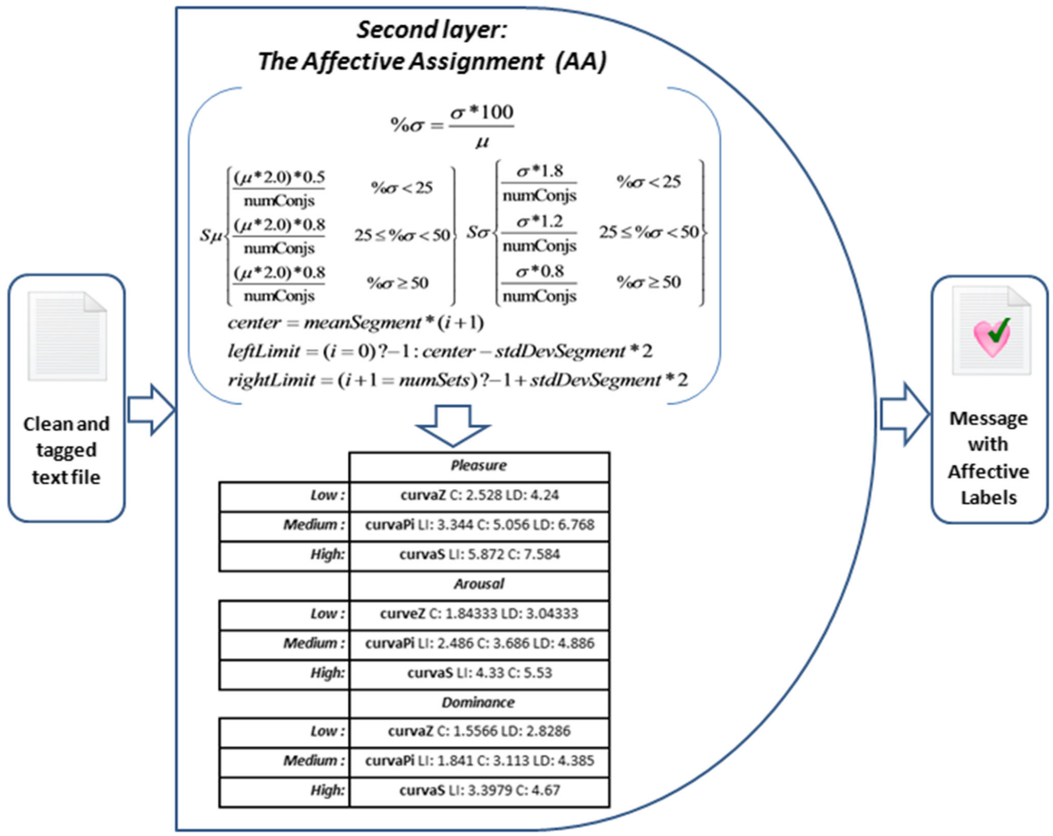


Fig. 3 Second layer: the Affective Assignment (AA)

interaction and negotiation students have an active and constructive role in the learning process (Dewiyanti et al. 2007).

Taking emotions into account, we need to provide teachers with different methods and tools to let them understand and analyze the emotional phenomenon and how it evolves over time.

Our approach lies on an emotion analysis model, which has been widely described in Arguedas and Daradoumis (2013) (Arguedas et al. 2016a, b). This model is based on the Activity Theory (AT) (Engeström et al. 1999) and describes a scenario where participants (teacher and students) work together and interact with specific objects to carry out goal-oriented activities.

Within this scenario we initially developed a discourse analysis method to analyze collaborative learning activities (that included written text and dialogues) in a nonintrusive way in order to capture process and identify the emotional information extracted from each student individually as well as from the students' group as a whole.

This information was presented to the human tutor and provided him/her with the necessary emotion awareness with regard to the way students' emotions appear and evolve over time. This enabled the tutor to offer students cognitive and affective feedback.

Apart from identifying emotional states and behavior, the result of this approach has been the graphical representation of the students' emotions that took place during these activities.

5.2 Research hypothesis and goals

Goal: The main goal of this work has been to extend the above approach and build a new model that provides an improved and more calibrated measurement and representation of students' emotions that can be used as input to a virtual tutor who can create adequate affective feedback.

At this stage of our research, our aim has been to analyze the combined effects of the emotion awareness produced by

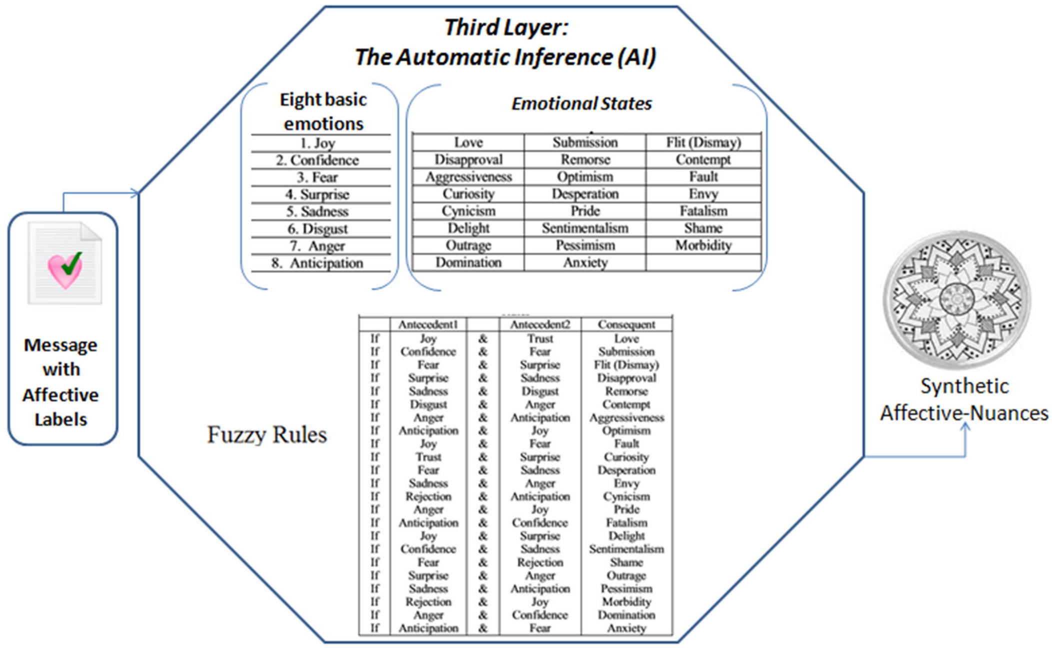


Fig. 4 Third layer: the Automatic Inference (AI)

our new model and of basic online tutorial affective feedback on students' learning performance in long-term blended collaborative learning practices.

Hypothesis: "Providing enhanced and more calibrated emotion awareness as well as automatic online tutorial affective feedback to learners improves their learning outcomes on time."

5.3 Research question

Is there any significant correlation between students' calibrated emotion awareness, the related virtual tutor affective feedback and students' learning outcome?

Independent Variable:

X = emotion awareness & affective feedback

Dependent Variables:

J = learning outcome

5.4 Participants and procedure

Participants were a sample of 48 fourth-year high school students attending the subject "Web Design." Among students, 24 were girls (50 %) and 24 were boys (50 %). We divided students in 16 groups of four and we chose 8 of them as the experimental group and the rest as the control group. The experiment was conducted for five weeks with a total of 15 sessions.

The *procedure* we followed was to design a scenario that included a collaborative learning activity which was implemented following the problem-based learning method and the Jigsaw collaborative strategy. The topic of the activity was "How to design a web page" and was carried out in the Moodle environment.

The *activity designed* by the human teacher was arranged in several synchronous and asynchronous tasks that included a Web site design, a forum debate and a chat, where students were encouraged to participate actively in building their knowledge.

In this way, the teacher's role was reduced to guide and give support to the learning activity, by providing appropriate advice or help when needed. Based on the Jigsaw collaborative strategy, the learning activity was divided in ten stages which in turn were grouped around five tasks to facilitate their implementation. For each task, the teacher provided all the necessary resources (documents and tools).

5.5 Research instruments

At the end of each task of the activity, we used our fuzzy-based classification model for processing and identifying the

Fig. 5 Gestural signals that were scheduled in advance in the APT

emotional information extracted from texts created by students in the chat and forum debate.

On the one hand, the data collected were used to trigger fuzzy rules according to Plutchick's model (Plutchik 2001) and obtain the emotional states that were experienced by students during the realization of the respective tasks.

On the other hand, we used the data gathered to represent graphically the arousal of text, according to the ANEW dictionary as well as the valence and the different types of emotion detected during the analysis, according to the NCR Emotion Lexicon.

Regarding the statistical techniques employed in the analysis of the gathered data, we used descriptive statistics, calculating relative frequencies (%), as well as graphics to represent reality objectively. We also used bivariate correlation and analysis of variance to find relationships between the variables under study for the research question of our study.

6 Model testing

As mentioned before, an experiment was carried out with high school students for testing our tool. We considered the texts produced by the students in various forum debates and chats. These texts along with the thesaurus built before served as an input for our tool.

The output of FBCM consists of a file that contains a line for each of the authors of the discourse with the obtained values for the dimensional and categorical characteristics, as well as the emotional states that result from the rules application to each set of categorical characteristics we obtained.

6.1 Data collection

At this point, in order to carry out the statistical analysis of the data resulting from our tool and the student grades, we defined the following indicators, as shown in Table 1:

(a) Dimensional characteristics (DI) include indicators that concern fuzzy values of three basic dimensions through which the entire range of human emotions can be organized: Pleasure, Arousal and Dominance or control,
(b) categorical characteristics (CI) include indicators that concern positive and negative emotions based on Plutchick's model and
(c) emotional states of fuzzy rules (CFR) include indicators that concern emotional states based on the results from applying our fuzzy rules.

6.2 Emotion awareness

In order to provide emotion awareness among participants in the experimental group, we applied our FBCM at all conversations that took place in the group during the learning activity.

The outcome of our model was a graphical representation of word clouds attributed to each student. This graphical representation was provided to both APT and students of the experimental group, at the end of each task, as shown in Fig. 6.

Table 1 Indicators and their tags used in statistical calculations

Tag	AXES/ indicators
Dimensional characteristics (DI)	
DI.1	Pleasure
DI.2	Arousal
DI.3	Dominance
Categorical characteristics (CI)	
CI.1	Joy
CI.2	Confidence
CI.3	Fear
CI.4	Surprise
CI.5	Sadness
CI.6	Disgust
CI.7	Anger
CI.8	Anticipation
Emotional states of fuzzy rules (CFR)	
CFR.1	Love
CFR 2	Disapproval
CFR.3	Aggressiveness
CFR.4	Curiosity
CFR.5	Cynicism
CFR.6	Delight
CFR.7	Outrage
CFR.8	Domination
CFR.9	Submission
CFR.10	Remorse
CFR.11	Optimism
CFR.12	Desperation
CFR.13	Pride
CFR.14	Sentimentalism
CFR.15	Pessimism
CFR.16	Anxiety
CFR.17	Flit (Dismay)
CFR.18	Contempt
CFR.19	Fault
CFR.20	Envy
CFR.21	Fatalism
CFR.22	Shame
CFR.23	Morbidity

In this way, the APT was aware of students' emotions during their interactions in the virtual learning space (chat and forum). In fact, the APT could observe not only which emotions and emotional states of its students were present but also, and most importantly, the level of Pleasure, Arousal and Dominance of these emotions. Figure 7 shows the evolution of dimensional and categorical emotions as well as the emotional states of one team of 5 students in the EG.

In this way, the APT could intervene on time. In addition, students were aware of the emotions, emotional states and the level of Pleasure, Arousal and Dominance that they experienced during the accomplishment of the task. In contrast, the students of the control group were not supported by this facility and carried out their activity in a conventional way.

6.3 Presentation of the results

(i) *The Cronbach's alpha coefficient*

To ensure the reliability of data collection, we applied the Cronbach's alpha coefficient to both experimental group (EG) and control group (CG). Cronbach's alpha is considered to be a coefficient of reliability (or consistency).

A reliability coefficient of .70 or higher is considered "acceptable" in most social science research situations.

All values of Cronbach's alpha in Table 2 are higher than .70, which reinforces the reliability of our indicators.

(ii) *Descriptive statistics*

The skewness and kurtosis of each variable were examined to check for multivariate normality.

The absolute values of skewness and the absolute values of kurtosis did not exceed a univariate skewness of 2.0 and a univariate of kurtosis of 7.0.

In our case, it was assumed that there was no critical problem regarding multivariate normality in EG.

However, in CG the only cases where the values of skewness and kurtosis did not exceed a univariate skewness of 2.0 and a univariate of kurtosis of 7.0 occurred for the items of DI.1, DI.2 and DI.3 in the control group, as shown in Table 3.

(iii) *Pearson's correlations*

Finally, we present the correlations between variables DI & Mark, CI & Mark and CFR & Mark that were found in the experimental group in Tables 4. Mark is directly related to students' learning outcome.

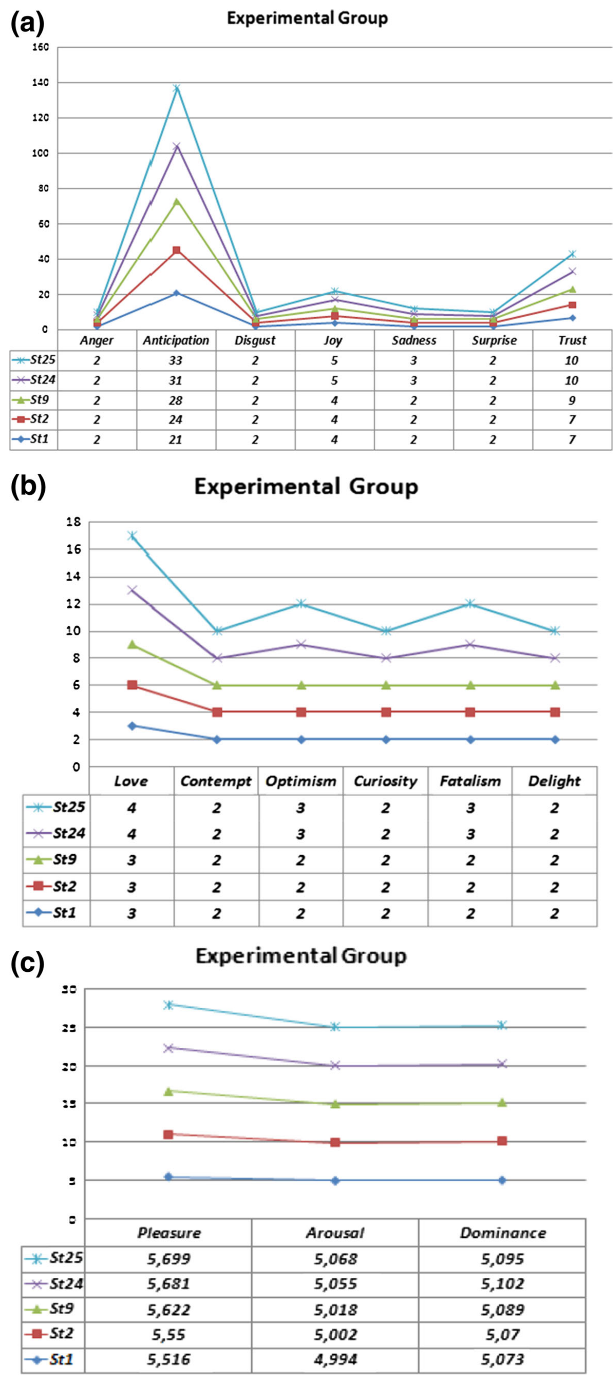
First, a significant positive correlation was found between DI (dimensional characteristics) and Mark in the experimental group. In particular, we found higher correlations between Mark and Pleasure (DI.1) (r $-.760$, $p<.01$), Arousal (DI.2) (r $-.755$, $p<.05$) and Dominance (DI.3) (r $-.556$, $p < .01$).

Second, a significant positive correlation was found between CI (categorical characteristics) and Mark. In particular, we found higher correlations between Mark and Joy (CI.1) (r $-.704$, $p < .01$), Sadness (CI.5) (r $-.895$, $p < .01$), Trust (CI.2) (r $-.785$, $p < .01$) and Anticipation (CI.8) (r $-.844$, $p < .01$).

Third, a significant positive correlation was found between CFR (emotional states of fuzzy rules) and Mark. In particular, we found higher correlations between Mark and Love (CFR.1) (r $-.704$, $p < .01$), Optimism (CFR.11) ($r$$-.704$, $p < .01$) and Fatalism (CFR.21) (r $-.704$, $p < .01$).

In contrast, in control group the only significant correlation found was between Mark and Arousal (r $.480$, $p< .05$).

Fig. 6 Example of Word Clouds provided emotion awareness to each participant in the experimental group



	Anger	Anticipation	Disgust	Joy	Sadness	Surprise	Trust
St25	2	33	2	5	3	2	10
St24	2	31	2	5	3	2	10
St9	2	28	2	4	2	2	9
St2	2	24	2	4	2	2	7
St1	2	21	2	4	2	2	7

	Love	Contempt	Optimism	Curiosity	Fatalism	Delight
St25	4	2	3	2	3	2
St24	4	2	3	2	3	2
St9	3	2	2	2	2	2
St2	3	2	2	2	2	2
St1	3	2	2	2	2	2

	Pleasure	Arousal	Dominance
St25	5,699	5,068	5,095
St24	5,681	5,055	5,102
St9	5,622	5,018	5,089
St2	5,55	5,002	5,07
St1	5,516	4,994	5,073

Fig. 7 Graphical representation of emotion awareness of one team of 5 students in the EG. **a** Categorical emotions shown by a 5-student team, **b** emotional states shown by a 5-student team, **c** dimensional emotions shown by a 5-student team

Table 2 The Cronbach's alpha coefficient of DI, CI and CFR, in EG and CG

THE CRONBACH'S ALPHA (EG)
((DI), (CI) (CFR))
.769
THE CRONBACH'S ALPHA
(CG) ((DI), (CI) and (CFR))
.900

Table 3 The descriptive statistics of DI, CI and CFR, in EG and CG

	Min	Max.	Mean	SD	Skewness	Kurtosis
	The results of descriptive statistics (EG)					
DI.1	5.27	5.70	5.4876	.12883	.327	−.628
DI.2	4.92	5.07	4.9930	.04047	.688	.046
DI.3	4.93	5.10	5.0454	.05081	−1.182	.661
CI.7	2	2	2.00	.000	.	.
CI.8	16	33	22.55	5.343	1.189	.064
CI.6	2	2	2.00	.000	.	.
CI.1	4	5	4.18	.395	1.773	1.250
CI.5	1	3	1.50	.802	1.220	−.202
CI.4	2	2	2.00	.000	.	.
CI.2	5	10	7.36	1.529	.548	−.067
CFR.1	3	4	3.18	.395	1.773	1.250
CFR.18	2	2	2.00	.000	.	.
CFR.11	2	3	2.18	.395	1.773	1.250
CFR.4	2	2	2.00	.000	.	.
CFR.21	2	3	2.18	.395	1.773	1.250
CFR.6	2	2	2.00	.000	.	.
	The results of descriptive statistics (CG)					
DI.1	5.59	5.75	5.6420	.04051	1.090	.391
DI.2	5.07	5.11	5.0958	.00918	−1.089	1.344
DI.3	5.04	5.12	5.0668	.02520	.878	−.593
CI.7	4	12	6.09	1.411	3.339	15.517
CI.8	35	84	40.70	9.484	4.720	22.519
CI.6	4	12	6.09	1.411	3.339	15.517
CI.1	5	16	7.48	2.129	2.988	12.095
CI.5	3	8	3.91	.996	3.210	13.730
CI.4	2	6	3.09	.668	3.906	18.526
CI.2	10	24	12.09	2.661	4.414	20.563
CFR.1	4	12	5.78	1.476	3.570	15.534
CFR.18	4	12	6.09	1.411	3.339	15.517
CFR.11	3	8	4.13	.869	4.284	20.216
CFR.4	2	6	3.09	.668	3.906	18.526
CFR.21	3	8	4.13	.869	4.284	20.216
CFR.6	2	6	3.09	.668	3.906	18.526

Table 4 Pearson's correlation of DI, CI and CFR with Marks, in EG and CG

	Mark		Mark		Mark
Pearson's correlation - EG					
DI.1	−.760**	CI.1	−.704**	CFR.1	−.704**
DI.2	−.755**	CI.5	−.895**	CFR.11	−.704**
DI.3	−.556**	CI.2	−.785**	CFR.21	−.704**
		CI.8	−.844**		
Pearson's correlation - CG					
DI.1	−.216	CI.1	.007	CFR.1	−.021
DI.2	.480*	CI.5	.119	CFR.11	.048
DI.3	−.229	CI.2	−.003	CFR.21	.048
		CI.8	.011		

* Correlation is significant at the 0.05 level (2-tailed)
** Correlation is significant at the 0.01 level (2-tailed)

7 Discussion

Based on the results we obtained in the above Sect. 6, we proceed to discuss and provide a response to the research question we set in this work:

RQ: Is there any significant correlation between students' calibrated emotion awareness, the related virtual tutor affective feedback and students' learning outcome?

Our results showed that this question had a positive answer in all aspects in the experimental group which was had been endowed with emotion awareness and emotional feedback facilities. Table 3 shows that dimensional characteristics (such as Pleasure, Arousal and Dominance), categorical characteristics (such as Joy, Sadness, Confidence/Trust and Anticipation) and emotional states (such as Love, Optimism and Fatalism) had significant positive effects on a better learning performance in the EG.

In particular, our experiment showed that dimensional characteristics had a higher positive impact in the outcomes of the learning activity of students in the EG, whereas in the control group only Arousal had an implicit positive relation with the students' obtained outcome.

Moreover, categorical characteristics (like Joy, Sadness, Trust and Anticipation) had significant positive effects on the activity performance for the EG students. No significant correlation was reported for CG students.

Finally, once our ECA fuzzy rules were triggered, the monitoring of emotional states such as Love, Optimism and Fatalism by the Affective Pedagogical Tutor (APT) had significant positive effects on the performance of EG students. In contrast, no significant correlation was reported for CG students.

8 Conclusions and future work

In this work we have presented a model for monitoring students' emotions using fuzzy logic in an e-learning environment, with the aim to provide both emotion awareness and affective feedback to students through an online Affective Pedagogical Tutor (APT). To test and validate our model we run an experiment in a real e-collaborative learning situation.

The results of the experiment showed that our model was highly effective in the experimental group (EG) of students who were supplied with both emotion awareness and affective feedback. In this group, the explicit graphical representation of dimensional and categorical emotions after every task proved to produce much better learning results than those in the control group (CG). In fact, the Word Clouds produced helped students be conscious of their emotions, overcome possible situations of sadness, enhance anticipation and trust and accomplish their task successfully. Regarding the function and influence of APT, the results showed that its affective feedback had really a very positive effect on EG students. CG students really missed this opportunity. In fact, the support offered by APT, through emotional expressions and advice, helped EG students both overcome emotional states such as Fatalism and increase their optimism, which led them to carry out their activities successfully.

Future work is focused on improving our fuzzy rules system in order to accomplish three important goals in virtual learning environments: increase its accuracy, include more emotional states in its monitoring capabilities and process and analyze the students' emotional states in real time.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical standard All procedures performed in our experiment that involved human participants (a human tutor and students) were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study.

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7.4. Patentes Internacionales

7.4.1. (1) Título del software: FUZZYEMOSYS

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7.5. Artículos en otras Revistas

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#03

Arguedas, M. & Daradoumis, T. (2013). Exploring learners' emotions over time in virtual learning. *eLC Research Paper Series, 6, 29-39.*

EXPLORING LEARNERS' EMOTIONS OVER TIME IN VIRTUAL LEARNING

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Exploring learners' emotions over time in virtual learning

ABSTRACT

Time constitutes an important factor influencing every process related to e-learning. Along these lines, we need to study how students manage time in their learning processes. We need to know if they feel that they have enough time to carry out a learning activity or whether they feel stressed and frustrated by the lack of time. We are also interested in what kind of emotions they express and how these emotions evolve over this period of time. Our work focuses on studying the nature and role time plays in the affective states learners experience during a long-term e-learning process. Our methodological design shows the type of data we need to collect, which methods are more suitable for analysing this data in order to detect and interpret the learners' emotions across time.

KEYWORDS

Affective learning, emotions, time factor in affective learning, virtual affective agent/tutor, affective management.

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INTRODUCTION AND RATIONALE

According to Demeure et al. (2010), time is an important variable in the analysis of teaching-learning processes that take place in e-learning and, more specifically, in CSCL contexts. Moreover, one of the main concerns in the educational field is that of making knowledge more meaningful and long-lasting. The e-learning process has to be an active process where technologies must serve as tools to support knowledge building and skill development in students by taking into account the students' specific, cognitive and emotional characteristics and skills that can facilitate and complement this process (Silva et al, 2006). In long-term virtual learning practices, it is important to investigate what kind of emotions students express and how these emotions evolve over this period of time. On one hand, we need to determine the factors that lead students to remain in the same negative affective state for a certain period of time, as this can lead to a significant reduction of the quality of learning and even withdrawal from studies. On the other hand, we need to study how students manage time in their learning processes. We need to know if they feel that they have enough time to carry out a learning activity or whether they feel stressed and frustrated by the lack of time. In this regard, we will establish a methodological design that shows the type of data we need to collect and which methods are more suitable for analysing the data in order to detect and interpret the learners' emotions across time.

An exhaustive analysis of all the data regarding the emotions students transmit is crucial for detecting and interpreting various types of emotions and anticipating the emotional states that students may experience at particular points in their learning process. Once we have completed our analysis, we need to develop a way of reacting to mediate and regulate students' e-learning processes. Affective pedagogical agents or tutors have been widely used in e-learning environments in a variety of ways (Beale & Creed, 2009; Frasson & Chalfoun, 2010). This study will lay the foundations for the design of an affective virtual agent/tutor able to intervene and mediate in students' e-learning processes, providing them with an appropriate affective feedback that will guide, advise and help them according to their needs and feelings. In order to achieve those challenges, this article will focus first on making a comprehensive and critical analysis of the state of the art of computer-based affective learning in relation to the time factor (i.e. evaluating important research work on the analysis of affective interactions, emotional feedback, affective tutor, etc.). Secondly, based on this analysis, we present our research questions. Thirdly, we describe our own proposal for explaining how we will address this issue in relation to the time factor and the advantages and innovations our proposal can offer regarding other proposals. Here we describe our approach at a conceptual design level.

BACKGROUND RESEARCH

During the past decade, emotion has emerged as a vital element of the learning process but many questions about emotional management in education remain unanswered. In his research, Pekrun (2005) recognises the lack of knowledge of the occurrence, frequency and phenomenology of emotions in different learning environments, and especially in e-learning. The emotional relationship with new tools and learning content are new research areas of particular interest to e-learning (Ekflides, 2006). The educational experiments being carried out in virtual learning environments require a redefinition of the agents involved (teachers and students), the spaces where educational activities are conducted, time and learning sequences (Perez, 2002). The teaching process involves preparing the teacher to generate an effective dialogue with/and among participants, by encouraging active learning and knowledge building through collaboration, by knowing how to identify feelings and emotions and by controlling and providing appropriate models of expression (Ibarrola, 2000). Emotional aspects play a fundamental role in the user's interaction, because they affect cognitive processes. In other words, the user's affective states have an influence on how well that person solves rational problems. More specifically, emotions affect attention and memorization, as well as the user's performance and assessment (Brave & Nass, 2002). In this section, we study students' emotions from several perspectives, such as time management, the relationship between time and affectivity, and technology use, both at individual and group level.

- **As regards time management**, we need to study how students manage time in their learning processes and how this is related with their emotions. Zimbardo & Boyd (1999) propose the following paradoxes about how to manage time perception effectively: (1) Understanding relativity, (2) Consistent awareness and (3) Conscious effort. However, even if students are good at time management, this does not guarantee that they will achieve effective learning. For instance, Roy & Christenfeld (2007) suggest that people underestimate how long it will take them to complete future tasks. There are three facts that one should take into account: (1) the tendency to underestimate future duration, which disappears when the task is new, (2) the existence of similar bias in estimating both past and future durations, and (3) variables that affect memory of duration, such as level of experience of the task and the duration of the delay before estimation, affect prediction of duration in the same way. It appears that, at least in part, people underestimate future event duration because they underestimate past event duration.

- **As regards time and affectivity**, we want to identify what kind of emotions students express and how these emotions evolve over a period of time. It is necessary to know if the negative emotions that have been detected remain and turn into other negative (and possible more harmful) emotions through time and set time limits to make them change to more positive emotions. Both D'Mello et al. (2007) and Baker et al. (2007) have shown that students are most likely to remain in the same affective state over time in these environments and that certain emotional transitions are more likely than others. Likewise, McQuiggan et al. (2008) have shown that when transitions to alternate affective states did occur, they followed interesting patterns. Moreover, Feidakis et al. (2012) argue that time and emotions have to be taken into account in three stages when assessing a task: before the task, in real time and at deferred time.

- **At an individual level**, we will have to take into account the time perception of learners in relation to their time perspectives and their time management skills. It is necessary to know whether students feel that they have enough time to carry out a learning activity or whether they feel stressed and frustrated by the lack of time. In this sense, lack of time may be caused because the format of learning content or the development of learning activities cannot be adapted to each student's learning style (Alonso et al, 1994). Learning style constitutes an important precondition for the design of any learning process. In this sense, Bloom (1968) explored the Model of School Learning by concluding that, given sufficient time and quality teaching, nearly all students could learn. Johnston & Aldridge (1985) proposed

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an exponential learning model, which included learner characteristics - specifically, aptitude and motive - as conditions related to learning achievement. Therefore, learning achievement can be predicted by a function of student characteristics and the time spent in learning. Demeure et al. (2010) argue that the major difficulty for individual learners is to balance all their professional, social, and academic activities.

- **At group level**, in Computer-Supported Collaborative Learning (CSCL) contexts, time is also an important factor in group work. Analysis of collaborative learning interactions requires a constant effort in trying to detect emotions through the application of a variety of methods, such as discourse and conversation analysis, analysis of feelings or opinion mining that allow non-intrusive automatic detection and extraction of emotions from student-created texts and dialogues. In this case, the teacher should apply an activity plan that takes time into account in terms of when it is suitable to proceed to emotion detection as well as when to provide dynamic recommendations and affective feedback, depending on the design and requirements of the collaborative activity concerned. Therefore, *with regard to group processing*, group formation needs time in order to establish the social norms to regulate member activities (Demeure et al. 2010). In this sense, the five stages of group development (orientation, conflict, cohesion, performance and dissolution) could be used to analyse temporal relationships in interaction, in terms of the succession of stages (Tuckman & Jensen, 1977). So, the teacher can influence or persuade learners by providing suitable affective feedback in order to regulate members' emotions in every planned stage. By doing so, group members can feel more confident through belonging to a community and they can even develop co-leadership skills.

- **As regards technology**, it is necessary to incorporate specific tools in the virtual classroom that will facilitate communication of both intentions and feelings at appropriate time intervals which can be easily recognized both by the teacher and the students. The latest research and development in the areas of artificial intelligence and robotics are reflected in the appearance of Intelligent Tutor Systems (ITS). As well as being educational programs, these simulate the behaviour patterns of a human tutor, aiming to improve learning in a field of knowledge. ITS are empowered with Affective Pedagogical Tutors (APT), which act as teachers and are able to interact with the student in human communication style (Beale & Creed, 2009). An APT's role is to solve problems, provide advice, guidance and emotional support in interaction with the student and to show contextuality, continuity and temporality. Learners experience a variety of emotions while interacting with a virtual tutor in the same way as in the context of traditional learning, when a human tutor can influence student emotions in order to improve efficiency in learning (Hargreaves, 2002). Similarly, a virtual tutor can be seen as a practitioner able to influence emotions in the learner. Moreover, these emotions will strongly influence their cognition (Isen, 2000). An APT can be invaluable when students do not recognize that their actions are inappropriate or simply not optimal. In such a case, a virtual tutor can intervene with the appropriate advice. In other circumstances, they may encounter situations that are unfamiliar due to insufficient knowledge, so they might benefit if they have someone to guide them, answer their questions and show them the right process. As such, several types of environments have been designed and evaluated (Table 1) and several types of effects have been detected (Table 2).

Table 1. Different types of virtual environment with APTs.

Types of virtual environments with APT (Affective Pedagogical Tutors)	
Embodied Agents	An embodied agent can be defined as a digital, visual representation of an interface, often taking a human form (Cassell, 2002). Affective issues such as empathy, self-efficacy and motivation have been implemented in various forms in a very broad range of different virtual environments. Because of their strong life-like presence, animated teaching agents can capture students' imaginations and play a critical motivational role in keeping them deeply engaged in a learning environment's activities (Lester et al. 1997). Indeed, one of the main goals of an ITS is to be able to recognize and address the emotional state of the learner and react accordingly through the presence of the pedagogical agent. Examples: Affective tutor (Kapoor, 2007), AutoTutor (D'Mello et al, 2005).
Narrative Learning Environments	Narrative has been an important way of transmitting knowledge across generations, and is innate in human nature. Narrative is also a valuable vehicle for structuring knowledge and helping us in the process of creating meaning. By applying a narrative approach, it is possible to achieve an application that may help learners by illustrating phenomena and procedures and by motivating them to stay engaged and immersed in learning tasks. In addition, narrative learning environments can facilitate activities associated with learning, such as role-playing and exploration, reflection and idea sharing that use different pedagogical strategies and affect the context of narration. Examples: Crystal Island (McQuiggan and Lester, 2008), FearNot! (Aylett et al. 2005).
Subliminal Learning	According to Chalfoun and Frasson (2008), emotions, especially motivation and engagement, are widely related in various cognitive tasks. A large body of work in neuroscience and other fields leads us to believe that simple to complex information can be learned without perception or complete awareness of the task at hand (Dijksterhuis and Nordgren 2006). In fact, the existence of perceptual learning without perception has been neurologically proven and accepted (Del Cul et al. 2007). In a recent work, Chalfoun and Frasson (2008) have suggested an increase in performance when using a subliminal teaching Intelligent Tutoring System.

Table 2. The most characteristic effects detected in virtual environment with APTs

The most characteristic effects detected in these environments
• ***Person Effect* (Lester et al, 1997):** The presence of an agent in an interactive environment, though not encouraged, can have a positive effect on the perception of the educational experience for the student. The time factor was not taken into account in these works. Examples: *Herman the Bug* (Lester et al, 1997); *Steve* (Johnson & Rickel, 2000); *AutoTutor* (Graesser et al, 2008).
• ***Proteo Effect* (Yee & Bailenson, 2007):** Students can learn because they are motivated by the characteristics of their avatars and they want to be like them. In this case, the role of the agent is not authoritarian, but fundamentally emotional/social support. Research on this effect is more focused on immersion in the 3D environments of educational games. This line of research does not take the time factor into account and it remains open without conclusive results in the literature. Examples: Troublemaker (Aimeur & Frasson, 1996); Jake & Jane (Arroyo et al, 2009).
• ***Protégé Effect* (Chase et al, 2009):** Students make a greater effort to learn how to teach their avatar than on their own learning. The focus of these agents is based on the "Learning by Teaching" paradigm; this means the student learns to teach the agent technical issues or concepts. The time factor was not taken into account in this work either. Examples: Betty (Biswas et al, 2009).

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RESEARCH QUESTIONS

Based on the analysis made of the literature described in the previous section, we proceeded to identify the following research questions that still remain open and for which we will try to provide some effective answers in our current and future work:

- **(Q1)** How do students manage time in their learning processes? How can we know if they feel that they have enough time to carry out a learning activity or whether they feel stressed and frustrated by the lack of time?
- **(Q2)** What kind of emotions do students express and how do these emotions evolve over a certain period of time? How do negative emotions turn into other (and possible more harmful) negative emotions over time? What time limits should we set to make them change to more positive emotions?
- **(Q3)** What are the factors that lead students to remain in the same negative affective state that is considered detrimental and dangerous for a certain period of time, leading to a significant reduction in the quality of their learning, failure and even withdrawal from studies?
- **(Q4)** How can we detect and interpret various types of emotions and anticipate the emotional states students may experience at a particular moment of their learning process?
- **(Q5)** How can we make students react in time, guide them and help them in an appropriate way so they can come out of a negative affective state and move into a more positive one?
- **(Q6)** How should a virtual tutor manage time with the aim of providing feedback at the right time, intervening and mediating in the students' e-learning processes, providing them with appropriate affective feedback that will guide, advice and help them, depending on their needs and feelings?

A CONCEPTUAL EMOTION ANALYSIS MODEL

In today's student-centred constructivist learning environments, where students develop their learning processes over time, teachers' work is highly demanding. To provide an effective answer to the above questions, we are proposing an emotion analysis model at a conceptual level which integrates an extension of learning and linguistic theories with a variety of methods and tools. Our approach is based on the Activity Theory (AT) (Engeström et al., 1999), which provides a theoretical framework to understand and analyse a phenomenon, find patterns and make inferences through interactions that describe those phenomena. AT provides a conceptual framework (Barros et al, 2004) to situate social and technological elements of a system in the same unit of analysis, called activity. In our case, we apply an extended AT scenario which consists of making several participants (teacher and students) cooperate and interact with specific objects (such as text and dialogue) through the use of specific tools (APTs, emotion analysis tools) to carry out goal-oriented activities. According to Barberà (2010), the "temporal dimension in e-learning is considered as a real tool which is always present and which spreads out into the planning and implementation of online education". In this sense, we include the time factor as a tool within our definition of the AT for providing both teacher and students with more control and flexibility in the development of their respective tasks. That is, with regard to resources and tools, they decide how and when to use them. In this way, the time perspective and time management both become an issue and a fact in planning and carrying out learning tasks, while they play an important role in the establishment and evolution of the emotional state of the learning community. Adequate time management is a necessary factor in facilitating and

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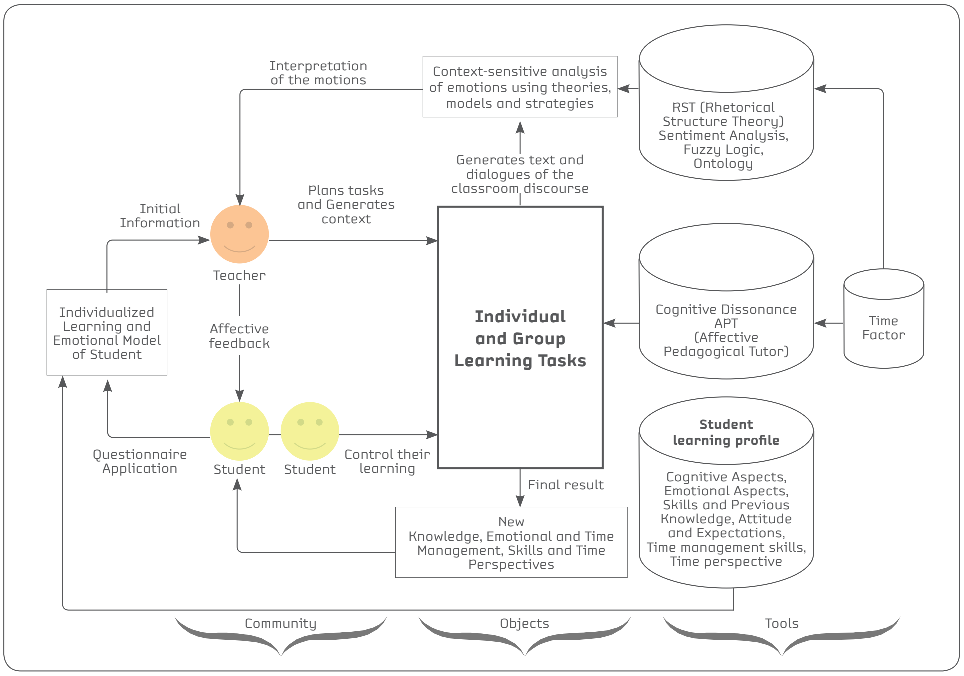
Figure 1. **Graphic Representation of the Emotion Analysis Model based on an Extended Activity Theory Scenario.**



enhancing the teaching-learning processes. Let us now briefly explain the components of the architecture of our conceptual Emotion Analysis model which is based on an extension of AT with emotional information and time factor (Figure 1).

In this context, emotion can be used to initiate actions that direct the student's attention to the cognitive goal that needs to be completed. At this point it is important that the teacher's feedback takes time into account. Without being obsessive or abusive, it will consider the duration of the student's learning process in three ways: the time needed to carry out an activity, the time the student has available, and the moment the tutor considers that he/she has to intervene with cognitive and emotional feedback. Concerning the tools used in our framework, first, the building of a robust student learning profile is an important component of our model. The resulting student profile enables the teacher to establish the content format, develop activities and choose the settings for using methods such as Project-based Learning, Problem-based Learning or Case-based Learning.

Secondly, we endow the Affective Pedagogical Tutor (APT) with several roles. Firstly, there is the capacity to design and apply *cognitive dissonance strategy* in both the planning and implementation of learning activities which are carried out cooperatively. In particular, in the design of learning activities, both at individual and group level, our APT plans evaluation tasks with dissonance questions based on the "Learning by Teaching" paradigm (Biswas et al, 2009). In addition, another role for the APT will be as a troublemaker classmate, i.e. a difficult student who sometimes gives incorrect answers in order to provoke cognitive dissonance, similar to the agent used by Aimeur & Frasson (1996). Here, it is important to study how the APT should manage time and know the moment when it should appear to play this role. As cognitive dissonance provokes "constructive conflicts" for students, it is more likely that several emotions will also appear and be openly expressed by students. For this reason, it is important that learning activities should be controlled by the APT with an appropriate time management strategy so that the "conflicts" can be resolved within a desired time interval and not leave space for unwanted negative emotions and situations among students. In particular, cognitive dissonance allows us to identify possible activating or inhibiting emotional causes and consequences, as well as its influence on students' emotional situations, behaviours, habits and behaviour modification, including their time management skills and their perception of time perspectives. Moreover, it allows us to know how students manage time in their learning processes. In this case, we need to know if they feel that they have enough time to carry out a learning activity or whether they feel stressed and frustrated by the lack of time. We are also interested in what kind of emotions they express and how these emotions evolve over this period of time. It is necessary to know if the negative emotions that have been detected remain and turn into other negative (and possible more harmful) emotions over time, and to set time limits for changing them to more positive emotions.

Thirdly, we need to find the best way to automatically detect and present the affective behaviours that participants show in their interactions in virtual spaces in order to label and display their emotions in an unobtrusive, relevant and non-intrusive way. To achieve this, we will apply an extension of Rhetorical Structure Theory (RST) and Sentiment Analysis (Liu, 2012), also taking the Time Factor into account. We are using these discourse analysis tools to analyse collaborative learning activities (such as the creation of a wiki and debates in forums or chats) in order to extract the emotional relationships between discourse units and provide a graphic representation of the emotional structure of discourse. Based on the time factor, we can determine how long students remain in the same negative affective state in their discourse and then we can search for the factors that have led to the situation. In this case, we need to specify a time limit after which continuation of this situation can be considered detrimental and dangerous, as it can lead to a significant reduction of the quality of learning, failure and even withdrawal from studies. An analysis of the emotional state will also take the context in which learning occurs into account. We understand as *learning context* all relevant information related to a student/group that participates in the learning activity. We will use ontologies as a computational approach to represent this context. Moreover, based on these context data and given that the emotional state is not a precise thing, the analysis will include machine learning techniques (such as fuzzy logic) to derive the emotional state as well as its relationship to the context and the learning outcome.

The application of the above tools provides important knowledge about when specific emotions arise and what causes them. Consequently, in response to the detection of students' affective states their occurrence over time, the tutor is able to provide appropriate feedback to make students react in time, guide them and help them in an appropriate way. This method helps students enhance their time perception, emotional safety and more effective and fruitful engagement in the learning experience. This is more evident when students

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become capable of coming out of a negative affective state and moving into a more positive one at a particular moment in their learning process.

FUTURE WORK

In order to evaluate and analyse the effects of this model in the collaborative learning process, our future work will first focus on developing a full computational model and then designing and carrying out three experimental scenarios which will assess the validity of our model and provide us with appropriate answers to the research questions set above. In all three scenarios we will conduct a controlled experiment for which two groups are needed: an experimental group and a control group. This will be an important part of our research, as a controlled experiment is a highly focused way of collecting data and will be especially useful for us in order to determine emotional and behavioural patterns of cause and effect.

CONCLUSION

At each step of the learning process it is important that both emotion detection and emotional feedback take time into account. At a conceptual level, this study proposes a methodological framework for managing students' emotions, especially when carrying out cooperative tasks and where time management plays an important role in students' participation, behaviour and performance and is directly related to students' emotional states during the learning process. In this context, emotions can be used to initiate actions that direct the student's attention to the cognitive goal that needs to be completed. The ultimate aim is to provide an environment where students feel safe, comfortable, valued and confident that they will receive the help they need to achieve their goals. All in all, we consider time as an important factor to be taken into account and this is clearly reflected in the design of our integrated approach and Emotion Analysis Model which includes the provision of timely affective feedback.

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7.6. Artículos en Congresos Peer-Review

7.6.1. (1) Referencia

1. Arguedas, M., Casillas, L., Xhafa, F., Daradoumis, T., Peña, A. and Caballé, S. (2016). A Fuzzy-based Approach for Classifying Students Emotional States in Online Collaborative Work. In proceedings of the 10th International Conference on Complex, Intelligent and Software Intensive Systems (CISIS-2016), Fukuoka, Japan, July 6-8, 2016, IEEE Computer Society, Los Alamitos, CA, USA. DOI 10.1109/CISIS.2016.141, ISBN: 978-1-5090-0987-9, pp. 61-68.

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A Fuzzy-based Approach for Classifying Students' Emotional States in Online Collaborative Work

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***Abstract* — Emotion awareness is becoming a key aspect in collaborative work at academia, enterprises and organizations that use collaborative group work in their activity. Due to pervasiveness of ICT's, most of collaboration can be performed through communication media channels such as discussion forums, social networks, etc. The emotive state of the users while they carry out their activity such as collaborative learning at Universities or project work at enterprises and organizations influences very much their performance and can actually determine the final learning or project outcome. Therefore, monitoring the users' emotive states and using that information for providing feedback and scaffolding is crucial. To this end, automated analysis over data collected from communication channels is a useful source. In this paper, we propose an approach to process such collected data in order to classify and assess emotional states of involved users and provide them feedback accordingly to their emotive states. In order to achieve this, a fuzzy approach is used to build the emotive classification system, which is fed with data from ANEW dictionary, whose words are bound to emotional weights and these, in turn, are used to map Fuzzy sets in our proposal. The proposed fuzzy-based system has been evaluated using real data from collaborative learning courses in an academic context.**

Keywords— Emotion Awareness, Fuzzy Clasification, Collaborative Learning, Automated Emotional Assessment.

I. Introduction

Our research work aims at investigating the effectiveness of the emotion labeling model to detect emotions in educational discourse (text and conversation) in a non-intrusive way making emotion awareness explicit both at individual and group level [1]. Studies have shown that emotional experiences influence student's motivation, learning strategies and achievement whereas such emotional experiences are influenced by personality and classroom characteristics [2][3].

Given that people are able to express a wide range of emotions, which vary in intensity, duration, context, etc. during activity time our model is based on dimensional categories of emotions [4]. It also makes use of affective dictionaries expressing the emotional weights of words as a function of affective dimensions (pleasure, arousal, etc.). Each of these dimensions is preprocessed to obtain fuzzy values corresponding to the magnitudes of each emotional dimension.

Then, there is performed a conversion of the qualified emotional state defuzzified in discrete affective states to provide awareness emotion to both teachers and students. Thus, the aim of this study is to present an effective approach to label affective behavior in educational discourse based on

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fuzzy logic, which will enable a human (or virtual) tutor to capture students' emotions, make students aware of their own emotions, assess these emotions and provide appropriate feedback to involved actors. In order to address these challenges, this paper is organized as follows. In Section II, we present a comprehensive analysis of the state of the art of affective dictionaries in Sentiment Analysis field, dimensional models of emotion as well as of applications of fuzzy logic to the field of classification of emotional states.. Based on this analysis, in Section III, we present our proposal that explains how we address these issues. We describe our approach at a conceptual design level. In Section IV we give an application example of our model in real case setting. Finally, in Section V, we present the results obtained so far, concluding with future work in Section VI.

II. Related Work

Our goal is to classify and later label the students' emotional state through the analysis of their educative discourse in a virtual learning environment. To that end, before starting the design of our model, we have extensively revised the literature related to three topics that concern its development.

First, we reviewed various existing models for the classification of the different emotional states. Secondly, we studied the different affective dictionaries that have been compiled so far, to identify how each one of them provides the use of information about the affective weights of words composing the educational discourse.

Finally, we checked the related works about the application of fuzzy logic in the Sentiment Analysis field

A. *Emotion models*

In Artificial Intelligence, affective computing is the branch of studies and developments systems and devices that can recognize, interpret, process, and simulate human affects, whose motivation is the ability to simulate empathy. The machine should interpret the emotional state of humans and adapt its behavior to them, giving an appropriate response to their emotions [5].

There are two leading models describing how humans perceive and classify emotion, namely, dimensional and categorical models [7], [8]. Categorical models classify emotions into *basic*, *secondary*, *tertiary*, etc. [11] [12] [13], while dimensional models specify gradual emotions as *arousal*, *valence*, *control*, *intensity*, *duration*, *frequency of occurrence*, etc. [14], [16], [17] and [19].

Emotions can be used in the learning context to increase student's attention as well as to improve memory and reasoning [10]. In this context, tutors must be prepared to create affective learning situations and encourage collaborative knowledge construction and identify students' feelings that difficult the learning [9].

For instance, the PAD (Pleasure-Arousal-Dominance) emotional state model is a psychological model developed in [27] to describe and measure emotional states. PAD uses three numerical dimensions to represent all emotions. Its initial use was in a theory of environmental psychology, the core idea being that physical environments influence people through their emotional impact. The PA part of PAD was developed into a circumplex model of emotion experience, and those two dimensions were termed "core affect". The D part of PAD was re-conceptualized as part of the appraisal process in an emotional episode (a cold cognitive assessment of the situation eliciting the emotion). A more fully developed version of this approach is termed the psychological construction theory of emotion. The PAD model has been used to study nonverbal communication such as body language in psychology [29]. It has also been applied to the construction of animated characters that express emotions in virtual worlds [28].

Plutchick offers an integrative theory based on evolutionary principles [15]. Emotions are adaptive—in fact, they have a complexity born of a long evolutionary history—and although we conceive the emotions as feeling states. According to [15], the feeling state is part of a process involving both cognition and behavior and containing several feedback loops.

As mentioned before, our goal in this work is to develop tools that report teachers with useful information about students' emotional state, to assess these emotions and provide appropriate affective feedback to students. To this end, we choose a mixed model composed by three dimensions [27] and eight emotional labels [15].

B. *Affective Dictionaries*

In Sentiment Analysis field, textual information includes, among others, subjective expressions that describe people's sentiments, appraisals or feelings toward entities, events and their properties [6]. Within this area, some affective dictionaries have been developed and are widely used.

These dictionaries provide a lexical repository in different languages. In particular, we have carried out a wide review of affective dictionaries in Spanish language on both models.

SentiWordNet is a lexical resource for opinion mining [26]. SentiWordNet assigns to each synset of WordNet three sentiment scores: positivity, negativity and objectivity. The method we have used to develop SentiWordNet is an adaptation to synset classification of our method for deciding the PN-polarity and SOpolarity of terms. The method relies on training a set of ternary classifiers, each of them capable of deciding whether a synset is Positive, Negative, or Objective. However, SentiWordNet is not available in Spanish.

The development of the framework Affective Norms for English Words (ANEW [23]) is an instrument into the dimensional perspective of emotions based on works as [21] and [22]. From this perspective, three basic dimensions are proposed, through which the entire range of human emotions can be organized: valence (which ranges from pleasant to unpleasant), arousal (which ranges from calm to excite) and dominance or control (ranging from in control to out of control). The ANEW list provides normative values in these dimensions for 1,034 words and there is a Spanish adaptation of the ANEW made by [20].

Whissell's Dictionary of Affect in Language, originally designed to quantify the Pleasantness and Activation of specifically emotional words, was revised to increase its applicability to samples of natural language. A third rated dimension (Imagery) was added, and normative scores were obtained for natural English.

Evidence supports the reliability and validity of ratings. The revised Dictionary, which contains ratings for words characteristic of natural language, is a portable tool that can be applied in almost any situation involving language [24].

The NRC Emotion Lexicon (EmoLex) is a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive) [25]. The annotations were manually done by crowd sourcing.

Despite some cultural differences, it has been shown that a majority of affective norms are stable across languages. Given that three basic dimensions, namely, valence, arousal and dominance are commonly used by researchers we decided to use the Spanish version of ANEW dictionary merged with the Spanish version of EmoLex.

C. Fuzzy Logic Applied to Sentiment Analysis

Regarding fuzzy logic supporting the sentiment analysis, most of authors involved refer to [18], which focuses on the WordNet dictionary, in order to grasp some awareness from text mining from the sentiment analysis approach.

The authors were able to capture average behaviors shown by words, based on regular statistics analysis to build a fuzzy logic scheme aimed at producing a qualitative description for words; turning quantitative magnitudes into literal terms bound to qualitative perceptions, such as: good, bad, etc.

Our proposal is to produce similar scheme for word treatment [18]. Nevertheless, our study focuses on the ANEW and fuzzy qualifiers bound to amounts: few, regular, many. These qualifiers will be later on crossed over throughout specific inference rules.

These inference rules provide the support to explain as qualitative terms, the amounts achieved by indicators. Hence, high level emotions could be implied from plain numbers. Inspired by [19], our proposal is a fuzzy classifier, more precisely, a statistical classifier, which provides a priori a qualitative assessment to the amounts assigned by ANEW to every word.

The advantage of the statistical approach is to reduce the classical *pollution* problem of training and analyzing the scenario using the same dataset. Affective dictionaries have, usually, a limited number of words. Our statistical classifier uses centrality and dispersion measures calculated from the ANEW analysis dimensions. These measures are used to build the fuzzy classifier, as explained later in this paper.

III. OUR FUZZY APROACH

Our model is formed by a set of tools implemented in Java. These tools process the students-created texts through various steps (see Fig. 1). Once the process has finished, we obtain the synthetic opinion of the original message, from the point of view of the author's emotional and affective state.

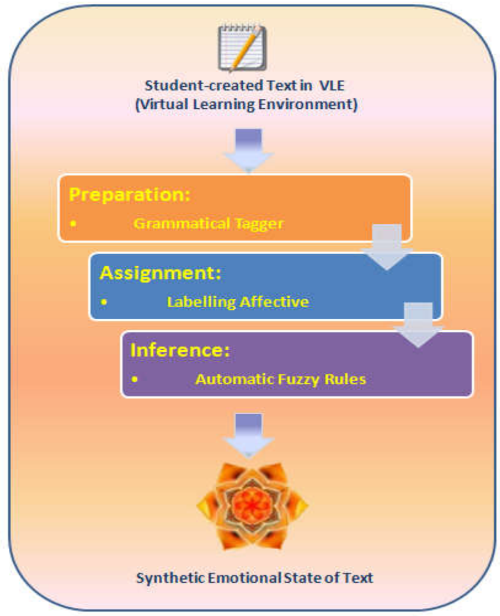


Figure 1. Proceses of Our Fuzzy Model Aproach

A. Affective Dictionairies

As mentioned in the previous section, there are different dictionaries and thesaurus that assign weights to each word for a certain group of dimensions and/or categories (DAL (Whisell Dictionary Of Affect), WordNet Affect, ANEW, etc.). Of these, in order to develop our tool, we took as a starting point ANEW Dictionary and NCR Emotion Lexicon.

Firstly, because of there are Spanish words' versions for each dictionary. Secondly, because the first dictionary (ANEW) scores each word assigning and affective weight based on a three dimensional emotional classification model: Pleasure, Arousal and Dominance. And, the other dictionary (NCR) affectively scores words as a combination of the primal emotions described in Plutchick's model. So EmoLex assigns a value from 0 to 1 to each of the emotional axis of Plutchick, if the word has an emotional weight in that axis. In order to use it in our model, we modified the original structure of the ANEW dictionary so we only use 4 columns (see Table 1).

In the table, the first column contains the words list of the Spanish dictionary and the rest of the columns contain the affective load of each word assigned to Pleasure, Arousal and Dominance, respectively.

Finally, the mean and standard deviation are calculated for each of the corresponding dimensions. Then, we match both dictionaries to obtain a new words combination with the words in common. Our resulting thesaurus was reduced to 822 words in Spanish. Using the dimensional and categorical information of the words' emotional load from a text, we aim at giving enough information to the teacher in order to determine the emotional state of the students during their work on the different tasks that form the learning activity in the virtual environments.

TABLE I. STRUCTURE OF OUR TESAURUS

	Dictionary ANEW			*Dictionary EMOLEX*							
Word	**Pleasure**	**Arousal**	**Dominance**	**Anger**	**Anticipation**	**Disgust**	**Fear**	**Joy**	**Sad**	**Surprise**	**Trust**
P_1	$V_{1.1}$	$V_{1.2}$	$V_{1.3}$	$V_{1.4}$	$V_{1.5}$	$V_{1.6}$	$V_{1.7}$	$V_{1.8}$	$V_{1.9}$	$V_{1.10}$	$V_{1.11}$
P_2	$V_{2.1}$	$V_{2.2}$	$V_{2.3}$	$V_{2.4}$	$V_{2.5}$	$V_{2.6}$	$V_{2.7}$	$V_{2.8}$	$V_{2.9}$	$V_{2.10}$	$V_{2.11}$
P_3	$V_{3.1}$	$V_{3.2}$	$V_{3.3}$	$V_{3.4}$	$V_{3.5}$	$V_{3.6}$	$V_{3.7}$	$V_{3.8}$	$V_{3.9}$	$V_{3.10}$	$V_{3.11}$
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
P_n	$V_{n.1}$	$V_{n.2}$	$V_{n.3}$	$V_{n.4}$	$V_{n.5}$	$V_{n.6}$	$V_{n.7}$	$V_{n.8}$	$V_{n.9}$	$V_{n.10}$	$V_{n.11}$
Mean	μ_1	μ_2	μ_3								
SD	σ_1	σ_2	σ_3								

B. Fuzzy Classification

An intelligent system (IS) needs to be able to evaluate the actual state of a phenomenon and act accordingly. In addition, such an IS needs a compact and discrete quantity of affective states to offer an efficient answer in a reasonable amount of time. In our case, it's needed that the teacher knows his/her students' emotional states as accurately as possible to give an effective affective feedback.

A fuzzy system (FS) allows us to process countless numerical values from a variable, mapping them in a practical discrete specter for the processing. That is to say, it allows us to conduct a qualitative evaluation from a magnitude, providing each value with a certain semantic. The most appealing characteristics of the fuzzy logic are its flexibility, its tolerance to imprecision, its capacity to model non-linear problems and its natural language base. In this case, the imprecision derives from the countless existent emotional states both clear and transitional that appears in ANEW dictionary's values, some are labeled but others are not.

The non-linearity happens because all this states are composed by various dimensions with different grades of magnitude, that aren't part of an arithmetic progression nor a geometrical one neither and exponential one. Their base in the natural language is due to the objective of detecting these affective states in the students' respective languages written texts in a virtual learning environment. Therefore, in order to conduct a qualitative evaluation of the words composing the texts, we set the base on an FS formed by a number of fuzzy groups that try to model the ambiguity of a perceived variable.

The theory of fuzzy or fuzzy sets was developed to the end of portraying mathematically the intrinsic imprecision of certain object categories. To determine the belonging to a certain group in the values range from a certain dimension we start from the Degree of Truth (DT).

The Degree of Truth is an element that belongs to a close interval between 0 and 1 but due to the interval belonging to the real numbers group, the Degree of Truth is infinite to the same manner that the number of a person's possible emotional states in a certain instant is infinite.

These fuzzy groups are obtained through the "membership functions". These functions determine the degree of belonging to a defined group by a qualitative label classifying the emotional state from a person or a group based on the emotional weight of the words used during their emotional discourse. The graphic representation of these functions may take various forms (trapezoidal, triangular, singleton, etc.) In our model, these functions take the form of an "S" as shown in Fig. 2.

The first step was to verify that the data had a normal distribution. We obtained the mean to get close to the values of the variable's area of interest, and then calculated the standard deviation to determine the thickness of the bell curves and the number of groups that the values are going to be divided into based on the qualitative values that will be used.

In this case, the qualitative values are three low, medium and high, so we will obtain three groups as shown in Fig. 2. We followed a series of steps to obtain the limits of each group as described next.

First, we calculated the percentage of deviation by formulae (1):

$$\%\sigma = \frac{\sigma * 100}{\mu} \tag{1}$$

Then, based on the number of group (numConjs=3) and applying the equations (2) and (3) we obtained the mean and standard deviation segments.

$$S\mu \left\{ \begin{array}{ll} \dfrac{(\mu * 2.0) * 0.5}{\text{numConjs}} & \%\sigma < 25 \\ \dfrac{(\mu * 2.0) * 0.8}{\text{numConjs}} & 25 \leq \%\sigma < 50 \\ \dfrac{(\mu * 2.0) * 0.8}{\text{numConjs}} & \%\sigma \geq 50 \end{array} \right\} \tag{2}$$

$$S\sigma \left\{ \begin{array}{ll} \dfrac{\sigma * 1.8}{\text{numConjs}} & \%\sigma < 25 \\ \dfrac{\sigma * 1.2}{\text{numConjs}} & 25 \leq \%\sigma < 50 \\ \dfrac{\sigma * 0.8}{\text{numConjs}} & \%\sigma \geq 50 \end{array} \right\} \tag{3}$$

Finally, we determined the centers, and the left and right limits that matched each group applying the equations (4).

$$\begin{array}{l} center = meanSegment * (i+1) \\ leftLimit = (i=0)\,?{-1} : center - stdDevSegment * 2 \\ rightLimit = (i+1 = numSets)\,?{-1} + stdDevSegment * 2 \end{array} \tag{4}$$

The values resulting from applying these equations to each dimension magnitude from the ANEW dictionary are shown in Tables II, III and IV, respectively.

TABLE II. RESULTING VALUES FOR PLEASURE

*Variable Name: ***PLEASURE***	
Mean:	4.74
Standard Deviation (SD):	2.14
Percentage DS :	45.14767932489451
Segment size:	2.528
Curves' data of three groups built related to Pleasure	
Pleasure _Low :	**curveZ** C: 2.528 LD: 4.24
Pleasure _Medium :	**curvePi** LI: 3.344 C: 5.056 LD: 6.768
Pleasure _High:	**curveS** LI: 5.872 C: 7.584

TABLE III. RESULTING VALUES FOR AROUSAL

*Variable Name: ***AROUSAL***	
Mean:	5.53
Standard Deviation (SD):	1.0
Percentage DS :	18.083182640144663
Segment size:	1.8433333333333335
Curves' data of three groups built related to Arousal	
Arousal_Low :	**curveZ** C: 1.84333 LD: 3.04333
Arousal_Medium :	**curvePi** LI: 2.48666 C: 3.68666 LD:
Arousal_High:	**curveS** LI: 4.33 C: 5.53

TABLE IV. RESULTING VALUES FOR DOMINANCE

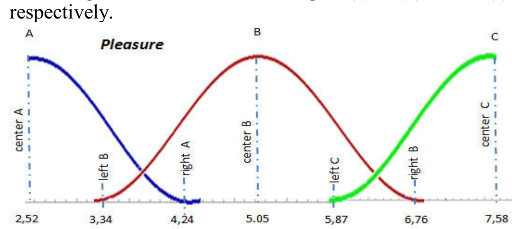
*Variable Name: ***DOMINANCE***	
Mean:	4.67
Standard Deviation (SD):	1.06
Percentage DS :	22.698072805139187
Segment size:	1.5566666666666666
Curves' data of three groups built related to Dominance	
Dominance_Low:	**curveZ** C: 1.5566 LD: 2.8286
Dominance_Medium:	**curvePi** LI: 1.84133 C: 3.113 LD: 4.3853
Dominance_High:	**curveS** LI: 3.3979 C: 4.67

In order to calculate the curves of each group corresponding to each magnitude (Pleasure, Arousal and Dominance), we run our tool three times, one for each dimension.

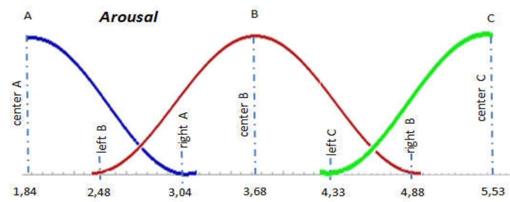
At each run we gave to the tool the mean of the values for that channel, its standard deviation, a file with the complete group of values for that dimension and a file with the qualitative values for that channel. In this case we used the same qualitative values for the three channels but we configured the tool to establish different qualitative values for each one of the channels.

From these results, we built the curves of the three groups related to each magnitude (Pleasure, Arousal and Dominance).

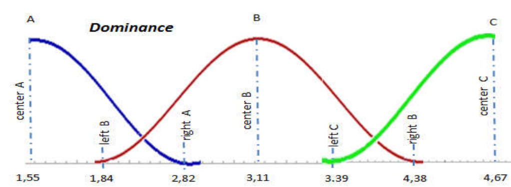
The graphical representation of the curves obtained for each magnitude are shown in Figs 2(a), 2(b) and 2(c), respectively.



(a) Pleasure



(b) Arousal



(c) Dominance

Figure 2. Resulting Curves for Pleasure (a), Arousal (b) and Dominance (c)

	A	B	C	D	E	F
1	Number	E-Word	S-Word	Pleasure-Fuzzy	Arousal_Fuzzy	Dominance_Fuzzy
2	249	knowledge	conocimiento	Pleasure_High	Arousal_High	Dominance_High
3	172	free	libre	Pleasure_High	Arousal_High	Dominance_High
4	967	safe	seguro	Pleasure_High	Arousal_Medium	Dominance_High
5	734	easy	fácil	Pleasure_High	Arousal_Medium	Dominance_High
6	1014	tidy	ordenado	Pleasure_High	Arousal_Medium	Dominance_High
7	355	respectful	respetuoso	Pleasure_High	Arousal_Medium	Dominance_High
8	62	capable	capaz	Pleasure_High	Arousal_High	Dominance_High
9	226	improve	mejorar	Pleasure_High	Arousal_High	Dominance_High

(a) Fuzzy Values

	A	B	C	J	K	L
1	Number	E-Word	S-Word	Ple-Mn-All	Aro-Mn-All	Dom-Mn-All
2	249	knowledge	conocimiento	7,73	6,29	7,22
3	172	free	libre	8,28	6,38	7,01
4	967	safe	seguro	7,48	4,34	6,90
5	734	easy	fácil	6,92	4,48	6,80
6	1014	tidy	ordenado	6,57	4,19	6,78
7	355	respectful	respetuoso	7,63	4,21	6,76
8	62	capable	capaz	7,52	5,92	6,70

(b) Discrete Values

Figure 3. File contents dicc_fuzzy.txt (a) y (b)

Furthermore, by applying our fuzzification tool to each magnitude results in a text file where each line contains a word from the dictionary, its term in English, its term in Spanish, the values for Pleasure, Arousal and Dominance, and their corresponding numerical values as shown in Fig. 3.

C. *Fuzzy Rules*

The fuzzy rules combine one or more fuzzy entrance groups named precedents or antecedents and they associate them a fuzzy output set named consequences or results. They involve fuzzy sets, fuzzy logic and fuzzy inference. These rules are propositions that allow us to express the available knowledge about the relationship between antecedents and consequents and they make affirmations of the *If-Then* type. The group of various rules constitutes a rules base or knowledge base.

In our model, there has been built 24 rules as a result of combining eight qualitative values obtained for each of the emotional axis of the Plutchick's model as primary, secondary and tertiary dyads as shown in Fig. 4.

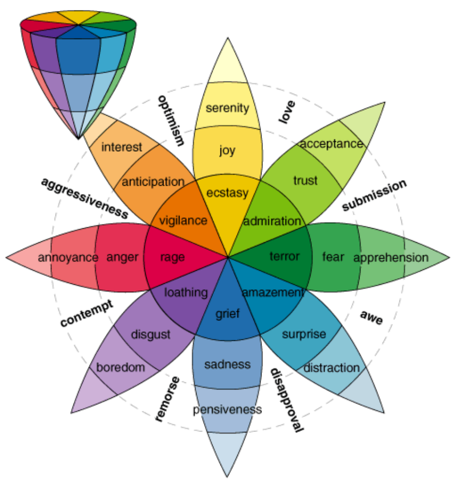


Figure 4. Plutchik's wheel of emotions

Thus, from the basic emotions detected in the text for each word contained in our thesaurus, we obtained by peer evaluation, the associated emotional states to that word. The basic emotions are the antecedents for our rules and the emotional states will be the consequents.

Antecedents
1. Joy
2. Confidence
3. Fear
4. Surprise
5. Sadness
6. Disgust
7. Anger
8. Anticipation

(a) Antecedents

Consequents		
Love	Submission	Flit (Dismay)
Disapproval	Remorse	Contempt
Aggressiveness	Optimism	Fault
Curiosity	Desperation	Envy
Cynicism	Pride	Fatalism
Delight	Sentimentalism	Shame
Outrage	Pessimism	Morbidity
Domination	Anxiety	

(b) Consequents

Rules				
	Antecedent1		Antecedent2	Consequent
If	Joy	&	Trust	Love
If	Confidence	&	Fear	Submission
If	Fear	&	Surprise	Flit (Dismay)
If	Surprise	&	Sadness	Disapproval
If	Sadness	&	Disgust	Remorse
If	Disgust	&	Anger	Contempt
If	Anger	&	Anticipation	Aggressiveness
If	Anticipation	&	Joy	Optimism
If	Joy	&	Fear	Fault
If	Trust	&	Surprise	Curiosity
If	Fear	&	Sadness	Desperation
If	Sadness	&	Anger	Envy
If	Rejection	&	Anticipation	Cynicism
If	Anger	&	Joy	Pride
If	Anticipation	&	Confidence	Fatalism
If	Joy	&	Surprise	Delight
If	Confidence	&	Sadness	Sentimentalism
If	Fear	&	Rejection	Shame
If	Surprise	&	Anger	Outrage
If	Sadness	&	Anticipation	Pessimism
If	Rejection	&	Joy	Morbidity
If	Anger	&	Confidence	Domination
If	Anticipation	&	Fear	Anxiety

(c) Fuzzy Rules

Figure 5. Antecedents (a), Consequents (b) and Fuzzy Rules (c)

If the number of obtained basic emotions for a given word is zero, no single rule is executed. If the number is equal to 1 the basic emotion assigned to that word is returned as its emotional state. Finally, if the resulting number is greater or equal to 2, the rules corresponding to the detected emotions are executed. For each rule two antecedents are evaluated. In case of satisfying it, a unique result is assigned, that result will be a discrete emotional value based in the Plutchick's classification model of emotions.

The dimensional aspect is determined by the color of each petal that varies from soft to intense on intensity according to the emotional experience grade as shown in Fig. 4. The dimensional information is determined from the three fuzzy values corresponding to Pleasure, Arousal and Dominance that allow the teacher to determine the degree of emotional experience from the student or the group of students during their involvements in the virtual classroom.

IV. Model Testing

An experiment was carried out with a class of twenty four fourth-year high school students, attending an activity about computer science, using the Moodle platform. We divided students in eight groups of three members each. The experiment was conducted along five sessions. Questions were proposed in a discussion forum, as shown in Fig. 6. Each member of the group selected one of them and made his/her contribution to the topic. We use students' created-text to train our tool.

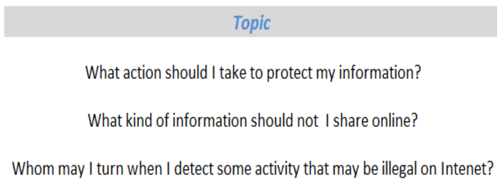


Figure 6. Dissonance cognitive quetions in discussion forum

For the testing our tool, we took the texts produced by the students in various discussion forums. Those texts along the thesaurus built before served as an input for our tool.

The output of the tool consists of a list with the words found in the dictionary and their respective fuzzy values, in addition to the resulting emotional states from the rules application to each one of them.

Once all the text has been processed, the mean of the obtained value for each characteristic is then calculated and the obtained mean values for Pleasure, Arousal and Dominance are fuzzified as shown in Fig. 7.

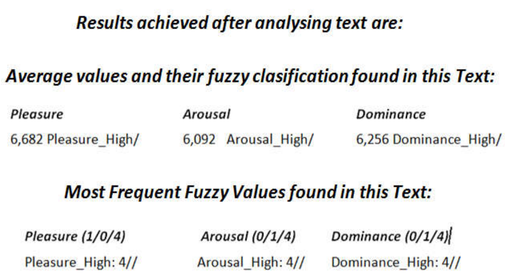
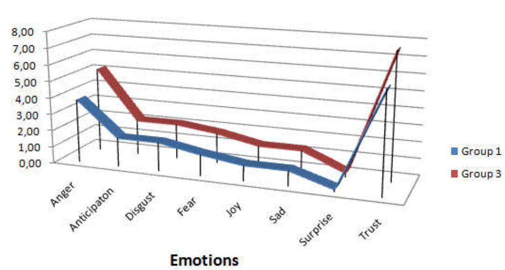
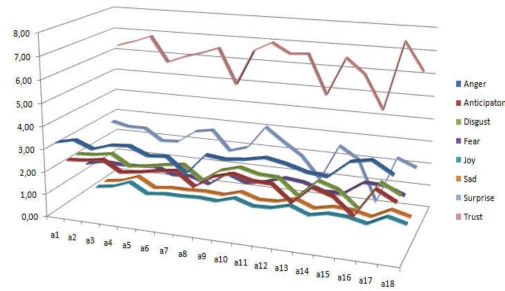


Figure 7. Results after analyzing a text with Fuzzy Model



(a) Groups' emtional states



(b) Students' emtional states

Figure 8. Emotional states of groups (a) and students (b)

The graphical representation of the emotional information associated to each student is shown to the teacher and each student individually. The group's graphical representation of the emotional information of the whole group will be showed to both the group and the teacher, as shown in Figure 8 (a) and 8 (b). Both representations are sent to the activity teacher for his/her knowledge so an appropriate affective feedback can be provided.

V. Conclusion and Future Work

In this work we have presented a model for Classifying Students' Emotional States in Online Collaborative Work. Our model is encompassed into the Sentiment Analysis Field and aims to be a supporting tool for feedback to teachers interacting with students in a virtual or semi-virtual learning environment.

Our system is based on a fuzzy classification system, which is fed with data from ANEW dictionary, whose words are bound to emotional weights and these, in turn, are used to map Fuzzy sets in our proposal. The proposed fuzzy-based system has been evaluated using real data from collaborative learning courses in an academic context. The results showed the efficiency of the proposed system to classify the emotive states of the involved users.

Our future work is focused on evaluating and improving the tool in order to increase its accuracy. We would like also to test the system with the various rules that we have identified. Those rules can easily be adjusted to different criteria of answers, based on the experience of different experts or different analysis expectations for virtual learning environments in real time.

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An ontology about emotion awareness and affective feedback in elearning

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***Abstract* — In this paper, we propose designing a specific ontology for representing relevant aspects of affective phenomena in e-learning. The ontology is aimed to include the different types of emotions, moods and behaviors that students experience in the e-learning environments, the different types of feedback that teachers can provide to their students and the different effects in students' behavior during the e-learning process. Once the ontology is formalized, it will be used to design a virtual Affective Pedagogical Tutor (APT) based on an Event-Condition-Action rule system to provide affective feedback, aiming to provide a positive change in students' behavior and performance. The ultimate goal is to provide means for effective emotion management in a collaborative learning environment.**

Keywords— Ontology, Emotion Awareness, Affective Feedback, E-learning, Collaborative Learning.

I. INTRODUCTION

Current research on web-based learning environments has shown the importance of taking into account not only the cognitive abilities and capabilities that students possess or need to acquire through learning processes, but also their affective abilities and capabilities. During the past decade, emotion has emerged as a vital element in the learning process but many questions remain still unanswered about emotion management in education [1]. Thus the study of antecedents and consequences of emotions in a variety of situations and settings is essential for understanding how to create learning environments that can promote positive emotional experiences, which in return enhance student's learning and performance. The nature of emotional phenomena both in text and dialogue is very complex. It can be interpreted in different ways and can be represented by different computational models [6] [7] [8]. In this sense, Semantic Web provides a distributed environment with well-defined data that can be understood and used by machines. This information has a well-defined meaning, so human agents and intelligent agents can parse it. In this context, ontology captures consensual knowledge in a generic and formal way so that it can be shared and reused by different groups of people and software applications.

In our case, we want to build an ontology as a knowledge representation system of the affective domain and then apply it on sentiment analysis methods in order to obtain a formal representation of how emotions evolve over time. Moreover, it will allow us to identify relationships between the different concepts (emotions, moods and behaviors) involved under the terms of "Emotion Awareness" and "Affective Feedback", in addition to the relationship between the concepts of both terms. Additionally, the ontology is constructed in relation to a context of use, because the ontology specifies a conceptualization of the world or a way of perceiving it. In our case, our ontology seeks to conceptualize virtual learning environments from the affective domain's point of view. This knowledge allows intelligent agents to make decisions and to perform tasks on our behalf, automatically. Affective pedagogical agents or tutors (APT) as intelligent agents have been widely used in a variety of ways in e-learning environments [2] [3]. Implementing an APT, it is possible to achieve an application that may help learners by motivating them to stay engaged and immersed in learning tasks, and by illustrating phenomena and procedures and. In addition, an APT can facilitate activities associated with learning, such as role-playing and exploration or deep thinking and idea sharing, which use different pedagogical strategies.

The ontology requires a logical and formal language to be expressed. In the field of Artificial Intelligence, have been developed a variety of languages to describe the behavior of a system through the definitions of statements about the system's behavior under certain conditions. For instance, OWL (Ontology Web Language) is a language for publishing and sharing ontologies on the Web that can be adapted to different types of applications (search engines, agents, etc.) so that this knowledge can be exchanged by software agents.

In this paper we present an ECA-rules system designed to allow robots and software agents to be able to retrieve information stored in the ontology and perform advanced automated tasks, such as providing feedback to the students

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and the teacher in the context of affective virtual learning. We introduce a prototype of ontology and knowledge base for affective domain and its use with ECA-rule system. We will set the basis for the design, based on our ontology, of an affective virtual agent/tutor able to intervene and mediate in students' e-learning processes, providing them with an appropriate affective feedback that will guide, advise and help them according to their needs and feelings.

In order to achieve these challenges, this paper will first present a background and main concepts related to detection and analysis of emotion in elearning in Section II. Then in Section III, we will focus on describing the context of our research by identifying issues and goals related to emotion awareness and affective feedback with regard to affective behavior in e-learning context. In Section IV, we describe our ontology's prototype for affective domain at conceptual design level. Consequently, Section V (Ontology Definition for Affective Domain) shows the use of knowledge base for affective domain with ECA-rule system. In Section VI, we give a possible implementation outlook of our prototype with different tools, and finally, we conclude with future work.

II. BACKGROUND AND MAIN CONCEPTS

During the past decade, emotion has emerged as a vital element of the learning process but many questions still remain open about emotion management in education [1] to efficiently impact in learners' attitude and therefore their learning outcomes. Considering the impact of emotions on learning, firstly, the tutor should be able to encourage active learning and collaborative knowledge construction, know how to identify feelings and emotions, monitor and provide appropriate models of expression especially when it comes to negative emotions that are often more difficult to communicate in an appropriate manner (Affective Feedback) [15]. And secondly, students have to understand the influence of emotions on their behaviour, by developing a range of skills related to the ability of understanding their own affective states, responding appropriately to the moods of others, and identifying that each emotional behaviour has a purpose (Emotion Awareness) [16].

Then, the main goal is to identify and classify human behavior in educational discourse and thereafter to provide relevant emotional feedback in virtual collaborative learning contexts.

With regard to classification of emotions, affective computing researchers often use two distinct approaches in the modeling and classification of human emotions: A categorical model in which text data are associated with emotional labels ("happy", "sad", etc.) [6] [17] [18] or a dimensional model where data are represented by coordinates in a dimensional space. [7] [8] [19] [20]

In regard of the emotions detection, another field research is Natural Language Processing (NLP). Within this field, conversation analysis (CA) and discourse analysis (DA) methods are an area where text is an important modality for emotion detection [9] in order to achieve a precise evaluation of opinion in texts, and identify a wide range of opinion expressions as well as how they are discursively related in the text.

In addition, Sentiment Analysis and the semantic orientation of texts recognition is another active research area in the field of natural language processing [21]. This new trend in emotion research consists in performing lexical analysis of texts with aiming to identify words that can predict the affective states of the authors [22]. The main problem of these systems is the lack of importance given to the semantic and linguistic aspect. Several tools have been developed in the field of sentiment analysis and data mining, there are several dictionaries such as: (1) the WordNet Affect [9] and (2) The Whissell's Dictionary of Affect [10] and several tools such as: (1) Weka [11], (2) TMG [12] and (3) FreeLing [13].

In short, the aim of our study is to present an effective approach to label affective behavior in educational discourse, which will enable a human (or virtual) tutor to capture students' emotions, make students aware of their own emotions, assess these emotions and provide appropriate feedback.

III. OUR CONTEXT

Based on the concepts, methods and tools to detect and analyze emotions in learning [23] mentioned before, we focused our work on two main issues: "Emotion Awareness" and "Emotional feedback" in e-learning.

Regarding the emotion awareness, our goals are: (1) detecting and representing the emotions students experience during their collaborative virtual learning processes (conversations, debates, and wikis) and (2) analyzing and interpreting these emotions in context, identifying also possible emotion causes.

Regarding the emotional feedback, our goals are (3) discovering in which learning situations an Affective Pedagogical Tutor (APT) may be effective and appropriate, by examining the role the affective virtual tutor plays in the design of learning contexts, and (4) allowing self-regulation of individual behavior and the development of abilities socio-cognitive and socio-emotional, in both professors and students, providing contextualized and personalized information, with the adequate cognitive and affective skills, in response to potential problematic situations along learning processes.

A conceptual Emotion Analysis model is proposed to attempt the mentioned goals [24]. We apply an extended Activity Theory (AT) scenario [4], as shown in Figure 1, which consists of making several participants (teacher and students) to cooperate and interact with specific objects (such as text and dialogue) through the use of specific tools (APTs, emotion analysis tools) to carry out goal-oriented activities.

One of the goals, with regard to this model, was the development and use of a discourse analysis method to analyze collaborative learning activities aiming to extract the emotional relations between discourse units and provide a graphical representation of the emotional structure of discourse [25].

Our purpose is to translate the conceptual model to a computational model that integrates a set of tools intended to achieve the research's proposed objectives.

Regarding the first objective of our research –detecting and representing the emotions–, we use known Sentiment Analysis tools for identifying and labeling emotions in the educational discourse. At this point, we use ontology to establish a knowledge base with concepts regarding emotion awareness that we want to recognize in text.

Regarding the second objective of our research –analyzing and interpreting these emotions in context–, the analysis of emotional states takes into account the learning context in which it occurs. We define as learning context all relevant information related to a group of students participating in a learning activity. At this step, we use ontology as computational approach to represent this context.

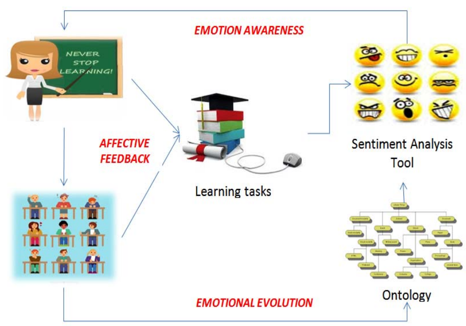


Figure 1. Our Extended Activity Theory Scenario.

IV. Ontology Definition for Affective Domain

Given that, an ontology is defined as an explicit specification of a shared domain, focused to represent a part of reality, we represent our ontology's emotional context of learning.

A. *First Step: The domain and scope of the ontology*

In order to determine the domain and scope of the ontology, we design a schema that contains concepts related to "Emotion Awareness" and "Affective Feedback" that contains emotions, moods and behaviors, besides of setting properties and constraints between them (e.g. the teacher feedback for a particular "mood"). Furthermore, the aim is to use this ontology in a virtual learning environment such as, for example, Moodle.

We started by identifying the following research questions that still remain open and for which we will try to provide some effective answers in our ontology model.

With regard to Emotion Awareness we want to answer questions as the following ones:

- In Computer Supported Collaborative Learning (CSCL), as well as in other online communication systems, what are the roles of emotions and how important is emotion awareness? Are emotions complementary or equally important to other types of awareness, e.g. opinion and activity awareness?
- How can we detect the emotions of a learner in an unobtrusive way? Can we take advantage of the interaction data generated in a CSCL activity?
- Having a tool to analyze past emotions and their causes can be beneficial to learners? What are the possible causes of emotions during e-learning activity and how can they be detected?
- Assuming that there is an intelligent system that informs about users' emotions and enable users be aware of each others' emotions, what are the methods to feed the system with user emotions? What are the methods to make users aware of each other's emotions effectively?
- What could be the impact of displaying emotions to learners on their collaborative learning activity and learning outcomes?
- What are the relevant emotions in the context of computer-supported collaborative work and learning?
- How do students manage time in their learning processes? How can we know if they feel that they have enough time to carry out a learning activity or whether they feel stressed and frustrated due to lack of time?
- What kind of emotions do students express and how do these emotions evolve over a certain period of time?
- How can we detect and interpret various types of emotions and anticipate the emotional states students may experience at a particular moment of their learning process?

Figure 2 shows the structure of our ontology prototype with regard to "Emotion Awareness".

With regard to Affective Feedback we want to answer questions as the following ones:

- How to investigate the impact of emotions and in particular emotion awareness on collaborative learning processes and outcomes?
- How can the teacher influence or persuade learners and provide suitable affective feedback in order to regulate members´ emotions in every moment?
- How can we give feedback on the emotions detected during a collaborative learning interaction without being actually orientating the debate between the participants as if the teacher were a participant ourselves?
- How affective and social information automatically computed by machines could be used in an efficient way, with regard to ethic, for computer-mediated interaction / collaboration / learning?
- What are the current challenges in affective computing that need to be addressed to allow self-regulation of individual behavior by providing both cognitive and affective contextualized and personalized feedback?
- How can we make students react in time, guide and help them in an appropriate way so they can change from a negative affective state to a positive one?

- How should a virtual tutor manage time with the aim of providing feedback at the right moment, intervening and mediating in the students' e-learning processes, providing them with appropriate affective feedback that will guide, advice and help them, depending on their needs and feelings?

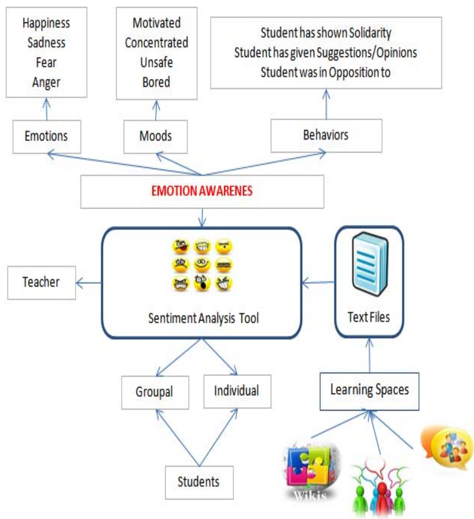


Figure 2. Relatioship between concepts with regard to emotion awarenes

Figure 3 shows structure of our ontology prototype with regard to "Affective Feedback".

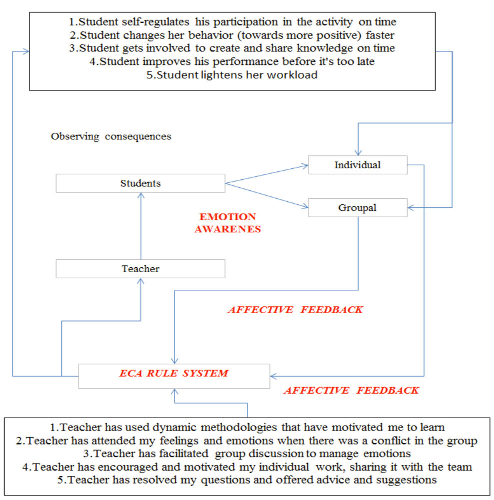


Figure 3. Relatioship between concepts with regard to affective feedback

In this way, with the data obtained from questionnaires and the emotional analysis from the educational discourse of the texts of the students during the development of learning activities in virtual spaces, we have to find relationships between the detected emotions and the moods and behaviors of students that were manifested both in the face-to-face classroom and in the virtual classroom.

We also have to relate this information to the feedback that the teacher may provide to scaffold groups of students or students individually. And finally, we want to know how to evolve the moods and behaviors of students as well as the potential consequences the teacher's feedback may have in their learning processes and outcomes.

B. Second step: The terms of the ontology

Given that our approach is based on AT (see Figure 1), the relevant terms of our ontology are those related to the three elements of our extended framework of AT: *Community* (teacher and students), *Objects* and *Tools*, in addition to those related to the emotional analysis of interventions of students, as shown Figure 4.

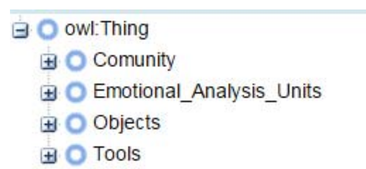
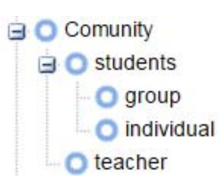


Figure 4. Relevant terms to our ontology.

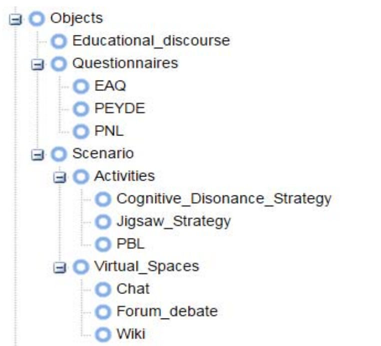
C. Third step: Classes and the hierarchy of ontology

In order to define the main classes in the hierarchy we follow a top-down strategy. First, we define four disjoint taxonomies that include: Community, Objects Tools and Emotional Analysis Units. Then, we define classes and subclasses within them, corresponding to the different elements of the framework as follows:

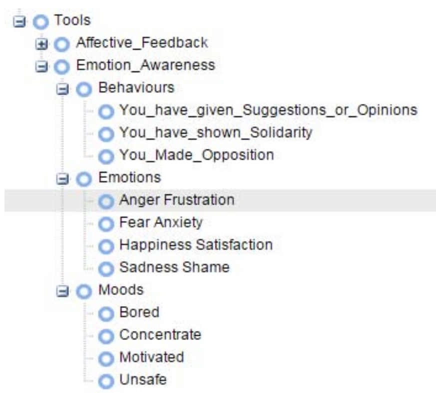
- *Community Class* is formed by the teacher and students, who perform an activity (Project Based Learning or Problem Based Learning, PBL) as shown Figure 2 a).
- *Objects Class* includes virtual spaces where learning activities are developed, as well as the emotional analysis and style of student learning questionnaires as shown Figure 2 b).



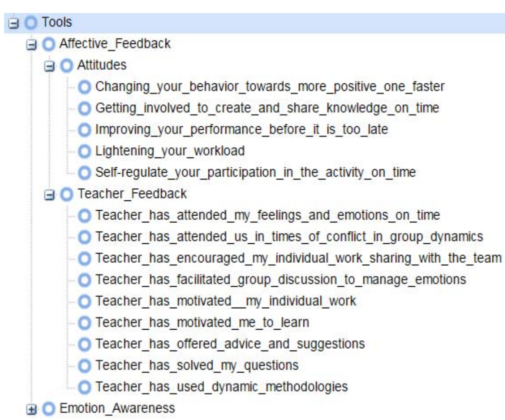
a) Subclasses in Community Class



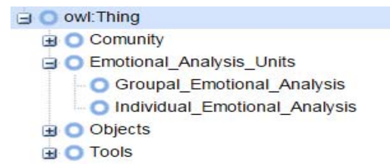
b) Subclasses in Community Class



c) Subclasses in Emotion Awareness Class



(d) Subclasses in Affective Feedback Class



(e) Subclasses in Emotional Analysis Units Class

Figure 5. Taxonomy of classes.(a) (b) (c) (d) and (e)

D. *Fouth step: Class properties*

Five object properties and two sub-properties have been defined to establish different relationships between classes of the affective domain as shown in Figure 6. With them we address the following issues:

- What kind of emotions influence on motivation?
- What kind of behaviors lead to boredom?
- What is the appropriate feedback for dealing with students' unsure situations?
- What are the benefits of providing feedback to students?

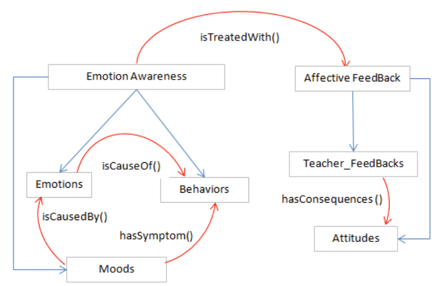


Figure 6. Relationships between Affective domain clases.

In Table 1 is shown the domain and range of properties mentioned before.

TABLE I. OBJECTS PROPERTIES.

Domain	***Object Properties***	***Range***
Moods	hasSymptom	Behaviors
Moods	isCausedBy	Emotions
Emotions	isCauseOf	Behaviors
Emotion Awarenes	isTreatedWith	Affective Feedbacks
Teacher Feedback	hasConsequences	Attitudes
Emotions Moods Behaviors	isTreatedWithTeacherFeedbacks	Teacher Feedback
Emotions Moods Behaviors	isTreatedWithStudentFeedbacks	Attitudes

In short, the defined object properties are as follows:

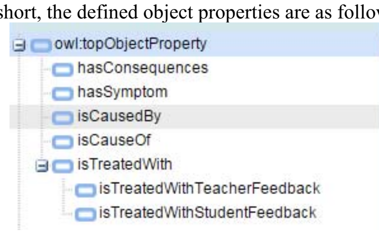


Figure 7. Object Properties.

E. Fifth step: Data properties

The following table examplifies the domain and range of the several data properties.

TABLE II. DATA PROPERTIES

Domain	*DataProperty*	*Range*	*Feature*
students teacher	hasIDNumber	Positive Integer	functional
Individual Group	hasEmotionalRecord	boolean	----
Individual Group	hasActivityText	string	----
students	hasQuestionnaire	string	functional
students	hasScientificName	string	functional
students	hasCodeWordNetAffect	string	functional

In short, the defined data properties are as follows:

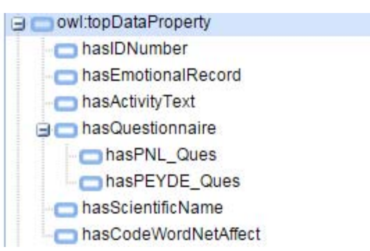
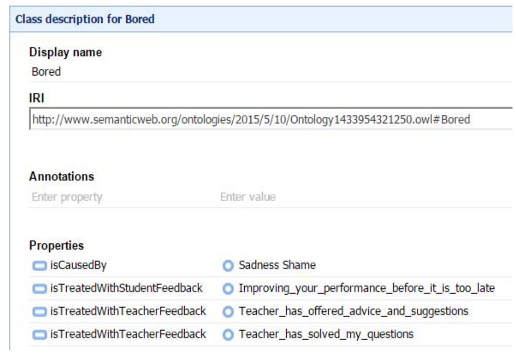
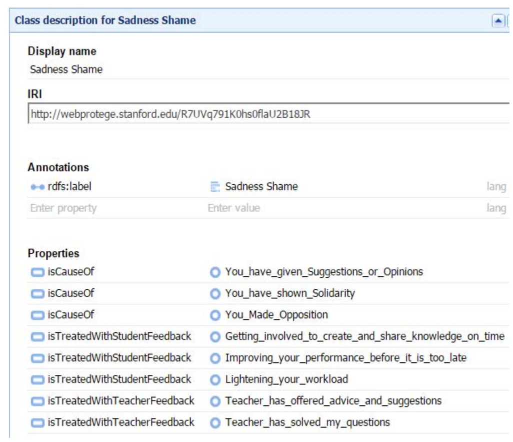


Figure 8. Data Properties

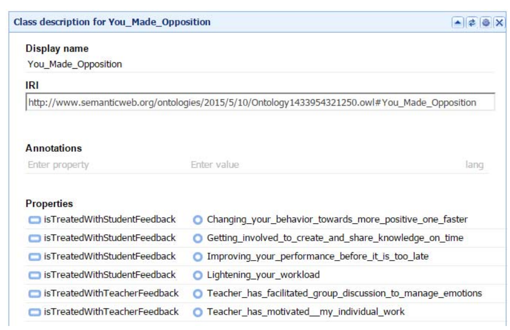
Finally, we have created constraints on the properties of the classes, based on correlations found in experiments that we have conducted before. In Figures 9 (a), (b) and (c), we present some of the constraints on emotions, moods and behaviors.



(a) Constraints on moods



(b) Constraints on emotions



(c) Constraints on behaviors.

Figure 9. Restrictions on the properties of the classes (a) (b) and (c)

These constraints will be subsequently used by the intelligent agents to assess the conditions of the different rules in the system.

V. KNOWLEDGE BASE(S) FOR AFFECTIVE DOMAIN AND ITS USE WITH ECA RULES

With regard to knowledge base for affective domain and its use with ECA-rules system, we will design our APT as an intelligent agent. An intelligent agent consists of a set of behaviors that are associated with different scenarios or conditions of an external world. Each behavior consists of a set of capabilities that provides the agent with a response for every situation. A capability represents a sort of rule event-condition-action, when a particular event happens if the trigger condition is satisfied the associated action is executed. In our case, the events are generated automatically in two levels.

A. First Level.

At first level, an event is generated automatically within the learning platform (Moodle) as follows:

1) For each individual intervention of a student in virtual spaces enabled or configured for each task of the activity:

- For each individual intervention in a wiki.
- For each individual intervention in a chat
- For each individual intervention in a discussion forum.

In response to the event, it is run the tool Sentiment Analysis on the text of the intervention and later with the analysis obtained, an instance is created within the individual_Emotional_Analysis subclass with the text of the statement, the name of virtual space, code of student and code of activity.

2) A completion of a task by a group of students:

- When the task is completed in a wiki
- When a chat conversation is finished
- When a discussion forum is closed

In response to the event, Sentiment Analysis tool is running over the full text of the task and later with the data obtained, an instance is created within the subclass Groupal_Emotional_Analysis related to the group in question, with the text of the item, the name of virtual space, the group code and the code of the activity.

B. Second Level

On a second level, each time a new instance is generated both Groupal_Emotional_Analysis subclass and the Individual_Emotional_Analysis subclass, a new event is triggered automatically. For each of these events there are evaluated conditions, the properties described in the preceding paragraph that set the restrictions on the data obtained in the emotional analysis. Finally, as action, the teacher receives an appropriate feedback, and the students get a different feedback also appropriate to the evaluated condition.

VI. IMPLEMENTATION OUTLOOK

Moreover, it will proceed to create a specific ontology that will contain detailed information about the concepts and relationships of the affective domain, taking into account the steps described in the previous section.

Protégé is a tool for the development of ontologies and knowledge acquisition systems. Applications developed with Protégé are used in problem solving and decision making in particular domains. The Protégé tool employs a user interface that facilitates the creation of a structure in an integrated manner.

When generating the ontology, Protégé creates a document with OWL extension. This document has a similar description to the XML shown in Figure 10. It shows the ontological relations, classes and elements by a hierarchical and relatively easy to read implementation. It's available for any system and efficiently manages the classification process of the ontology's query.

To manage the ontology we use Jena software for the management and consultation of an ontology. Through Jena, we will access the affective domain's ontology by proposing the appropriate feedback for a particular emotional state.

As we outlined above, there are various different ontologies. Through the Ontology API, Jena aims to provide a consistent programming interface for ontology application development, independent of which ontology language you are using in your programs.

The Jena Ontology API is language-neutral: the Java class names are not specific to the underlying language. For example, the OntClass Java class can represent an OWL class or RDFS class. To represent the differences between the various representations, each of the ontology languages has a profile, which lists the permitted constructs and the names of the classes and properties.

```
▼<!--
    http://www.semanticweb.org/ontologies/2015/5/10/Ontology1433954321250.owl#Activities
  -->
▼<owl:Class rdf:about="#Activities">
    <rdfs:subClassOf rdf:resource="#Scenario"/>
  </owl:Class>
▼<!--
    http://www.semanticweb.org/ontologies/2015/5/10/Ontology1433954321250.owl#Affective_Feedback
  -->
▼<owl:Class rdf:about="#Affective_Feedback">
    <rdfs:subClassOf rdf:resource="#Tools"/>
  </owl:Class>
▼<!--
    http://www.semanticweb.org/ontologies/2015/5/10/Ontology1433954321250.owl#Anger/Frustration
  -->
▼<owl:Class rdf:about="#Anger/Frustration">
    <rdfs:subClassOf rdf:resource="#Emotions"/>
  </owl:Class>
▼<!--
    http://www.semanticweb.org/ontologies/2015/5/10/Ontology1433954321250.owl#Attitudes
  -->
▼<owl:Class rdf:about="#Attitudes">
    <rdfs:subClassOf rdf:resource="#Affective_Feedback"/>
  </owl:Class>
```

Figure 10. XML of ontology file in OWL.

VII. CONCLUSIONS

We have presented a general process for the preparation of ontology and Web application for emotion awareness and affective feedback in e-learning. As a result, we have laid the basis for the further development of a virtual Affective Pedagogical Tutor (APT).

As future work we will perform the development of ATP application using the ontology module and finally the Web application within a Moodle environment, which will be able to predict the occurrence of emotional states with their corresponding affective feedback during e-learning activity.

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Towards an Emotion Labeling Model to Detect Emotions in Educational Discourse

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***Abstract* — In a collaborative e-learning environment, students are usually involved in learning activities such as collaborative writing (e.g., an essay in Wiki form) and debates in the form of a chat or asynchronous forum. Capturing students' feelings and emotional states enclosed in such textual information is important, since sentiments can influence individual behavior and consequently group dynamics as well as individual and group performance. For this reason, emotion awareness becomes an important issue for both tutors and students themselves. Especially for tutors, if they have as accurate affective information as possible about the emotional state that every individual and group is encountered, they might be able to provide more effective feedback to the students that includes not only cognitive but also affective scaffold. A first important step to this endeavor is to develop an approach that enables labeling affective behavior and then presenting the emotional information to all the actors involved in the learning process.**

Keywords—Emotion, collaborative e-learning, emotion awareness, emotions labeling.

I. INTRODUCTION

Users' emotions and relationships are constantly present in e-learning environments, which are supported by new tools and learning content; as such, they represent a new interesting research area [4]. Considering the impact of emotions on learning, the role of the tutor should be enhanced with new competencies and skills, since they must be prepared to create effective learning situations (such as dialogues) with and between participants.

Doing so, the tutor should be able to encourage active learning and collaborative knowledge construction, know how to identify feelings and emotions, monitor and provide appropriate models of expression especially when it comes to negative emotions that are often more difficult to communicate in an appropriate manner.

Emotional intelligence is the ability to identify, use, understand and manage emotions in positive ways to relieve stress, communicate effectively, empathize with others, overcome challenges and diffuse conflict. Therefore, emotional learning involves the acquisition of skills to recognize and manage emotions, develop care and concern for others, make responsible decisions, establish positive relationships, and handle challenging situations effectively. This is particularly important in collaborative learning, where the learning objectives are achieved in collaboration among a group of students.

Emotion awareness and the ability to manage feelings appropriately is the basis for effective communication and can help to understand and empathize with what is really troubling other people. As such, this research topic is gaining the interest and attention of more and more researchers in the field of affective learning.

One of the current topics in emotion awareness is how to label (i.e., quantify) human behavior for relevant emotional feedback in learning and Computer Supported Collaborative Learning (CSCL). Humans can display various affective behaviors that have an impact on various factors of collaboration and learning during CSCL [6].

The aim of this study is to present an effective approach to label affective behavior in educational discourse which will enable a human (or virtual) tutor to capture students' emotions, make students aware of their own emotions, assess these emotions and provide appropriate feedback.

In order to achieve these challenges, in Section II, we first specify our research questions and goals with regard to labeling affective behavior in educational discourse. Then in Section III, we describe our approach at a conceptual design level. Section IV shows an application example of our model in a real case. Finally in Section V we present the results obtained and in Section VI we discuss the achievements made so far, concluding with future work in Section VII.

II. RESEARCH QUESTIONS AND GOALS

A. Goal:

Our study aims to investigate the effectiveness of the emotion labeling model to detect emotions in educational discourse (text and conversation) in a non-intrusive way making emotion awareness explicit both at individual and group level.

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B. Hypothesis:

Students who learn in a virtual environment endowed by our emotion labeling model improve motivation, engagement and learning achievements.

C. Research Aims:

- identify the emotions that students experience during the realization of collaborative learning activities
- explore the ways these emotions influence and affect learning experience
- build explicit emotion awareness both at individual and group level
- provide adequate and effective cognitive and affective feedback to the students.

To achieve these objectives, an emotion labeling model is designed based on a specific discourse analysis method.

III. RESEARCH METHODOLOGY

In a previous work [3], we have defined a global Emotion Analysis framework that is based on an extension of the Activity Theory (AT) [5], while it integrates and expands on existing learning and linguistic theories, methods and tools, as well as on time factor [1].

On the one hand "Emotion awareness" is an important component of this framework. With regard to this perspective, we need to find the best way to automatically detect and present the affective behaviors that participants show in their interactions in virtual spaces in order to label and display their emotions in an unobtrusive, relevant and non-intrusive way.

On the other hand, with regard to the "Emotional feedback" perspective, we need to investigate the impact of emotions on students' behavior and performance and how these emotions influence their learning experience. To that end, we use questionnaires, such as the AEQ [11] and LSI [9] both at the beginning and at the end of the learning activity.

The aim of the first questionnaire is to extract the initial information context that concerns students' cognitive level, skills, emotional status, attitudes and expectations, time management skills and time perspectives as regards the learning process.

The resulting student profile enables the teacher to establish the content format, develop activities and choose the settings where to use methods such as Project-based Learning, Problem-based Learning or Case-based Learning.

The aim of the final questionnaire is to explore specific emotions that students experience during the realization of collaborative learning activities as well as relate these emotions with their impact on certain students' behaviors in learning (such as motivation and engagement, among others) which in turn are linked to student achievement and learning performance.

The backbone of our research work is the development and use of a discourse analysis method to analyze collaborative learning activities (such as a wiki and debates in forums or chats) with the ultimate aim to extract the emotional relations between discourse units and provide a graphical representation of the emotional structure of discourse. Our discourse analysis method is described in five layers as shown in Figure 1.

At a conceptual level, our discourse analysis method incorporates non-intrusive automatic detection and extraction of emotions from student-created texts and dialogues that will allow us to analyze students' collaborative learning interactions in the above-mentioned virtual learning spaces (wiki, chat and forum) from an emotional point of view.

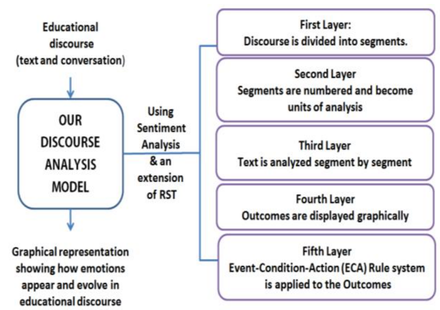


Fig. 1. A layered discourse analysis approach with respect to emotion.

First layer: Discourse (text and conversation) is divided into segments which are going to be analyzed in order to discover and show all the emotions that appear in them. Doing so, we create a clear association between the intentional and the emotional structure of discourse in both modes (text and dialogue).

Second layer: All segments are numbered sequentially and we refer to them as units of analysis.

Third layer: Both the Wiki text and the conversation are analyzed segment by segment by applying first the extended Rhetorical Structure Theory (RST) and then Sentiment Analysis.

Fourth layer: The obtained outcomes are displayed graphically by applying again both tools (RST and Sentiment Analysis). The emotional structure of educational discourse is constructed by providing a neat graphical representation of how emotions appear and evolve in the discourse.

Fifth layer: In this layer it is important to associate the emotional with the intentional structure of discourse in order to explore how participants' emotions affect their goals and vice-versa. To this end, we apply the Event-Condition-Action (ECA) rule system to the outcomes obtained in the fourth layer.

This method will also provide the teacher with the necessary information to offer students an effective and affective feedback. It is meant to provide feedback based on both recent participants emotions and historical participants emotions (e.g. during a concrete scenario of the learning activity or for the whole learning activity).

IV. RESEARCH DESIGN: CASE STUDY DESCRIPTION

A. Methodology.

At an experimental level, we have designed an experiment following the control vs. experimental group paradigm. We applied the emotion labeling model in the experimental group, whereas in the control group we just asked the students to answer the final questionnaire.

The experiment has been conducted in a high school involving 16 students with the aim of investigating the effectiveness of the emotion labeling model. Students participated in collaborative activities, such as collaborative writing (e.g., an essay in Wiki form) and debates in the form of a chat or asynchronous forum.

Our approach has been tested and evaluated as concerns the degree of accomplishment of the four objectives set above.

B. Leaning Scenario and Activity.

1) Participants:

Participants were a group of sixteen fourth-year high school students attending the subject "Introduction to computer science". We divided students in four groups and we chose a couple of them as experimental group and the rest as control group. Each group worked in a collaborative way to carry out the activity that the teacher had planned previously. The experiment was developed during three weeks with a total of 11 class sessions.

2) Scenario.

Our scenario focused on designing and implementing a learning activity based on the Problem-Based Learning method that demands students' participation in the Moodle environment. It has been developed around the topic "Introduction to Internet" and arranged in several synchronous and asynchronous tasks such as wiki creation, forum and chat realization.

Students' role was to be active participants within proposed activities that leaded their own learning, reducing teachers' role to guide and support learning activity and meeting points. As such teachers were asked to plan and design tasks for eliciting whether students had previous knowledge, ideas, believe and so on about the issue at hand and providing appropriate affective and effective feedback.

Our main goals were to:

a) Stimulate affective and collaborative learning.

b) Use ICT as tools in the development of learning-teaching process.

c) Explore the difference in behaviors, attitudes, affective states and performance between students of the experimental group and the ones of the control group.

Moreover, we elaborated two questionnaires, one of them at the beginning of activity, with the aim of obtaining the learning profile of every student. At the end of activity, we used the other one, with the aim of obtaining quantitative and qualitative data about the success of experience.

3) Activity

Based on our emotional discourse analysis method, the design and implementation of the learning activity focused on involving the students to interact with their classmates, teacher and materials within the active tasks. *With regard to the design of the activity*, we divided it at ten stages by following the JIGSAW collaborative strategy. We gathered these stages around five tasks to improve their implementation.

a) First Task: Division of the activity on topics and organization of groups (Initial chat)

b) Second Task: Individual development of each topic (Creation of the wiki)

c) Third Task: Meeting of "experts" prior to the meeting of the group in order to improve the individual reports (asynchronous forum)

d) Fourth Task: Meeting of the groups and presentation of each "expert" approach (Final chat)

e) Fifth Task: Preparation and presentation of final report.

The teacher set up every task with the activity name, a summary of work, apart from establishing the number of teams, four members per group and dividing the activity in so many issues as group members. In this way every group member became an expert about an issue. For each task, the teacher added on all the necessary resources and documents and supervised every task while she had access to the individual and group documents all the time.

C. Data collection.

First, the conversations among group members were carried out in three virtual spaces: an initial and final chat and an asynchronous debate in a forum. These were split in several segments (i.e., the different exchange types and moves issued by each participant in the conversation)– denoted by numbers in parentheses– which represent the linguistic structure of the conversation. Each move is seen as a contribution to discourse and carries a specific goal [14].

The combination of different moves forms the so-called Exchange Structure that consists of three main exchange types, called Give-information, Elicit-information and Ascertain-information exchange [2, 13].

Besides, each group elaborated a wiki space inside over Moodle in which every member of group was responsible to create one page with its part of task. The data collected resulted from both dialogues and wiki texts of the experimental group and were then analyzed by our *Emotion Labeling Model*.

At the end of the experiment, we elaborated a questionnaire with the aim of obtaining quantitative and qualitative data about the *real emotions that students experienced during the realization of the collaborative learning activities*.

Given that emotion and cognition are closely linked [7], we also asked students specific questions that concerned the role of emotions in students' behavior in learning, since emotions certainly have an impact on students' cognitive effort and learning process [8].

D. Techniques and instruments for data analysis.

Concerning the tools we employed, we first applied Rhetorical Structure Theory (RST) [12] to text and the dialogic RST model of Daradoumis [2] to dialogues in order to annotate the role (nucleus or satellite) that each text or dialogue unit plays in each segment of discourse as well as identify the discourse relations that hold between the different units. As segment we consider a small paragraph in the text or an exchange in dialogue. Then, a unit can be a sentence (or part of it) in the text or a move in the exchange.

Furthermore, each segment was analyzed by a sentiment analysis method [10] in order to determine whether the valence (positive, neutral or negative) of emotions is explicit in the discourse.

Finally, we combined the outcomes of these two analysis processes to build a graphical representation of the rhetorical and emotional structure of the discourse that leads to understand part of the context under which participants act and interact and learning takes place.

Regarding the statistical techniques employed in the analysis of the questionnaire data, we used descriptive statistics, calculating relative frequencies (%) and graphics, to represent reality objectively. Also, we used bivariate correlation and analysis of variance to find relationships between the variables under study for each of the objectives of our study.

V. PRESENTATION OF THE RESULTS

Here, we present the results obtained in our experiment focusing on the current objectives of our research.

T*he application of our Emotion Labeling Model was done both at individual and group level*. As far as the Wiki texts are concerned, they were split in segments (denoted by numbers in parentheses) that convey a specific goal, following the paradigm of Grosz &Sidner [15].

The intentional structure captures the discourse-relevant purposes, expressed in each of the linguistic segments as well as relationships among them.

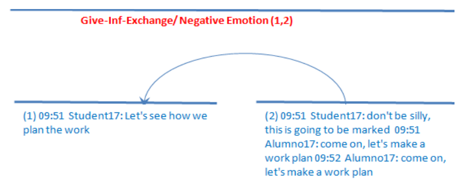
The attentional state is an abstraction of the focus of attention of the participants as the discourse unfolds. Again, upon this resulting structure we proceeded to apply our Emotion Labeling Model to obtain the emotional structure of the text.

Due to space limitation, we cannot show a specific example of text analysis; however, the emotional structure of the text has a similar representation as the one shown for conversation below.

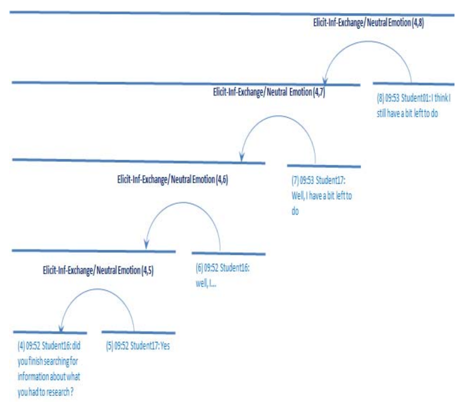
As regards conversations, our model aims at letting students be aware both of their own emotions and of their peers by showing them the graphic representation of the emotional structure of the conversation they produced.

In this way, we could *explore the ways these emotions influence and affect learning experience*. This can cause a motivational effect on their attitudes, making them be more collaborative and supportive to each other to conclude their task. *For instance, Isabel said "...I have felt more confident when I was doing something that I had never done. It has been great, different and fun. I liked it". Daniel also said "I liked a lot the creation of Wiki pages and the debate forum where we were able to share our ideas".*

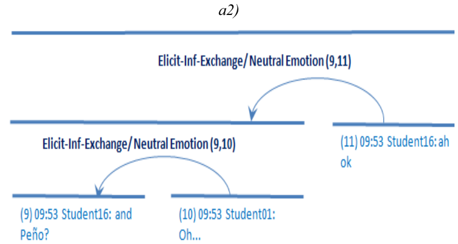
At this stage of our research, our initial analysis showed how the valence of emotions were changing and evolving in all exchange types. Figure 2 (a1, a2, a3, a4, a5, a6 and a7) shows the RST and Sentiment analysis performed in a conversation segment carried out by students of the experimental group, in which a give-information and several elicit information exchanges took place.



a1)



a2)



a3)

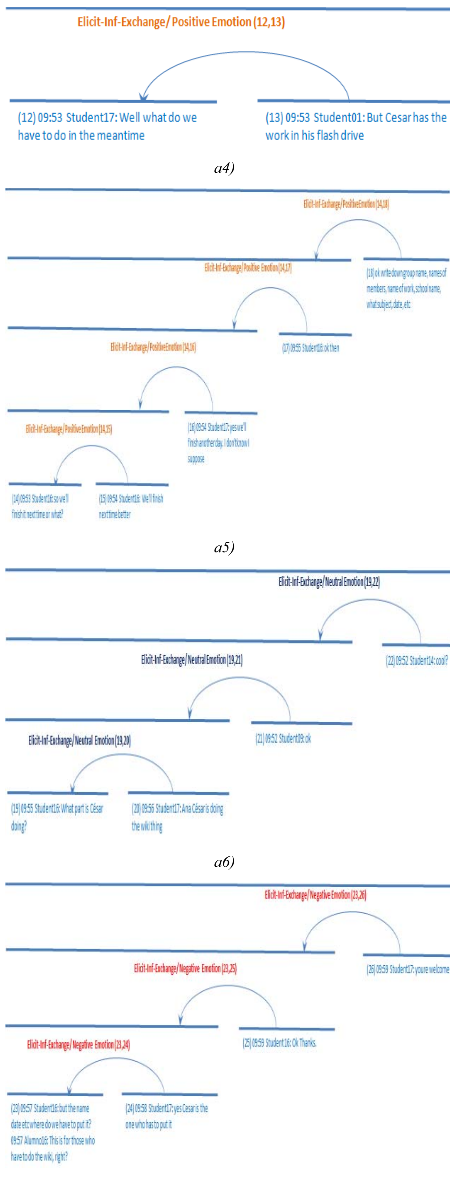


Fig. 2. Evolution of the Emotional structure of the conversation represented through RST and Sentiment Analysis during an initial chat carried out by students of the experimental group (a1, a2, a3, a4, a5, a6 and a7).

Figure 3 shows the student's emotions of the experimental group, in the different virtual spaces, obtained by the final questionnaire.

This questionnaire confirmed the effectiveness of the emotion labeling model to detect the right valence of emotions in educational discourse (text and conversation) in a non-intrusive way making emotion awareness explicit both at individual and group level.

For instance, as shown in Figure 2, the valence of emotions was negative several times during the conversation in the chat. According to the answers of the questionnaire, shown in Figure 3, students' emotions such as frustration, fear, shame and anger, correspond to the negative valence detected by Sentiment analysis.

This situation was caused by the use difficulty of the chat tool itself as shown by students' answers such as: "I learnt a lot though sometimes I was afraid no to make mistakes by using the chat tool" (Ana); "I liked working on the Wiki page and discussing in the Forum though I felt frustrated when I had to participate in the chat because the tool works very bad" (David); "I think it was very positive when the team work was fun but not when it provoked me lack of concentration" (Alex).

Next, we also explored the learning outcomes of the two groups. We saw that 75% of the marks of experimental group was over seven compared to the 33% of marks of control group.

Finally, we analyzed engagement based on the amount of students' participation in the different virtual spaces. In all of them, the participation of the experimental group students was higher than the participation of the control group students.

As a consequence, we validated our hypothesis set in Section II.B, according to which "students who learn in a virtual environment endowed by our emotion labeling model improve motivation, engagement and learning achievements".

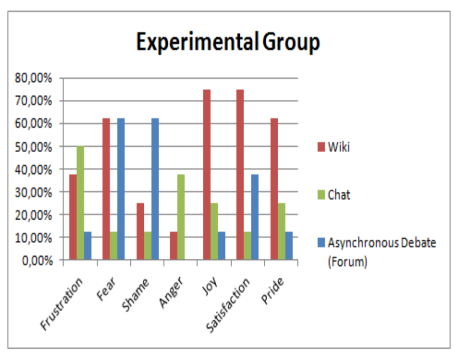


Fig. 3. Emotions of the experimental group students in the different virtual spaces, obtained by the final questionnaire

With regard to emotional feedback, the graphical representation of the emotional evolution of learning groups helped the teacher *provide adequate and effective cognitive and affective feedback to the students, mediate* their feelings and emotions in case of conflict, thus reinforcing group dynamics, *improve self esteem* and *build individual and group well-being*, which facilitated discussion in the group, and enhanced students' performance.

At the final questionnaire, we also asked students their opinion about the emotional feedback provided by the teacher during the activity as shown in Figures 4 (control group) and 5 (experimental group).

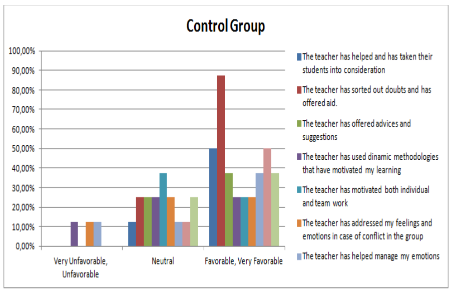


Fig. 4. Assesment of emotional feedback in control group

Taking into account that the teacher offered feedback to both groups in the same way and time intervals, the questionnaire data show that the experimental group students were very positive that the teacher had helped them, had taken them into consideration (62,5%), had motivated both individual and team work (62,5%), had offered advices and suggestions (50,0%), and had used dynamic methodologies that motivated their learning (37,5%) in contrast to the 50,0%, 37,5%, 25,0% and 25,0% of control group students, respectively.

However, control group students were very positive that the teacher had sorted out doubts and had offered aid (87,5%), had answered questions timely (37,5%), had helped manage students' emotions (37,5%) and had induced a good atmosphere in the team (50,0%) in contrast to the 75,0%, 25,0%, 25,0% and 37,5% of the experimental group students, respectively.

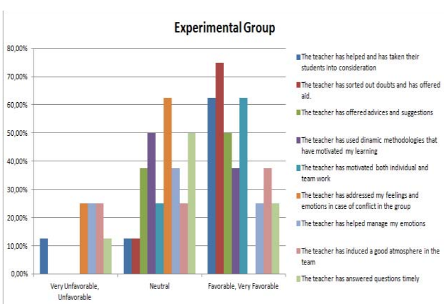


Fig. 5. Assesment of emotional feedback in experimental group

VI. DISCUSSION OF THE RESULTS

We now turn to provide a brief discussion and interpretation of the results of our analysis.

In each step of the activity we applied our extension of RST combined with sentiment analysis both to the text (Wiki) and to the dialogue (chats and asynchronous debate) in every task of the JIGSAW collaborative strategy.

In this way, we achieved the construction of the emotional structure of the produced discourse in terms of the valence of emotions.

However, as shown by the comparison of the impact of the teacher's emotional feedback on the two groups (control vs. experimental), the current utility of the emotion labeling model is still away from the desired outcome. That is, the teacher does not yet possess an effective means in order to have a clear image of the individual and group affective state, since experimental group students were not so pleased with teacher's feedback in some aspects (such as, help them resolve doubts, answer questions timely, help manage their emotions, and induce a good atmosphere in the team).

As a consequence, our emotion labeling model should be further elaborated and extended so that it achieves to provide a more precise detection of students' emotions in terms of real emotions and not just the valence of emotions. Our final questionnaire showed that students did felt and expressed real specific emotions during the co-construction of discourse (in wiki text and conversations).

Thus, if our emotion labeling model detects these emotions in a non-intrusive way and represents them clearly and explicitly and further combines them with the individual intentions (the intentional structure of discourse), we believe it will allow the teacher to critically revise the learning situation, intervene and monitor students' performance more effectively.

In such situation, our final questionnaire will be designed to explore and validate whether the new learning experience will be successful, that is, on the one hand, to evaluate the usefulness and effectiveness of emotional awareness on individual behavior and group dynamics as well as on improving motivation, engagement and learning achievements at individual and group level.

On the other hand, specific questions will address the effectiveness of teacher's feedback as regards learning and team work motivation, students' emotion management and appropriate assistance to students' lack of competence to deal with the learning activity.

The analysis of the emotional structure of discourse together with the evaluation of the students' mental states that are affected by students' emotions not only can assess whether new knowledge has been assimilated and new skills have been acquired but also can provide the interpretation and transformation of the emotions that arose during the learning process, thus helping their development.

In this sense the teacher needs to act timely and provide the adequate scaffold. An in-depth analysis requires the identification and evaluation of the students' emotional states as well as the evaluation of their impact on students' mental states, and consequently on students' learning achievements, in each step of the learning process.

In addition, group members can become aware of their partners' emotional state, which allows them to become supportive when needed. Positive feelings can also liven up group's mood, which increases self-esteem and cognitive efforts, reduces abandonment and pushes the group towards the successful completion of its tasks. This is still under further investigation.

VII. CONCLUSION AND FUTURE WORK

This work presents an initial model for detecting emotions in Educational Discourse, and building intelligent emotion awareness with the aim to improve collaborative e-learning.

Our model has been applied in a small-scale, initial, experimental learning situation in order to analyze and evaluate the effects of this model in the collaborative learning process.

There is still a lot of work to be done in order to obtain a complete and robust framework of Emotion Labeling and Analysis. In this work, the focus of interest of our research has been the analysis of educational discourse as concerns the appropriate detection and representation of the valence of students' emotions, and how this influences students' motivation, engagement and learning achievements as well as teacher's feedback.

In general, there are as many ways of learning as there are human beings, and in the same way we believe that there are as many ways of feelings as there are individuals. So our concern focuses on the combination of both to favor an affective-effective learning process.

As a consequence, emotion and cognition cannot be separated when designing teaching-learning processes in a virtual environment. Furthermore, it is necessary to help teachers understand the role and influences of emotions in teaching processes better and guide them so they can plan these processes in a better and more effective way.

To this end, our future work first focuses on developing a full computational Emotion Labeling model and then designing and carrying out three more experimental scenarios which will assess the validity of our model and provide us with appropriate answers to the research questions set above. In all three scenarios we will conduct a controlled experiment for which two groups are needed: an experimental group and a control group.

This is an important part of our research, as a controlled experiment is a highly focused way of collecting data and will be especially useful for us in order to determine emotional and behavioral patterns of cause and effect.

The ultimate aim is to provide an environment where students feel safe, comfortable, valued and confident and where they will receive the help they need to achieve their goals.

The application of the above tools will provide important knowledge about when specific emotions arise and what causes them.

Consequently, in response to the detection of students' affective states and their occurrence over time, the tutor will be able to provide appropriate feedback to make students react in time, guide and help them in an appropriate way. We believe that this method will help students enhance their time perception, emotional safety and more effective and fruitful engagement in the learning experience.

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Capítulo 8

Anexo.

8.1. Otros Artículos en Congresos Peer-Review

8.1.1. (1) Referencia

1. Daradoumis, T., Arguedas, M. and Xhafa, F. (2013b). Building Intelligent Emotion Awareness for Improving Collaborative e-Learning. In proceedings of the 5th International Conference on Intelligent Networking and Collaborative Systems (INCoS 2013), September 9-11, 2013, Xian, China, IEEE Computer Society, Los Alamitos, CA, USA. DOI: 10.1109/INCoS.2013.49, ISBN: 978-0-7695-4988-0. pp. 281 - 288.

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Building Intelligent Emotion Awareness for Improving Collaborative e-Learning

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***Abstract*— In CSCL contexts it is necessary to study new forms of interaction that stimulate and promote the necessary skills for human communication and critical thinking in order to improve learning experience. Consequently, we have to take advantage of the interaction data generated in CSCL activities to extract important information related to the emotions manifested by group members and build emotional intelligence that supports awareness and regulation of emotions at both individual and group level. This raises important issues that concern, on the one hand, the ways to label affective behavior in educational discourse and, on the other hand, the ways to present emotional information to group participants. This paper focuses on the first issue and describes an approach that considers participant's affective behaviors when interacting in virtual spaces and labels their emotions in a non-intrusive way.**

Keywords: Emotion, collaborative e-learning, emotion awareness, emotional intelligence.

I. INTRODUCTION

Emotions are defined as subjective experiences which are dependent on the context in which they arise. They are experienced in various situations and serve a variety of functions in the academic environment including promoting or undermining behavioral and cognitive engagement, self-regulation of learning activities and achievement [26]. Pekrun, in an analysis of the state of educational research about emotions recognizes the limited knowledge available yet on the occurrence, frequency and phenomenology of emotions in different learning environments and especially in online learning [37]

Users' emotions and relationships are constantly present in e-learning environments which are supported by new tools and learning content; as such, they represent a new interesting research area [10]. Educational experiences carried out in virtual learning environments require a redefinition of the organizational elements of learning in relation to the agents involved (teachers and students), the spaces where they conduct training activities, time factor and learning sequences [38]. Learning involves three particular cognitive processes, attention, memory and reasoning; with respect to each of them student's cognitive ability depends on their emotions [15]. According to them, emotions can be used in the learning context to increase student attention as well as to improve memory and reasoning. As a consequence, relationships between objects or ideas are made more easily while they promote efficiency and rigor in decision making and problem solving [22]. In general, positive emotions lead to a more creative flexible and divergent thought process, while negative emotions cause a more linear convergent and sequential thinking [37].

Considering the impact of emotions on learning, the role of the tutor should be enhanced with new competencies and skills, since they must be prepared to create effective learning situations (such as dialogues) with and between participants. Doing so, the tutor should be able to encourage active learning and collaborative knowledge construction, know how to identify feelings and emotions, monitor and provide appropriate models of expression especially when it comes to negative emotions that are often more difficult to communicate in an appropriate manner. At this point, *emotional intelligence* significantly influences the way the tutor may create a classroom climate which can be emotionally healthy and be managed well in the sense that emotions can be expressed without fear of being judged or ridiculed [21].

Emotional intelligence is the ability to identify, use, understand and manage emotions in positive ways to relieve stress, communicate effectively, empathize with others, overcome challenges and diffuse conflict. Therefore, emotional learning involves the acquisition of skills to recognize and manage emotions, develop care and concern for others, make responsible decisions, establish positive relationships, and handle challenging situations effectively. Studies have shown that emotional experiences influence student's motivation, learning strategies and achievement whereas such emotional experiences are influenced by personality and classroom characteristics [16]. Some authors indicate the important role of social emotions in technological environments and found the nature of the

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emotions to be based on student's perceived control over the learning activity [24]. Thus the study of the antecedents and consequences of emotions in a variety of situations and settings is essential for understanding how to create learning environments that can promote positive emotional experiences which in turn enhance student learning and performance.

Emotion awareness and the ability to manage feelings appropriately is the basis for effective communication and can help to understand and empathize with what is really troubling other people. As such, this research topic is gaining the interest and attention of more and more researchers in the field of affective learning. According to Feidakis et al. [14], emotion awareness entails the detection of emotion signals, recognition of emotion patterns and affective responses and plays an important role in both individual and collaborative learning. A change in the learners' emotional state can reorient their attentional focus and can induce a change in the way they think, act and interact with others as well as regulate their behaviour in a learning situation. Current research on emotional learning points out the necessity to better understand which emotions are most important for different kinds of learning activities. There is also a need to help learners become more aware of their emotions and how they affect their learning experiences. In the field of computer-supported collaborative learning (CSCL), there is on-going research on how emotion awareness influences the way people interact and learn together [14]. Based on group awareness technologies, emotion awareness tools can be developed to display and share information about collaborators' emotions. At the same time they should allow each collaborator to explicitly express his/her feelings, while they should provide implicit and non-intrusive ways to automatically assess the collaborators' emotions.

In order to achieve these challenges, this paper will first carry out a comprehensive and critical analysis of the state of the art of emotion awareness in e-learning in Section II. Then in Section III, we will focus on setting up the context of our research by identifying issues and goals related to emotion awareness and specifying our own research questions and goals with regard to labelling affective behaviour in educational discourse. In Section IV, we present our own proposal that explains how we address these issues, emphasizing the advantages and innovation that our proposal offers with respect to other proposals. Here we describe our approach at a conceptual design level. Consequently, Section V shows an application example of our model in a real case. Finally in Section VI we discuss the results obtained and the achievements made so far, and we conclude with future work.

II. Emotion Awareness in E-learning

One of the current topics in emotion awareness is how to label (i.e., quantify) human behaviour for relevant emotional feedback in learning and CSCL. Humans can display various affective behaviours that have an impact on various factors of collaboration and learning during CSCL. However, such behaviours are difficult to detect automatically, because they can vary significantly from people to people due to idiosyncrasies and the communication media noise when used in a real-life setting. As a consequence, the methodologies used to label these behaviours certainly need further research. The aim of the present study is to present an effective approach to label affective behaviour in educational discourse which will enable a human (or virtual) tutor to capture students' emotions, make students aware of their own emotions, assess these emotions and provide appropriate feedback.

Educational discourse, in which students are mostly involved in their learning tasks, may consist of text (e.g. a Wiki construction) and dialogue (e.g. debates and discussions in synchronous and asynchronous forums). The nature of emotional phenomena both in text and dialogue is very complex, can be interpreted in different ways and be represented by different computational models.

According to Feidakis et al. [14], labels (verbal or pictorial) can be used to classify emotions (into basic, secondary, tertiary, etc.) or to specify gradual emotion (i.e., arousal, valence, etc.) so that to show user's state in an emotional space. Psychologists and affective computing researchers often use two distinct approaches in the modelling and classification of human emotions: A categorical model in which text data are associated with emotional labels ("happy", "sad", etc.) or a dimensional model where data are represented by coordinates in a dimensional space. The representation is based on a set of quantitative measures using multidimensional scaling (e.g. "pleasant-unpleasant", "excitement", and "yielding-resisting") i.e., dimensions used instead of emotion labels to show user's affective state in an emotional space.

Research work on emotion awareness in e-learning, that deals with the issue of labelling affective behaviour within a categorical model, has taken the next three models of emotions as a main reference: (1) Ekman & Friesen [11] classified facial expressions that are linked to six *basic* emotions: (anger, disgust, fear, joy, sadness, and surprise). (2) Ortony et al. [32] in their OCC model have proposed 5 *basic* (anger, fear, happiness, joy, love) and 14 *secondary* emotions. (3) Pekrun [36] examined the impact of the so-called *academic* emotions (four positive: joy, hope, pride, relief and five negative: boredom, anger, anxiety, shame, hopelessness).

With regard to the dimensional models, research on learning theories revealed the following dimensions according to Hascher [19]: arousal, valence, control, intensity, duration, frequency of occurrence, time dimension, reference point and context. Most research work in this category have taken as reference: (1) the model of Russell [40], where emotions are seen as combinations of arousal (high activation / low activation) and valence (positive/ negative). (2) the wheel of emotions of Plutchik [39] which consists of 8 *basic* emotions arranged as four pairs of opposites (joy-sadness, trust-distrust, fear-anger, surprise-anticipation), and 8 *advanced* emotions each composed of 2 basic ones. (3) Kort & Reilly [25] suggested a model with 6x6 possible emotion axes (anxiety-confidence, ennui-fascination, frustration-euphoria, dispirited-enthusiasm, terror-excitement, humiliated-proud) that may arise in the course of learning ranging from negative (rank -1.0) to positive (rank +1.0) valence. And, (4) the Geneva Emotion Wheel (GEW) [41], where the emotion families are arranged in a wheel shape with the axes being defined by two major dimensions of emotional experience: Five degrees of intensity are being proposed, represented by circles of different sizes. In addition, "None" (no emotion felt) and "Other" (different emotion felt) options are provided.

The advantage of categorical representation is that it represents human emotions intuitively with easy to understand emotion labels. In contrast, a major benefit of dimensional models is that they are not correlated to a certain emotional state (e.g. angry or happy). Two or three dimensions of emotional meaning are commonly identified by means of rating. Due to their gradual nature, emotion dimensions are able to capture subtle emotion concepts that differ only slightly in comparison with broad emotion categories. Emotion dimensions can represent very specific identification and a large range of people's emotion concepts. In particular, a dimensional description is well-suited for the task of measuring the full defined emotional states. Moreover, there are several shortcomings with the categorical model of emotions due to (1) the limited number of labels, (2) the categories do not cover all emotions adequately because numerous emotions are grouped together under one category, and (3) the same affective states can be expressed by means of different emotional categories that are defined according to cultural, environmental, linguistic or personality differences, which leads to poor agreement among emotional categories. Nevertheless, the categorical model has been dominant and there are many variations of the model due to its simplicity and familiarity. A categorical model is appropriate for capturing the affective states in the lower valence and higher arousal focus. In contrast, a dimensional model is better when emotions are high in valence focus and low in arousal focus.

Sentiment analysis and the recognition of the semantic orientation of texts is an active research area in the field of natural language processing [35]. The analysis of feelings and opinions towards an entity are classified on a scale that is similar to the valence scale used in emotion models, in order to determine for example whether it is a positive or negative critique. This new trend in emotion research consists in performing lexical analysis of texts with the aim of identifying the words that can predict the affective states of the authors [6]. The main problem of these systems is the lack of importance given to the semantic and linguistic aspect. On the one hand, most approaches do not take the emotional meaning of words into account, and are simply based on the appearance and frequency of terms; yet, the few approaches that use polar expressions usually work with terms instead of concepts, without taking into consideration the multiple meanings a word can have. On the other hand, this type of systems do not usually take into account the linguistic constructions that can affect subjectivity detection, such as negation, quantifiers or modals; again, the few works that have addressed this issue usually identify only their presence, without studying or treating their effect [7].

Several tools have been developed in the field of sentiment analysis and data mining. On the one hand, there are several dictionaries such as: (1) the Wordnet Affect [42], an affective lexical resource that can be useful for affective computing, computational humour, text analysis, etc. It provides a lexical repository of direct affective words that has an emotional hierarchy of affective domain labels (A-Labels) and contains two types of tagging information as new extensions (stative/causative and valence tagging). (2) The Whissell's Dictionary of Affect [43], an instrument designed to measure the emotional meaning of words and texts by comparing individual words to a word list for activation, evaluation and imagery. One the other hand, there are several tools such as: (1) Weka [18], a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from one's own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes. (2) TMG [44] is a Matlab toolbox for text mining, particularly appropriate for text mining applications where data is high-dimensional but extremely sparse. The current version provides a wide range of tools such as Dimensionality Reduction, Clustering, and Classification. (3) FreeLing [34] is designed to be used as an external library from any application requiring this kind of service. Nevertheless, a simple main program is also provided as a basic interface to the library, which enables the user to analyze text files from the command line. Main services offered by this library are text tokenization, morphological analysis; WordNet based sense annotation and disambiguation, rule-based dependency parsing, etc. Moreover, currently supported languages are Spanish, Catalan, Galician, Italian, English, Russian, Portuguese, Welsh and Austrian.

Yet, in recent research work, [27] proposed a model that aims to describe subjectivity relations that exist between the different actors and are labeled with information concerning both the identity of the attitude holder and the orientation (positive vs. negative) of the attitude. The model includes a categorization into semantic categories relevant to opinion mining and sentiment analysis and provides means for the identification of the attitude holder and the polarity of the attitude as well as for the description of the emotions and sentiments of the different actors involved in the text. Furthermore, the study carried out by [3] for the development of EmotiNet represents an appropriate semantic resource to capture and store the structure and semantics of real facts and the prediction of emotional responses caused by chains of actions.

Another field of research in detecting emotions is through conversation analysis (CA) and discourse analysis (DA) methods, where text is an important modality for emotion detection [42]. Likewise, in order to achieve a precise evaluation of opinion in texts, Natural Languages Processing (NLP) systems must go beyond the expressions of positive and negative feelings and identify a wide range of expressions of opinion, including motivations, recommendations and speculations, as well as how they are discursively related in the text. For instance, [13] created a useful framework that includes a catalog of codes and writing rules that serve to reinforce or "complement "virtual educational communication for the analysis of emotional speech in online communication, with the term "Complemented Language". These codes, which users use, include: emoticons, onomatopoeia (haha, mua, m-mhmm), acronyms, repetition of words (excelenteeeeee), intensification and repetition of punctuation (thanks!!), use of capitalization (PLEASE), etc.

Finally, another theory widely used as a discourse analysis method is Rhetorical Structure Theory (RST). RST is a text organization theory which has led to areas of application that are beyond its original objectives: discourse analysis and text generation. Some of these areas in which RST has been applied include the studies conducted in other media, such as dialogue and multimedia [5], [8]. Although RST has never been applied to the study/analysis of emotions, we consider its inclusion in a comprehensive model and face it as an important challenge in our research.

In sum, the relationship between rationality and emotion allows to determine one's behavior as the result of a process that involves reflection about the situation that arises. Given that emotion and cognition are closely linked [15], there are also several mind states that we have to bear in mind in addition to affective states. Therefore, we need tools, such as the ones presented before, that will enable us to label not only academic emotions as positive and negative (such as joy, pride, anxiety, shame) but also behaviors that arise during learners' interaction, such as solidarity (shows/releases), suggestion (makes/asks), antagonism (shows/releases), opinion (asks/gives), etc. In addition, we need to label cognitive and motivational states such as certainty (or uncertainty), agreement (or disagreement), interest (or no interest), thoughtfulness (or not), concentration (or not), etc. [20]. To this end, we propose an Event-Condition-Action (ECA) rule system, based on tools such as WEKA [18]. The aim of this system is to obtain the affective relational attitudes of the teacher (friendly, dominating, paternalistic, secure base, etc.). Our ultimate aim in CSCL, as well as in other online communication situations, is to show how important emotion awareness is together with other types of awareness that are complementary to emotions, such as, opinion awareness.

III. Labelling Human Behaviour in CSCL: Setting up the Context of Research

As we mentioned before different affective behaviours produce different impact in collaboration and learning during CSCL practices. Most recent research looks for identifying ways of labelling affective behaviour and emotional states with the aim to improving quality interaction between peers and providing support to the teachers for facilitating more effective and intelligent affective feedback. Within our work, we are looking for answering various questions regarding these aspects:

In CSCL, what are the roles of emotions and how important is emotion awareness? Are emotions complementary to other types of awareness, e.g. opinion awareness, or equally important? How are group members' emotions related to their motivation to interact and learn together? To what extent do group members' emotional experiences mediate the relationship between group behaviours and performance? How do learning contexts and environments affect group members' emotional experiences? What do group members understand about each other's emotions?

How do students express their emotions? What kinds of emotions do they preferentially share? What could be the benefits of sharing emotions for the co-construction of knowledge and for learning? In what kinds of situations do students express their emotions?

How can we detect the emotion of a learner in an unobtrusive way? What are the methods to make users aware of each other's emotions effectively? Can we take advantage of the interaction data generated in a CSCL activity? What kind of approach, method (e.g. writing text, choice of colours) or tool is it necessary to use for labelling automatically these affective states? How can we follow the emotions' evolution across time?

In this sense, the purpose of our work is to design an emotion labelling model that integrates several learning and linguistic theories, methods and tools in order to detect affective behaviour and states during learner interactions in virtual learning spaces (wiki, chat, forum, debate) in an automatic way. The ultimate aim is to develop, on the one hand, more effective group awareness, dynamics and performance and, on the other hand, to provide the teacher with affective information for giving affective and effective feedback to the students.

Next section describes the way our approach integrates methods such as sentiment analysis and an extension of Rhetorical Structure Theory (RST) to detect emotions in educational discourse (text and conversation) in a non-intrusive way, making emotion awareness explicit both at individual and group level. Later, we plan to incorporate ontologies and Fuzzy Logic in order to enhance our model with more capabilities and more effective predictive power.

IV. Our Proposal

In a previous work [9], we have defined a global Emotion Analysis framework that is based on an extension of the Activity Theory (AT) [12], while it integrates and expands on existing learning and linguistic theories, methods and tools, as well as on time factor [4]. "Emotion awareness" is an important component of this framework which we are going to analyze in this work. In particular, we are going to present a discourse analysis method with respect to emotion. Concerning the tools we employ, we first apply Sentiment Analysis [35] and then combine it with an extension of the Rhetorical Structure Theory (RST), taking also Time Factor into account. We are using these discourse analysis tools to analyze collaborative learning activities (such as a wiki and debates in forums or chats) with the ultimate aim to extract the emotional relations between discourse units and provide a graphical representation of the emotional structure of discourse. In long-term virtual learning practices, it is important to investigate what kind of emotions students express and how these emotions evolve over this period of time Based on time factor, we are able to determine how long students remain in the same negative affective state in the discourse and then we can search the factors that have led to this situation.

Our discourse analysis method is described in five layers as shown in Figure 1:

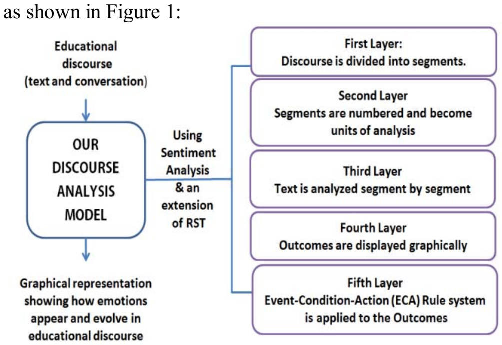

Figure 1. A layered discourse analysis approach with respect to emotion

First layer: Discourse (text and conversation) is divided into segments which are going to be analyzed in order to discover and show all the emotions that appear in them. With regard to Wiki text, division is carried out according to the intentional structure of the text [17]; that is, each segment conveys a specific goal which is the result of the contribution issued by each group member. With regard to the chat dialogue, divisions are carried out at two levels, first at the exchange level and then at the move level inside each exchange [29]. Doing so, we create a clear association between the intentional and the emotional structure of discourse in both modes (text and dialogue).

Second layer: All segments are numbered sequentially and we refer to them as units of analysis.

Third layer: Both the Wiki text and the conversation are analyzed segment by segment by applying first Sentiment Analysis and then the extended RST.

Sentiment Analysis is applied in two stages:

1. Every segment is analyzed by an open source linguistic analysis tool (e.g. Freeling [34]) in order to identify every linguistic element and the grammatical role that each word (noun, adjective, verb, adverb, etc.) plays in the segment.

2. The words of each segment that convey emotion are extracted and associated with their value of polarity and strength using affection dictionaries (such as Whissell's Dictionary of Affective Language [43]).

Then, we apply our extension of RST in two stages:

1. Every segment is analyzed by the extended RST Tool.

2. All emotions detected in each segment are tagged and represented internally in the text.

Fourth layer: The obtained outcomes are displayed graphically by applying again both tools (Sentiment Analysis and RST). Sentiment Analysis is applied by showing the text of each segment with emotional words in different color and size regarding to their polarity and their strength.

Finally, RST is applied to construct the emotional structure of educational discourse by providing a neat graphical representation of how emotions appear and evolve in the discourse.

Fifth layer: In this layer it is important to associate the emotional with the intentional structure of discourse in order to explore how participants' emotions affect their goals and vice-versa. To this end, we apply the Event-Condition-Action (ECA) rule system to the outcomes obtained in the fourth layer. This method will also provide the teacher with the necessary information to offer students an effective and affective feedback. This layer is currently under research and more work is still needed to find and describe solid results.

V. APPLICATION OF OUR MODEL IN A REAL COLLABORATIVE LEARNING PRACTICE

We designed a case study with an experimental group of twenty 3rd-year college students of Technical Engineering in Computing Systems, taking Operative Systems II, using the Moodle Platform. We divided students in 5 groups of 4 members. Each group worked in a collaborative way to create a Wiki page that explains how to install a content delivery platform (Moodle, Blackboard, etc) through an Apache server (Wamp, Xamp, etc). In parallel, students were expected to express their opinions, criticisms and arguments in a free way on the Wiki (in this sense they also implicitly expressed their feelings both in the text that they produced themselves and in the text their group members produced). Also, in order to take part in decision-taking processes, they had to use a chat at specific moments.

We applied our model to analyze the emotions produced among the contributions that students made during the Wiki construction, which lasted 2 weeks, and during the conversation that lasted 1 hour. Applying our method of sentiment analysis and an extension of RST both to the Wiki text and to the dialogue we finally achieved the construction of the emotional structure of the produced discourse.

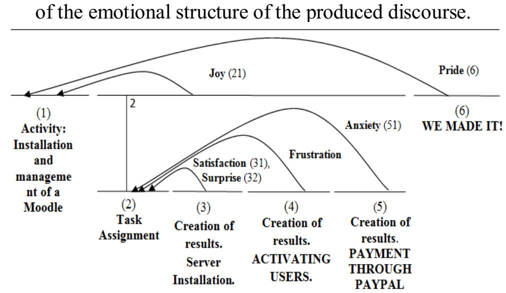

Figure 2. Emotional structure of the text (wiki)

The Wiki text was split in segments (denoted by numbers in parentheses). Upon this resulting structure we proceeded to analyze each segment by applying first our method of sentiment analysis to obtain lexicon analysis of the text (Figure 3) apart from showing the emotional words in every segment with different colours and sizes (Figure 4).

Finally, we applied our extension of RST model to obtain the emotional structure of the text. To carry out the analysis of discourse we based our work on the latest implementation of the RST tool [31] which we extended in order to cover and supply additional relations of emotional type. Then, we provide a neat graphical representation of the emotional structure of educational discourse (Figure 2).

Activity	:	Installation	and	management	of	a	Moodle	.
activity	:	installation	and	management	of	1	moodle	.
NN	Fd	NN	CC	NN	IN	Z	NP00V00	Fp

Creation	of	results	,	Server_Installation	.
creation	of	result	,	server_installation	.
NN	IN	NNS	Fc	NP00SP0	Fp

WE_MADE_IT	!	!
we_made_it	!	!
NP00000	Fat	Fat

Figure 3. Lexicon Analysis of the text (Wiki) with Freeling Tool.

Activity: Installation and management of a Moodle
Creation of results. Server Installation
WE MADE IT!!

Figure 4. Graphical Representation of the text with Sentiment Analysis Using Whissell's Dictionary of Affective Language.

Gabriel: (1) I choose blue to write in the Wiki Choose a color, friends!
(N11) (Give Information Exchange) (Joy)
(2) *I just tried Google Docs, I shared a document as a test with David and Laura, which are whose emails I have, get in and write something in the document. Everyone else, sent me your email privately, in person or through here and I'll give you the codes*
(N21) (Give Information Exchange) (Satisfaction)
Laura: **(3)** *Ok, then, I choose pink*
(S11) (Give Information Exchange) (Joy)
Pablo: **(4)** *Orangeeeee*
(S12) (Give Information Exchange) (Joy)
José Luis: **(5)** *Hi there, I choose red*
(S13) (Give Information Exchange) (Joy)
(6) *and I'd name Gabriel as a spokesperson since he's the most responsible of all of us…..*
(S21) (Give Information Exchange) (Satisfaction)
(7) *what do you think?*
(S31) (Elicit Information Exchange) (Satisfaction)
(S41) (Elicit Information Exchange) (Pride)
Laura: **(8)** *I agree with José*
(N31) (Elicit Information Exchange) (Satisfaction)
Pablo: **(9)** *Yes,*
(S32) (Elicit Information Exchange) (Satisfaction)
(10) *I think he is the most prepared and serious for such a responsible position.*
(N41) (Elicit Information Exchange) (Pride)
(11) By the way, Gabi, mi email is the same we use to communicate for projects.
(S22) (Elicit Information Exchange) (Satisfaction)

Figure 5. Chat conversation with linguistic structure and RST analysis.

Furthermore, the conversation among group members that was carried out in the chat was also split in several segments – again denoted by numbers in parentheses– which represent the linguistic structure of the conversation (i.e., the different exchange types and moves issued by each participant in the conversation), as shown in Figure 5.

Hi	there	,	I	choose	red
hello	there	,	i	choose	red
UH	RB	Fc	PRP	VBP	JJ

and	I	'	d	name	Gabriel	as	a	spokesperson
and	i	'	d	name	gabriel	as	1	spokesperson
CC	PRP	Fz	NN	NN	NP00SP0	IN	Z	NN

since	he	'	s	the	most	responsible	of	all	of	us
since	he	'	s	the	many	responsible	of	all	of	us
IN	PRP	Fz	VBZ	DT	RBS	JJ	IN	DT	IN	PRP

Figure 6. Lexicon Analysis of text conversation with Freeling Tool

Hi there I choose red
and I'd name Gabriel as a spokesperson
since he's the most responsible of all of us

Figure 7. Graphical Representation of the conversation with Sentiment Analysis Using Whissell's Dictionary of Affective Language

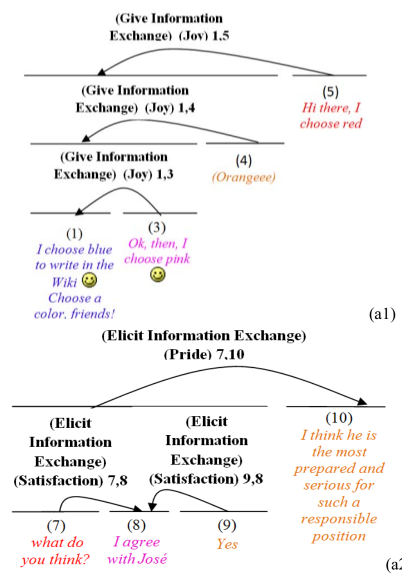

Figure 8. Emotional structure of the conversation with RST (a1, and a2)

First we apply our sentiment analysis method in the same way as in the wiki text. The application of this method shows what kinds of emotions are explicit in text, as well as their valence (positive or negative) and their degree of activation, as shown in Figures 6 and 7. Second, we apply the dialogic RST model of [8] to annotate the role (nucleus or satellite) that each move plays in the exchange structure together with each emotion obtained in previous stage, as shown in Figure 5.Then we apply a further extension of RST to obtain the emotional structure of the conversation, as shown in Figure 8 (a1 and a2).

VI. DISCUSSION

We now turn to provide a brief discussion and interpretation of the results of our analysis. First, during the construction of the wiki, our analysis showed that positive emotions such as satisfaction, joy, surprise and pride predominated, especially when the activity was in its planning phase and when it was completed. Negative emotions, such as frustration or anxiety, appeared while the activity was under construction, but they disappeared due to constant support among members. At this point sentiment analysis allowed students to be aware both of their own emotions and of their peers by showing them the graphic representation of the text they produced. This caused a motivational effect on their attitudes, making them be more collaborative and supportive to each other to conclude their task. Then, during the conversation, our analysis showed only positive emotions in all exchange types. In the two "give information exchange" types, joy and satisfaction are relations that dominate the participants' moves, whereas in the "elicit information exchange" type satisfaction and pride relations appear.

Both discourse types (and especially the conversation one) convey a good harmony among group members, and thus a smooth and effective collaboration among them, which facilitated the expression of their emotions and contributed to carry out the activity successfully. In the general case, this approach could show the teacher how the virtual class is behaving and evolving as an on-line community, how tasks are shared and progress, whether problems or conflicts appear across time and how affect the individuals and the group as a whole. Having a graphical representation of the emotional structure of discourse gives both the teacher and the students a means to have a clear image of the individual and group affective state which, combined with the individual intentions (the intentional structure of discourse), will allow the teacher to critically revise the learning situation, intervene and monitor students' performance. In addition, group members can become aware of their partners' emotional state, which allows them to become supportive when needed. Positive feelings can also liven up the group's mood, which increases self-esteem and effort, reduces abandonment and pushes the group towards the successful completion of its tasks. Finally, difficult situations such as anxiety or fear can be detected easily and supported accordingly either by the teacher or by the group partners. Moreover, social norms modulate the expression of emotion because they ease or inhibit its manifestation depending on the context in which the emotional experience unfolds. This is still under further investigation.

VII. CONCLUSION AND FUTURE WORK

This work presents a model for building intelligent emotion awareness with the aim to improve collaborative e-learning. Our model has been applied in a small-scale, initial, experimental learning situation in order to analyze and evaluate the effects of this model in the collaborative learning process. There is still a lot of work to be done in order to obtain a complete and robust framework of Emotion Analysis. To this end, our future work first focuses on developing a full computational model and then designing and carrying out three experimental scenarios which will assess the validity of our model and provide us with appropriate answers to the research questions set above. In all three scenarios we will conduct a controlled experiment for which two groups are needed: an experimental group and a control group. This is an important part of our research, as a controlled experiment is a highly focused way of collecting data and will be especially useful for us in order to determine emotional and behavioural patterns of cause and effect. The ultimate aim is to provide an environment where students feel safe, comfortable, valued and confident and where they will receive the help they need to achieve their goals. All in all, we consider time as an important factor to be taken into account and this is clearly reflected in the design of our integrated approach and Emotion Analysis Model which includes the provision of timely affective feedback.

In our future work, the analysis of emotions will also take the context in which learning occurs into account. We understand as *learning context* all relevant information related to a student/group that participates in the learning activity. With regard to the context, the idea is to detect the influence of "learning context" in student learning process indicating which factors favour/disfavour positive emotional/ affective states, thus contributing to better learning performance. We will use ontologies as a computational approach to represent this context. Moreover, based on these context data and given that the emotional state is not accurate, the analysis will include machine learning techniques (such as fuzzy logic) to derive the emotional state as well as its relationship to the context and the learning outcome. The application of the above tools will provide important knowledge about when specific emotions arise and what causes them. Consequently, in response to the detection of students' affective states and their occurrence over time, the tutor will be able to provide appropriate feedback to make students react in time, guide them and help them in an appropriate way. We believe that this method will help students enhance their time perception, emotional safety and more effective and fruitful engagement in the learning experience.

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Current Trends in Emotional e-Learning: New Perspectives for Enhancing Emotional Intelligence

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***Abstract* — This paper explores the role and impact of emotion on learning and specifically analyzes issues related to emotion awareness and emotional feedback in e-learning. After a detailed analysis of current research work in these issues, important research questions in emotional e-learning are set and a conceptual Emotion Analysis model is proposed to answer these questions.**

Keywords: Emotion, e-learning, emotion awareness, emotional feedback, affective pedagogical tutors.

I. INTRODUCTION

Current research on web-based learning environments has shown, on the one hand, the importance of taking into account not only the cognitive abilities and capabilities that students possess or need to acquire through learning processes, but also their affective abilities and capabilities. The later cannot be separated from the former; instead we should maintain a holistic perspective of the student profile during these processes. On the other hand, there is a growing tendency to study the new forms of interaction that stimulate and promote the necessary skills for human communication and critical thinking in more depth, with the objective to improve the learning experience. This tendency is seen in the development of graphic environments directed by virtual agents that operate as virtual tutors or teachers who are able to interact with the student following the face-to-face model of human interaction to achieve communication.

From a constructivist point of view, on the one hand, our goal is to show the emotions that students feel during the collaborative learning process in virtual environments and how these emotions influence their learning as well as to assess the emotions obtained, monitoring and scaffolding students throughout their learning process. On the other hand, our purpose is to analyze learning situations with the aim of identifying when affective pedagogical tutors (APT) are necessary and can prove to be effective and appropriate, while determining the abilities or skills that these tutors should have in order to optimize student learning.

In order to achieve these challenges, this article will focus, in Section II, on making a comprehensive and critical analysis of the state of the art of the role and impact of emotion on learning. Then in Section III, we will specifically analyze issues related to emotion awareness, and in Section IV, we will study the impact of the emotional feedback in e-learning. Based on this analysis, in Section V, we present our own proposal that explains how we address these issues, emphasizing the advantages and innovation that our proposal offers with respect to other proposals. Here we describe our approach at a conceptual design level. In this regard, we conduct a methodological design that shows the type of data we need to collect, and which methods are more suitable to analyze these data in order to detect, analyse and interpret the learners' emotions across time.

II. THE ROLE AND IMPACT OF EMOTION ON LEARNING.

Recent work in Computer Science, Neurosciences, Education, and Psychology has shown that emotions play an important role in learning. Learner's cognitive ability depends on his emotions [17]. People often separate emotions and reason, believing that emotions are an obstacle in rational decision making or reasoning but recent work have shown that in every case the cognitive process of an individual is strongly dependent on his emotions which can drastically influence performance [9].

On the one hand, according to [26], emotions are balanced affective states focused on events, agents or objects. The collaboration between rational and emotional mind helps that our behaviour is the result of a process that has involved a reflection about the situation that arises. Students have to understand the influence of emotions on their behaviour, by developing a range of skills related to the ability of: understanding their own affective states, responding appropriately to the moods of others, and identifying that each emotional behaviour has a purpose. This is what has been defined as emotional intelligence [18].

On the other hand, the learning process involves three cognitive processes: attention, memorization, and reasoning. With respect to each of them, the learner's cognitive ability depends on his emotions [17]. In general, positive emotions lead to a more creative, flexible, and divergent thinking process, whereas negative emotions cause a more linear, convergent, and sequential thinking [20].

During the past decade, emotion has emerged as a vital element of the learning process but many questions still

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remain open about emotion management in education [29]. Research has identified both classes of emotion and specific discrete emotions as predictive of student academic outcomes. Next, we present some basic research work that identifies and classifies some key emotions that have an important role and impact on learning.

Basic Emotions Sets for Learning

- [11] classified facial expressions that are linked to the six *basic* emotions: (anger, disgust, fear, joy, sadness, and surprise).
- According to the model of [33], emotions are seen as combinations of arousal (high activation/low activation) and valence (positive/negative).
- [26] in their OCC model have proposed 5 *basic* (anger, fear, happiness, joy, love) and 14 *secondary* emotions.
- [8] has identified a *zone*, where most of the people have concentrated their attention so intensely on solving a problem or doing things that they lose track of time. Such *flow* is optimal experience that leads to happiness and creativity. If a task is not challenging enough, boredom sets in, while too great a challenge results in anxiety, and both cases result in task, and thus learning, avoidance.
- [28] examined the impact of the so-called *academic* emotions (four positive: joy, hope, pride, relief and five negative: boredom, anger, anxiety, shame, hopelessness)
- [14] built a computing system combining facial expression and voice tones, based on 13 couples of opposed emotions. This system produced emotions which were better recognized by users than emotions expressed by humans.
- [9] has distinguished between *primary* (anger, fear, happiness, and sadness) and *secondary* emotions.
- [32] created a wheel of emotions which consisted of 8 *basic* emotions arranged as four pairs of opposites (joy-sadness, trust-distrust, fear-anger, surprise-anticipation), and 8 *advanced* emotions each composed of 2 basic ones.
- [23] have suggested 6x6 possible emotion axes (anxiety-confidence, ennui-fascination, frustration-euphoria, dispirited-enthusiasm, terror-excitement, humiliated-proud) that may arise in the course of learning raging from negative (rank -1.0) to positive (rank +1.0) valence.
- [19] has shown how different emotions can change the tone, articulation and intensity of the voice.
- [16] made an attempt to classify the aforementioned fundamental models and theories of basic emotion, which resulted in ten basic emotions: anger, happiness, fear, sadness, surprise, disgust and love, anticipation, joy and trust.

Research has found that emotions play essential roles in attention [17], memory [17], judgement, decision making, creative problem solving [20], and persuasion [7]. Emotional expression is also one of the primary ways in which we can communicate to others how we are feeling [13], which is of great importance in building and maintaining social relationships with others. Given the important role that emotions play in human–human interaction, it is essential that we understand in detail the impact they have on student's interactions.

Nevertheless, the outputs from much empirical research have produced conflicting results. Indeed, it can become problematic when attempting to analyse and compare the results of different emotion studies as each study often measures different aspects of the interaction, and a number of different experimental approaches can be used.

Moreover, a number of studies have recently explored the affective states that occur during complex learning [10]. These studies have revealed that the basic emotions identified by [12], namely anger, fear, sadness, joy, disgust, and surprise, typically do not play a significant role in learning [23]. Instead they documented a set of affective states that typically do play a significant role in learning, at least in the case of college students learning about computer literacy with an intelligent tutoring system. These affective states were boredom, flow, engagement, confusion, and frustration [8]. They also monitored the affective states of delight and surprise, which occurred less frequently. While some of these affective states might be viewed as purely cognitive in nature, our position is that they should be classified as affective states (or emotions) because these states are accompanied by significant changes in physiological arousal compared with a "neutral" state of no apparent emotion or feeling [4]. Furthermore, affective-cognitive composites are particularly relevant to higher-order learning.

In this sense, the control-value theory of achievement emotions [30] posits that students' motivational beliefs, perceptions of their learning environment, cognitive quality, and other environmental factors influence students' control and value appraisals of academic situations, which in turn predict student emotions and eventual learning and achievement outcomes. Adaptations of this model, in combination with theory from self-regulated learning that includes personal factors, consisting of motivational beliefs and achievement emotions, predicting personal behaviours related to cognitive strategy use, and academic outcomes [2], have been used in research on online learning environments.

III. EMOTION AWARENESS IN E-LEARNING.

In this Section we are going to deal with challenging issues that are dominating current research in emotional learning, and specifically in Computer-Supported Collaborative Learning (CSCL). First, we identify some important topics set for further research. Then, we define some research questions to address these topics. Finally, we set our research goals and proposed solutions.

A. Research Topics

Topic 1: *Labelling human behaviours for relevant emotional feedback in learning and CSCL*: Humans can display various affective behaviours that impact various factors of collaboration and learning during CSCL. However, such behaviours are difficult to detect automatically, because they can vary significantly from people to people due to idiosyncrasies and the communication media noise when used in a real-life setting. As a consequence, the methodologies used to label (i.e., quantify) these behaviours certainly need further research.

Topic 2: *Presenting emotional information*: Considering that we already have a suitable technology for automatically assessing affective behaviours during CSCL, we need to find the best way to present such information to participants, so that they could understand the feedback well and fast, while being less disturbed as possible.

B. Research Questions

- In case of automatic detection and display of emotions during collaboration, how can we deal with the fact that people would prefer to keep some of their emotions private?
- If people have the possibility to share their emotions by themselves – which means that they are able to label their own emotions – how to deal with the fact that it is usually difficult to “put a word” to an emotion they are experiencing.
- In CSCL, as well as in other online communication systems, what are the roles of emotions and how important is emotion awareness? Are emotions complementary to other types of awareness, e.g. opinion awareness, or equally important?
- How can we detect the emotion of a learner in an unobtrusive way? Can we take advantage of the interaction data generated in a CSCL activity?
- How having a tool to analyze past emotions and their causes can be beneficial for people? What are the possible emotion causes and how can they be detected?
- Let's suppose there is a system that is intelligent enough to know all users' emotions and let users be aware of each others' emotions perfectly. What are the methods to let the system 'know' user emotions? What are the methods to make users aware of each other's emotions effectively?
- How to display emotions during collaboration? What could be the impact of the display of emotions on collaborative learning processes and outcomes?
- If we aim to help users express their emotions themselves, what kinds of method (e.g. writing text, choice of colours) and tool can we suggest to use?
- Are visualizations an efficient mechanism to provide emotion awareness in a CSCL scenario? If so, what kinds of visualizations are better for each situation?
- What are the emotions of interest in the context of computer-supported collaborative work and learning? Are dimensional models of emotions useful in this context?

C. Our Research Goals

The purpose of our work is to design a complete emotion analysis model that integrates several learning and linguistic theories, methods and tools aiming at:

(1) detecting and representing the emotions that students experience during their collaborative virtual learning processes (conversations, debates, wikis)

(2) analysing and interpreting these emotions in context, identifying also possible emotion causes.

(3) developing more effective group awareness, dynamics and performance.

D. Our Research Solutions

With regard to the above goals we need to:

- ➢ detect, represent and analyse educational discourse (text and conversation) through non-intrusive methods such as ontologies, an extension of Rhetorical Structure Theory (RST), sentiment analysis or opinion mining, and Fuzzy Logic.
- ➢ apply constructivist strategies such as *cognitive dissonance* as well as information stored in students’ learning profile in order to identify possible emotion causes.
- ➢ make emotion awareness explicit both at individual and group level

IV. EMOTIONAL FEEDBACK IN E-LEARNING

As in the previous Section, we first identify some important topics set for further research. Then, we define some research questions to address these topics. Finally, we set our research goals and proposed solutions.

A. Research Topics

Topic 3: *Evaluating the role and the impact of emotion on collaboration and Learning*. Here we need to investigate the impact of emotions on students’ behaviour and performance and how these emotions influence their learning experience.

Topic 4: *Affective computing methods and technologies for CSCL*. We need to design and implement a suitable Affective Pedagogical Tutor (APT) for providing affecting feedback in real-time during CSCL. Consequently, we need to explore what could be the protocols to follow for measuring and quantifying the benefits of such technology on CSCL.

B. Research Questions

- How to investigate the impact of emotions and in particular emotion awareness on collaborative learning processes and outcomes?
- How can the teacher influence or persuade learners and provide suitable affective feedback in order to regulate members´ emotions in every moment?
- How can we give feedback on the emotions detected during a collaborative learning interaction without being actually orientating the debate between the participants as if we were a participant ourselves?
- What are the computational options (online software tools, such as easily produced Expressive Avatars with dialogue moves) that can be triggered in CSCL environments once specific emotions recognised? Which form is better to use (.swf, embedded videos)?

- How affective and social information automatically computed by machines could be used in an efficient way, with regard to ethic, for computer-mediated interaction / collaboration / learning?
- What are the current challenges in affective computing that need to be addressed to allow self-regulation of individual behaviour by providing both cognitive and affective contextualized and personalized feedback?
- How to perform dynamic emotion assessment (i.e. assess emotional states with a reasonable time resolution)? This can be decomposed in (at least) two sub-questions: how to gather a dynamic ground-truth? How to perform multimodal fusion of modalities with different time resolution?

C. *Our Research Goals*

Our emotion analysis model is also aiming at:

(1) investigating the impact of emotions on students' behaviour and performance and how these emotions influence the learning experience.

(2) discovering in which learning situations an Affective Pedagogical Tutor (APT) may be effective and appropriate, by examining the role the affective virtual tutor plays in the design of student-centred CSCL contexts.

(4) allowing self-regulation of individual behaviour by providing both cognitive and affective contextualized and personalized feedback at appropriate time and in response to the problematic situation

(5) assessing both individual and group emotions more objectively

(6) developing individual socio-cognitive and socio-emotional skills both as regards the teachers (who need to have to optimize the students' learning processes) and the students (when they come to learn new concepts and procedures and to develop skills and attitudes within a dual cognitive and emotional process).

D. *Our Research Solutions*

With regard to the above goals we need to:

- apply constructivist strategies such as *cognitive dissonance* as well as information stored in students' learning profile in order to measure the impact of emotions on students' learning process.
- develop an Affective Pedagogical Tutor (APT) with the capability of designing and applying the *cognitive dissonance strategy* both in the planning and the implementation of learning activities which are carried out collaboratively**.**
- incorporate time as an important factor so that to explore and manage both learners' emotions and tutor's emotional feedback across time.
- provide students with personalised dynamic cognitive recommendations and affective support for the activities they are doing, based on the emotion impact at specific time intervals.
- explore the way both teachers and students develop individual socio-cognitive and socio-emotional skills within a dual cognitive and emotional process.

V. A CONCEPTUAL EMOTION ANALYSIS MODEL.

Based on the above research topics, questions, goals and solutions proposed, we have defined a solid conceptual framework (Fig. 1) that is based on an extension of the Activity Theory (AT) [15] [5], while it integrates and expands on existing learning and linguistic theories, methods and tools, as well as on time factor [3], to build a new integrated approach.

With regard to the "Emotion awareness" perspective, we need to find the best way to automatically detect and present the affective behaviours that participants show in their interactions in virtual spaces in order to label and display their emotions in an unobtrusive, relevant and non-intrusive way. To achieve this, we will apply an extension of the Rhetorical Structure Theory (RST) and Sentiment Analysis [27] [24], taking also Time Factor into account. We are using these discourse analysis tools to analyze collaborative learning activities (such as a wiki creation and debates in forums or chats) in order to extract the emotional relations between discourse units and provide a graphical representation of the emotional structure of discourse. Based on time factor, we are able to determine how long students remain in the same negative affective state in the discourse and then we can search the factors that have led to this situation. The analysis of the emotional state also takes the context in which learning occurs into account. We understand as *learning context* all relevant information related to a student/group that participates in the learning activity. We use ontologies as a computational approach to represent this context. Moreover, based on these context data and given that the emotional state is not accurate, the analysis includes machine learning techniques (such as fuzzy logic) to derive the emotional state as well as its relationship to the context and the learning outcome.

Moreover we need to identify the causes that produce this affective behavior. In this sense, the cognitive dissonance strategy allows us to identify possible activating or inhibiting emotional causes and consequences of the dissonance. We also need to measure its influence both on students' emotional states and behaviors as well as on habits and behavior modification, including their time management skills and their perception of time perspective. Moreover it allows us to know how students manage time in their learning processes, what kind of emotions they express and how these emotions evolve over this period of time.

With regard to the "Emotional feedback" perspective, on the one hand, we need to investigate the impact of emotions on students' behaviour and performance and how these emotions influence their learning experience. For this purpose, we use questionnaires (Achievement Emotions Questionnaire (AEQ) [31] and the Learning Style Inventory (LSI) [21]) at the beginning and at the end of the learning activity to extract the initial information context that concerns students' cognitive level, skills, emotional status, attitudes and expectations, time management skills and time perspectives as regards the learning process. The resulting student profile enables the teacher to establish the content format, develop activities and choose the settings where to use methods such as Project-based Learning, Problem-based Learning or Case-based Learning.

On the other hand, we need to design and implement a suitable APT for providing affective feedback at appropriate time during CSCL. We endow our APT with the capability of designing and applying the *cognitive dissonance strategy* both in the planning and the implementation of learning activities which are carried out collaboratively.

In particular, in the design of learning activities, both at individual and group level, our APT plans evaluation tasks with dissonance questions based on the "Learning by Teaching" paradigm [6]. In this case the role of APT is a troublemaker classmate, i.e. a conflicting student who sometimes is giving incorrect answers with the aim to provoke cognitive dissonance, similar to the agent that [1] used. It is important to study how the APT should manage time and know the moment at which it should appear to play this role. Since cognitive dissonance provokes "constructive conflicts" to students, it is more likely that several emotions will appear and be expressed by students openly. For this reason it is important that learning activities be controlled by an appropriate time management strategy by the APT so that the "conflicts" could be resolved in a desired time interval and not leave space for unwanted negative emotions and situations among students.

The application of the above tools provides important knowledge when specific emotions arise and what causes them. Consequently, in response to students' affective state detection and time occurrence, the tutor is able to provide appropriate feedback to make students react in time, guide them and help them in an appropriate manner. Doing this way, it helps students enhance their time perception, emotional safety and a more effective and fruitful engagement in the learning experience. This is more evident when students become capable of coming out of a negative affective state and get into a more positive one at a particular moment of their learning process.

Extended Activity Theory Scenario (that includes emotional information and time factor)

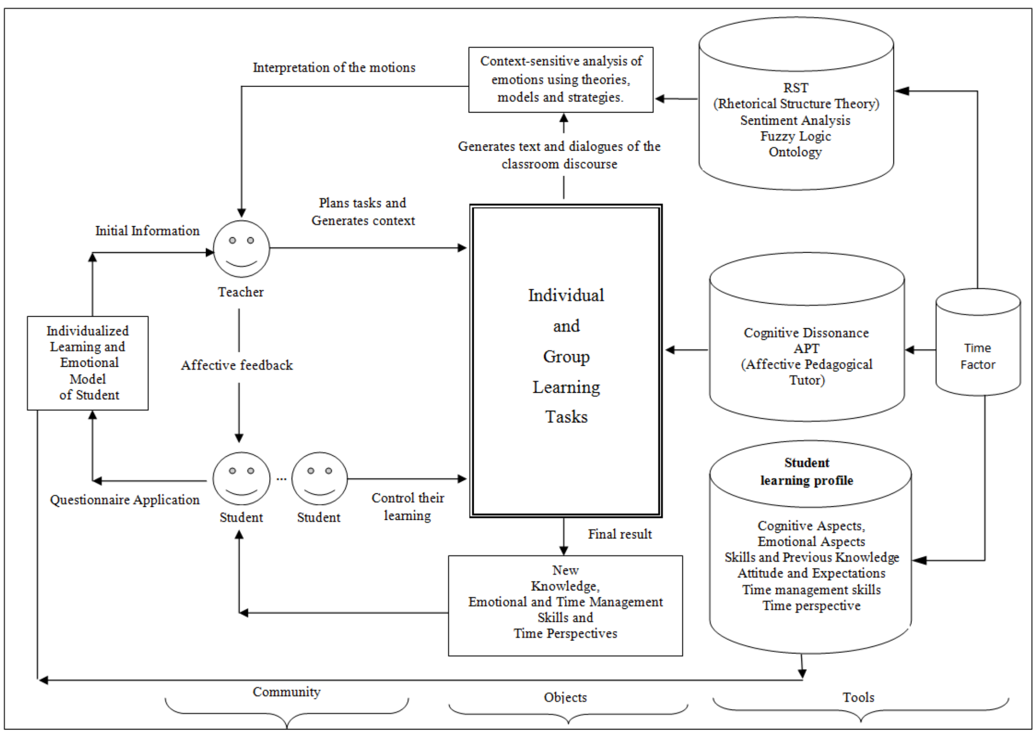

Figure 1. Graphical Representation of the Emotion Analysis Model based on an Extended Activity Theory Scenario.

VI. Conclusion and Future Work

Our proposal pretends to:

- add an important value to CSCL from the affective computing perspective, trying to offer solutions to the problem of students' emotions management, which has an enormous influence in students' behaviour and performance.
- help teachers understand better the effect and the influence of the emotions in the learning processes and guide them to provide a better and more effective planning of such processes.

Further work focuses on issues such as:

- The analysis of the reasons that caused the emotions to arise at a specific time and how we can transform them to achieve effective learning,
- The consideration that this transformation may depend on individual factors, such as a resistance to change, social and cultural factors, peer support to alter cognition, or the need to acquire new skills to overcome dissonance.

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Workshop on Tools and Technologies for Emotion Awareness in Computer-Mediated Collaboration and Learning.

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Proposed paper title: "Paying attention to the learner's emotions in virtual collaborative learning"

Keywords: Affective learning, emotions, virtual affective agent/tutor, affection management.

Goals for the workshop

- **Focus 1: Emotion awareness in CSCL**. This focus will be on understanding how learners' emotions and emotion awareness influence collaborative learning processes and outcomes. In the CSCL context, we will address the questions of how to display learners' emotions during interaction and how such a display affects the processing of emotional information and also the appraisal of the collaborative situation and its consequence on the quality of collaboration and the group outcomes.
- **Focus 2: Affective computing and CSCL**. This focus will be on emotion awareness in CSCL from an affective computing perspective. What can CSCL and affective computing bring to each other? What can CSCL gain from research on automatic emotion recognition? And how can the affective computing field include CSCL issues to its research agenda? We will also address the question of how to develop adaptive systems able to automatically display emotional awareness information depending on the moment-to-moment characteristics of the interaction.

Relationship between the position paper and the workshop research goals:

The latest investigations that took place in virtual environments for teaching-learning processes showed, on one hand, the importance of taking into account not only the cognitive abilities and capabilities that the students possessed or needed to acquire through those processes, but also their affective abilities and capabilities, which we cannot separate from the former, trying to maintain a holistic perspective of the student during those processes. On the other hand, there is a growing tendency to study the new forms of interaction that stimulate and promote the necessary skills for human communication and critical thinking in more depth, with the objective to improve the learning experience. This tendency is seen in the development of graphic environments directed by virtual agents that operate as virtual tutors or teachers who are able to interact with the student following the face-to-face model of human interaction to achieve communication.

With regard to the first focus point of the workshop, our research aims, on the one hand, at showing the emotions that students experience during their collaborative virtual learning processes and how these emotions influence the learning experience. In that way we can obtain an integral and better understanding of the learning process, and also evaluate the recorded emotions to classify them, observing them within the period of time that the formative action lasts. When trying to detect the emotions in CSCL contexts we need to pay attention, not only to their manifestation but also to their expression. For this reason we need methods to analyze the discourse and the conversation used for educational purposes such as *sentiment analysis* or *opinion mining*. Through these methods, we can incorporate non-intrusive automatic detection and extraction of emotions from student-created texts and then provide them with dynamic recommendations and affective feedback for the activities depending on those emotions at every moment. In this sense we also take into account the idea of emotion based on content adaptation (Rodríguez, P. et al, 2012). Along these lines, our approach is using elements from the sentiment analysis (Pang and Lee, 2008) (Liu 2012) to detect emotions both in the works resulting from the students' individual tasks and from the product of teamwork (for example, during wikis creation).

On the other hand, we need to analyze what kind of approaches, tools or methods we can use to influence, model and manage these affective situations in the best possible way. Current research (Hascher 2010; Pekrun et al, 2011) shows that the quality of the relationships, when they happen in pairs (student-student) or between several users (students-teacher), is the key for effective learning. To model affective interaction, it is important to analyze the emotional structure of discourse in virtual and blended learning settings, in any spaces emotions arise (debates, chat-rooms, teamwork - e.g., a wiki creation, an evaluation task, etc). We achieve this by applying an extension of the RST (Rhetorical Structure Theory), which was originally applied in Natural Language Processing area and was based on the use of *coherent relations* between two adjacent text units to analyze discourse (text and dialogue) (Mann and Thompson 1988). The extension of this theory focuses on finding the *emotional relations* between two text or dialogue units, thus providing a rich and graphical representation of the discourse emotions.

With regard to our second focus point, on the one hand our study aims at discovering in which learning situations affective virtual tutors may be effective and appropriate. This is done by examining the role the affective virtual tutor plays in the design of student-centered CSCL contexts, in which the teacher follows constructivist methods such as, *activity theory*. In this sense, our approach includes the use of questionnaires at the beginning of the learning activity in order to build an initial learner model and determine both the cognitive and emotional characteristics, as well as the skills, attitudes and initial expectations of each student, as the start point of the learning process. This serves as a reference for the teacher to establish the content format, to develop the activities and to choose the settings where to use methods such as Project-based Learning, Problem-based Learning or Case-based Learning. Moreover, we are using constructivist strategies such as *cognitive dissonance* to arouse and detect emotions in interactions between different users (student-teacher or student-student) during the knowledge exchange phases. The application of our integrated approach will help the system (and thus the teacher) to induce, in a controlled manner, the dissonant elements and their emotional relationship, both in collaborative tasks that students are asked to complete and in conversation settings between students and teacher. In this way we are able to know when particular emotions arise and why, i.e., what caused them, and thus to provide the appropriate feedback.

On the other hand, we can determine which capabilities or skills the teachers need to have to optimize the students' learning processes. Here we can emphasize the affective role the users play when they come to learn new concepts and procedures and to develop skills and attitudes within a dual cognitive and emotional process. The most recent studies, trends and advances in the area of artificial intelligence, robotics and human-computer interaction, are characterized by the development of graphical environments managed by virtual agents that act as virtual tutors or teachers, and are able to interact with the student following the face-to-face human model to manage communication (Beale and Creed, 2009; Frasson and Chalfoun, 2010). This reflects the role an affective virtual tutor can play when resolving problems, providing advice and explanations, affectively supporting the student interaction and exhibiting coherence, continuity and temporality within the learning context. Virtual tutors can have human appearance or be "cartoonish", but they need to offer the following skills": cognitive and emotional intelligence, affective bidirectional abilities, and neutral language communication capability. Our ultimate aim is to design and construct a prototype based on the results obtained by the aforementioned objectives, which can provide affective-effective feedback to the students, guide, orientate and help them, always with regard to their needs and detected emotions. This will be done by studying the learning settings in which virtual avatars and worlds are effective and appropriate, as well as the characteristics that such environments and tools need to have in order to optimize the teaching-learning process.

Our proposal pretends, on the one hand, to add an important value to CSCL from the affective computing perspective, trying to offer solutions to the problem of students' emotions management, which has not been widely treated so far and which has an enormous influence in students' participation and performance. On the other hand, we want to help teachers understand better the effect and the influence of the emotions in the learning processes and guide them to provide a better and more effective planning of such processes. Our interest focuses on detecting which emotions arise, the degree they are perceived by students and when they occur. In particular, it is important to analyze the reasons that caused the emotions to arise and how we can transform them to achieve effective learning, considering that this transformation may depend on individual factors, such as a resistance to change, social and cultural factors, peer support to alter cognition, or the need to acquire new skills to overcome dissonance.

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Innovative Methods and Technologies for Electronic Discourse Analysis

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Chapter 6

Studying the Suitability of Discourse Analysis Methods for Emotion Detection and Interpretation in Computer-Mediated Educational Discourse

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ABSTRACT

Conversation analysis (CA) and discourse analysis (DA) methods have been widely used to analyse classroom interaction in conventional educational environments and to some extent in e-learning environments, paying more attention to the 'quality' and purposes the discourse serves to accomplish in its specific context. However, CA and DA methods seem to ignore emotion detection and interpretation when analysing learners' interaction in online environments. Effective regulation of emotion, motivation and cognition in social interaction has been shown to be crucial in achieving problem-solving goals. The aim of this chapter is to provide an in-depth study on the possibility of applying discourse analysis methods in e-learning contexts with implications for emotion detection, interpretation and regulation. The result of this study shows whether a comprehensive approach that includes DA methodological solutions and constructivist strategies (e.g., cognitive dissonance) for emotion detection and interpretation can be elaborated and applied.

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INTRODUCTION

According to Ortony et al. (1988), emotions are balanced affective states focused on events, agents or objects. Since emotions play such an essential role in human life, they cannot be left aside when modelling systems that interact with human beings. A new branch named "affective computing" appeared in this research line in the late 90s. This branch is divided in turn into two other branches. The first one studies the mechanisms to recognise human emotions or express emotions by means of a computer in a man-machine interaction (Jacques & Vicari, 2007). The second branch investigates the simulation of emotions in machines (synthetic emotions) with the aim of finding out more about human emotions (Laureano-Cruces, 2006).

Many scientific studies have tried to understand what emotions are and how they take place in human beings. For instance, Fehr and Russell (1984, p. 464) state that everyone knows what an emotion is until asked to give a definition. Then it seems that no one knows. Some of the detection methods used has merely classified emotions into categories. The four most common emotions that appear in the lists of many theorists are fear, anger, sadness and happiness (Ekman & Friesen, 1971; Izard, 1977; Plutchik, 1980). The classification of the emotions that are defined as primary, that is to say, that are not composed of other emotions, varies according to the theory that is taken as a reference. The list of models and theories that analyse basic emotions is very long. Feidakis et al. (2011), in a preliminary study in an attempt to classify models and theories of basic emotion, proposed ten basic emotions: anger, happiness, fear, sadness, surprise, disgust and love, anticipation, joy and trust.

According to Ballano (2011), there are also other methods that widen the number of classes with secondary emotions (Abrilian et al., 2005) or mental states such as "concentrated," "interested," and "thoughtful" (Kapoor et al., 2007). However, all these approaches imply discrete representations, with no relation among each other, and they are not able to reflect the wide range of complex emotions a human being is able to express.

Furthermore, studies about the dimensions of emotions have also been carried out. In the literature, research on learning theories and models revealed the following dimensions according to Hascher (2010): arousal, valence, control, intensity, duration, frequency of occurrence, time dimension, reference point and context.

Starting from the dimensions of emotions, Ballano (2011) argues that certain researchers, such as Whissell (1989) and Plutchik (1980), prefer not to see affective states independently, but rather as interrelated states. These authors consider emotions as a bi-dimensional continuous space, whose axes represent the evaluation and activation of each emotion.

These stimuli and what a person is feeling at all times can be captured by means of techniques such as: facial recognition, recognition of movements and body language, capture of speech patterns and intonation, pupil dilation, heart rate and respiratory rate monitoring, as well as detection of typical smell patterns. For all these purposes, more and more sophisticated devices (sensors) are able to obtain all these data and can be found in the market with no major difficulty. Nonetheless, as regards teaching/learning processes, the least invasive possible techniques should be used.

Another part of the process is to give machines the ability to "understand" human emotions and make them capable of realising what humans are feeling. The aim is to improve people's relationship with them, make the interaction more flexible and offer a pleasant user interface, as well as to allow users to focus their attention on a specific element or situation and improve their decision-making, by adapting to the context of each moment.

In order to do so, and following the objective of this chapter, we carried out an in-depth study about the possibility of applying discourse analysis methods in e-learning contexts with implications in the detection, interpretation and regulation of emotions.

In section 2 we set the base of our work, while in section 3 we review the state of the art of the discourse analysis methods used for educational purposes, such as *sentiment analysis* or *opinion mining,* and *rhetorical structure theory*. In section 4, we carry out a study of the different teaching models and strategies that can be implemented in the virtual classroom and used by teachers, in order to analyse the interaction of the different participants in the classroom and give students an appropriate affective feedback to guide them, advise them and help them according to their needs and states of mind. In section 5, we focus on technologies and how both synchronous and asynchronous computer-mediated communication technologies as well as new media and web 2.0 technologies (e.g. social networks and wikis) apply to educational discourse. Finally, we end this chapter with a section in which we discuss the existing issues and the solutions that have been proposed, as well as our main perspectives. The result of this study shows whether a comprehensive approach that includes DA methodological solutions and constructivist strategies (e.g. cognitive dissonance) for emotion detection and interpretation can be elaborated and applied.

BACKGROUND

One of the main concerns in the educational field is that of making knowledge more meaningful and long-lasting. The teaching-learning process has to be an active process where technologies must serve as tools to support knowledge building and skill development in students by taking into account the students' specific cognitive characteristics that can facilitate and complement this process (Silva et al., 2006).

The topic we want to develop in this chapter is in line with the latest research carried out in virtual environments dedicated to teaching-learning processes. These studies do not only take into account the skills and/or cognitive abilities that students must have or acquire in this process, but also their affective abilities and/or skills, which cannot be separated from the previous ones.

Our research focuses on the development of models of the teaching-learning process that go deeper into new forms of interaction that emulate and improve human communication skills and promote critical thinking with the objective of improving learning. This is done by showing that the quality of the relationships, whether it is those taking place in pairs (student-student) or among the different users of the classroom (student-teacher), is the key to an effective learning.

To this end, it is important to analyse and evaluate the emotional state of the participants in the discourse in the virtual classroom, so that we can achieve a better and more thorough understanding of their learning process. In turn, we must be able to give them an appropriate affective feedback that will guide them, advise them and help them according to their needs and states of mind.

Gross and Silva (2005) propose that the appropriate incorporation of communication tools into education and teaching processes can favour the collaboration between learners. In this sense, Computer-Mediated Communication (CMC) can support an interactive and collective process of knowledge construction where students produce knowledge by actively formulating ideas and which are constructed and shared as a consequence of the reactions and responses of others (Harasim et al., 2000). To this end, emotional learning should take advantage of it in order to improve the whole potential of motivation, affective and social consciousness in the cognitive, affective and emotional relationships that take place in a virtual environment.

One of the raised challenges originates from the fact that the communication of emotions among people is carried out in a natural way through various channels such as the tone of voice, facial expression, words, etc. Therefore, a multimodal system, that uses information from several sources to perform an analysis of emotional communication among people, will achieve a better understanding of the user's emotional state.

Another limitation is the availability of resources. The search for resources should consider those that are the least invasive in the learners' environment so that their attention is not distracted from their learning process. Furthermore, resources must be accessible both socially and economically to the largest possible number of students. For example, most of the computers in a laboratory as well as almost all the portable devices are equipped with a camera that can be used for facial expression recognition.

In this respect, text is an important modality for emotion detection, because most computer user interfaces nowadays include text tools (Valitutti et al., 2004). Once the information we want to use is obtained from different means, a new challenge consists in merging the different information types to obtain a global and consistent result. Once again, this gives rise to a new field of study in which new works are constantly appearing (Gunes et al., 2008). Finally, it is necessary to add the lack of annotated multimodal databases and the complexity of evaluating the results obtained to all the elements that have previously been explained (Ballano, 2011).

EXPLORING DISCOURSE ANALYSIS METHODS USED FOR EDUCATIONAL PURPOSES

The main question we face in this work is how we can measure emotions by applying discourse analysis methods. Emotion is never objective or systematically measurable. It is a subjective "commotion," a response to an external stimulus with physical and organic manifestations. The brain receives sensory information which it decodes and to which it gives a meaning. This generates manifestations and phenomena in our body.

We therefore need to model a personalised learning system that will allow not only the analysis of the learners' expressions, but also let them express both their knowledge and their emotions, making them improve not only their knowledge and cognitive abilities but also their social abilities and self-understanding.

In addition, we need to bear in mind that an emotion is not only expressed through words (written text or dialogue in the virtual classroom) but also implies connotations in both their oral expression (intonation, emphasis, pauses, silences, etc.) and their expression through gesture (body language, eye movement, face colour, etc.).

The analysis of feelings and opinions towards an entity are classified on a scale that is similar to the valence scale used in emotion models (Calvo, 2009). The text is classified by its general feeling, in order to determine for example whether it is a positive or negative critique. This new trend in emotion research consists in the lexical analysis of texts with the aim of identifying the words that can predict the affective states of the authors (Calvo & D'Mello, 2010).

Carrillo de Albornoz (2011), in his doctoral thesis, describes a new approach to the classification of texts according to emotional polarity and intensity, based on the semantic analysis of the text and on the use of advanced linguistic rules. The objective is to determine when a sentence or document expresses a positive, negative or neutral feeling, as well as its intensity. The method uses an algorithm of semantic disambiguation to work at a conceptual rather than term level, and uses the *SentiSense* affective lexicon, developed to extract emotional knowledge and represent each text entry as a group of emotional categories.

Asher et al. (2009) distinguish three main approaches: the discrete approach where emotions are a small set of basic, innate and universal concepts (Ekman, 1970; Izard, 1971), the dimensional approach that proposes dimensions underlying emotional concepts (Osgood et al., 1957; Russell, 1983) and finally, the appraisal approach where emotions are defined as the evaluation of the interaction between someone's goals, beliefs, etc., and his environment (Ortony et al., 1988; Martin & White, 2005).

In the field of sentiment analysis, in order to achieve a precise evaluation of opinion in texts, Natural Languages Processing (NLP) systems must go beyond the expressions of positive and negative feelings and identify a wide range of expressions of opinion, including motivations, recommendations and speculations, as well as how they are discursively related in the text.

According to Carrillo de Albornoz (2011), the main problem of these systems is the lack of importance given to the semantic and linguistic aspect. On the one hand, most of the approaches do not take into account the emotional meaning of words, and are simply based on the appearance and frequency of terms; and the few approaches that use polar expressions usually work with terms instead of concepts, without taking into consideration the multiple meanings a word can have and which can considerably affect the correct identification of subjectivity. On the other hand, this type of systems do not usually take into account the linguistic constructions that can affect subjectivity detection, such as negation, quantifiers or modals, and the few works that have addressed this issue usually merely identify their presence, without studying or treating their effect. Finally, these works depend too much on the domain; that is to say, once the system has been trained with documents on a certain domain, its application on texts in a different domain, especially if the vocabulary is very different, produces very deficient results.

In one of the most recent research works, Maks and Vossen (2012) proposed the development of the Lexicon model that opens new lines in the development of systems in this field. Their model combines the insights from a rather complex model like Framenet (Ruppenhofer et al., 2010) with operational models like SentiWordNet (Esuli & Sebastiani, 2006), where simple polarity values (positive, negative, neutral) are applied to the entire lexicon, in addition to accounting for the fact that words may express multiple attitudes.

Furthermore, the study carried out by Balahur et al. (2012) for the development of EmotiNet, although it is limited by the domain and the small amount of knowledge it currently contains, represents an appropriate semantic resource to capture and store the structure and semantics of real facts and the prediction of emotional responses caused by chains of actions.

In the field of Natural Languages Processing (NLP) and Intelligent Tutoring Systems (ITS), discourse analysis methods have been applied in recent research to interpret user language inputs. For instance, the "AutoTutor" project developed by Graesser et al. (2012) presents components that include an animated conversational agent, dialogue management, speech act classification, a curriculum script, semantic evaluation of student contributions, and electronic documents (e.g., textbook and glossary).

In this line, Lintean et al. (2012) have presented "Meta Tutor," a project that describes the architecture of an intelligent tutoring system that puts emphasis on two components that rely on natural language processing (NLP) techniques: (1) detection of students' mental models during prior knowledge activation (PKA), a meta-cognitive strategy based on student-generated PKA paragraphs, and (2) a micro-dialogue component that handles sub-goal assessment and feedback generation during sub-goal generation (SG).

Finally, another theory widely used as a discourse analysis method is Rhetorical Structure Theory (RST). RST is a text organisation theory which has led to areas of application that are beyond its original objectives: discourse analysis and text generation. Its application has been important in several areas: discourse analysis, theoretical linguistics, psycholinguistic and computational linguistics. Its applications in computational linguistics are multiple: generation of translations, analysis, synthesis, evaluation of arguments, performance test, etc. (Taboada & Mann, 2006). Some of these areas in which RST has been applied include, in addition to the work carried out in other languages, the studies conducted in other media, such as dialogue and multimedia (Daradoumis, 1995; Hovy & Arens, 1991; Matthiessen et al., 1998; Bateman et al., 2000). In addition, RST has been used not only to generate coherent texts with the appropriate discourse markers (Grote et al., 1997b; Scott & de Souza, 1990), but also to generate the appropriate intonation in speech synthesis (Grote et al., 1997a.).

RST was developed through the analysis of texts from written monologues, but it does not exclude the analysis of dialogues in their original phrasing. A few studies have tried to apply the original or modified RST to dialogues. Fawcett and Davies (1992) propose the RST analysis of conversations.

Later on, Daradoumis (1995) developed a new application of RST in its extended version (Dialogic, RST), with new relations to capture the exchange structure of conversation (tutorial dialogue in this case). The analysis of the data he carried out was based on an approach that integrated several models and methods in order to model educational interactions, including rhetorical structure theory. He analysed how knowledge distribution can be seen in the context of the student-student interaction and how it can be studied in a virtual learning environment. This involves the definition of the appropriate situations of collaborative learning and the distinction of two levels of student interaction, discourse and action level. At discourse level, the essential element is the interaction between pairs (the participants must interact with one another to plan an activity, distribute the tasks, explain, clarify, give information and opinions, obtain information, evaluate and contribute to the resolution of problematic issues, and so on). At the level of action, the working objects (e.g. documents, graphs), which are created and used by the actors who participate in the interaction, have been considered.

One of the principles that have characterised Rhetoric since antiquity is its statement that human emotions are an essential component of action and individual and collective thinking (Tapia, 2007). Though emotion is not an obstacle to cognition, there are widely spread theories on the emotional difficulties that can occur during learning. Although RST has never been applied to the study/analysis of emotions, we consider its inclusion in a comprehensive model and face it as an important challenge in our research. Given the dynamics of RST in discourse analysis, we propose its extension on the basis of new relations, called emotional relations, by means of which we are able to analyse not only the cognitive aspect of discourse but also its emotional aspect. The objective of this work is the construction of the emotional structure of discourse (text or dialogue), expressed by means of emotional relations.

TEACHING MODELS AND STRATEGIES

The educational task of training students in a comprehensive way has found its place and an answer in several environments that show their advances both in the understanding of socio-affective and ethical skills and the way to train them, and in the studies that reflect the benefits and great impact of respective research programmes. This type of social and emotional learning experiences (SEL - Social and Emotional Learning) constitutes a process to help the members of the educational community in which students are taught to develop the skills that we all need to manage our relationships and work in a an effective and ethical manner.

These skills include recognising and managing our emotions, developing affection and concern for the others, establishing positive relationships, responsible decision-making and managing difficult situations constructively and ethically. A large body of scientific research has determined that students' academic performance and their attitudes towards school can be improved significantly thanks to SEL. SEAL in the United Kingdom (Department for education and skills, UK, 2005a; 2005b) or CASEL in the United Stated (Collaborative for Academic, Social and Emotional Learning, 2006) are examples of that.

In addition to achieving great progresses in the development of educational policies that make up these dimensions, several studies and international research give relevant results that show how socio-affective and ethical education integrated in the school curriculum, in addition to promoting mental health, benefiting the ethical development of students and their development as citizens, and preventing risk behaviours, leads to improvements in academic learning (Romagnoli & Valdés, 2007).

Moreover, knowing the student's learning style allows the teacher to plan a personalised learning strategy that is appropriate to the student's learning style, which includes managing an effective communication with the student and among students, which will in turn favour effective learning. For instance, identification of a personalised learning style can take place in the analysis of a conversation carried out in the virtual classroom among all its participants. At the same time, identifying the emotional state of each participant during the conversation and combining it with their learning style will let the teacher apply the necessary strategies to give the emotional support that is suitable for each student. Finally, teachers will also need to have the necessary means to follow up the students' cognitive and emotional states during the learning process.

There are different projects that have analysed the role played by emotions in communication among people. Emotalk is one of these projects and shows the need to get rid of this false dichotomy between rational communication and emotional communication. This way, every emotional process is built from a cognitive perception. That is to say, every feeling is built from what is known, thought and elaborated, but, in order to be operative, every rational decision implies emotions or concerns. No decision can be totally objective and free from emotional or sentimental implications. Therefore, beyond the "dichotomous" discourse, it is interesting to know how we can develop "skills" to give emotional importance to our structures of persuasion.

As a consequence, our analysis of conversation must lead us to the building of a model in which students can grow cognitively, favouring attitudes in an emotional environment that is affective, effective and stable, as well as attitudinally, that is to say, allowing them to develop their skills and offering them the possibility to acquire new ones.

Student Learning Styles

The analysis of learning styles offers indicators that help to guide a person's interactions with existential realities. One of the clearest and most precise definitions is the one proposed by Keefe (1988): "Learning styles are characteristic, cognitive, affective and physiological behaviours that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment."

This way, students can become aware of their own learning resources, review the most needed aspects of optimisation, reflect on their own learning process, in function of the requirements of their academic and social environment, thus achieving not only a better academic performance in terms of qualification, but also a wider range of learning resources. According to constructivist theories, the educational process consists in teaching students to learn by means of active and participative teaching models that are focused on teaching-learning processes and individual differences. In fact, based on this paradigm learning is a process of processes

(Beltrán, 1993) whose identification and diagnosis will allow the implementation of programmes of educational intervention aimed at improving the quality of learning from a global perspective. In addition, from this perspective, the concept of autonomous self-regulated students, who know their own cognitive process and are responsible for the control of their learning, prevails.

The student style can be induced and generated at the beginning of a course. Different authors have shown diagnostic tools whose validity and reliability has been proved in different studies over the years through widely used and scientifically proven methods that include surveys and questionnaires. Some of them are shown in Table 1.

Teaching Strategies

Once the student's learning style has been determined, we need to capture and process all the emotional information obtained as a result of the student interaction with the e-learning environment in an intelligent manner; besides, the generated feedback must adapt to the student style in the most effective and least intrusive way.

People learn to behave in a coherent manner at several levels (in particular, when they think, feel, do and say). As such, we should consider any element of cognition, especially any previous knowledge or perceptions one may have, as well as any attitudes, beliefs or feelings about their physical environment or other groups of people.

In line with the constructivist theory, *cognitive dissonance* emerges as an important strategy in the student's learning. Most of the research on this strategy focuses on one of the four great paradigms: the false-belief paradigm (discrepancy), the induced-compliance paradigm, the free-choice paradigm and the effort-justification paradigm. In educational discourse analysis, creating and solving cognitive dissonance can have a powerful impact on the learning motivation of students (Aronson, 1995). Psychologists have incorporated cognitive dissonance in the styles of basic learning processes, in particular in constructivist models. Meta-analytical methods suggest that interventions, which cause cognitive dissonance to achieve directed conceptual change, have been demonstrated through numerous studies to significantly improve science learning and reading (Guzzetti et al., 1993).

However, studies have only been carried out at a cognitive level, without taking into account the emotions experienced by the students to whom

Table 1. Diagnostic tools

AUTHORS	INSTRUMENT
Jerome Kagan (1966)	*Matching Familiar Figures Test*
Herman Witkin (1971)	*Group Embedded Figures Test*
A. Grasha & S. Riechmann (1974)	*Student Learning Styles Questionnaire*
David Kold (1976)	*Learning Style Inventory*
Ronald Schmeck, Fred Ribich & Nerella Ramanaiah (1977)	*Inventory of Learning Processes*
Rita Dunn & Kennel Dunn (1978)	*Learning Style Inventory*
James Keefe (1979)	*Learning Style Profile*
Bert Juch (1987)	*Learning Profile Exercise*
Bernice McCarthy (1987)	*4MAT System*
Richard M. Felder & Linda K. Silverman (1988)	*Index of Learning Styles*
Honey & Mumford (1988)	*Learning Styles Questionnaire*
Alonso, Gallego & Honney (1992, 1994)	*Learning Styles Honey-Alonso Questionnaire (CHAEA)*
Robert Sternberg (1997)	*Thinking Styles Inventory*
Catherine Jester (1999)	*Learning Style Survey for College*
S. Whiteley & K. Whiteley (2003)	*The Memletics Learning Styles Inventory*

Sources: Alonso (1992) & García Cué (2006) dissonance is induced. Our interest focuses on detecting which emotions students feel as well as the degree to which they experience these emotions and the moment at which they occur. In particular, it is important to analyse the causes that trigger these emotions and how we can transform them into an effective learning, taking into account that their transformation can depend on individual factors, such as resistance to change, socio-cultural factors, support from other fellow students to perform the change of cognition, or acquisition of new necessary skills to overcome dissonance.

NEW GENERATION AND WEB 2.0 COMMUNICATION TECHNOLOGIES APPLIED TO EDUCATIONAL DISCOURSE

Constructivism "proposes that learning environments should support multiple perspectives or interpretations of reality, knowledge construction, and context-rich, experience-based activities" (Jonassen, 1991). New technologies now have a great impact on students' learning styles, and this should lead to changes in the teaching methods.

According to Piaget's constructivist theory, there are two principles in the teaching and learning process: learning can be seen as an active process; it should be complete, genuine and real learning (Piaget, 1978). In this respect, emotional aspects play a fundamental role in the user's interaction, not only from a hedonic perspective of the use of interactive products (Jordan, 1998), but also because emotional states affect cognitive processes (Norman, 2002). In other words, the user's affective states have an influence on how well this person solves rational problems. More specifically, according to Brave and Nass (2002), emotions affect attention and memorisation, as well as the user's performance and their evaluation.

As regards technology, it is necessary to incorporate specific tools in the virtual classroom that will facilitate communication of both intentions and feelings that can be easily recognised both by the teacher and the students. The incorporation of these tools is based on the design of man-machine interaction systems in which communication is carried out as naturally as possible.

To do so, Web 2.0 has numerous synchronous (chats, videoconferences, etc.) or asynchronous tools (debate areas, forums, etc.) that allow the development of communication among the different members of the classroom and help the teacher analyse the conversation in order to determine when and how he or she should intervene (with the help of an audio file, a video, an image, a virtual reality, music, etc.) (Feidakis et al., 2010).

With the upcoming of new technologies (such as wikis, social networks, blogs...), students not only have instantaneous access to a world of unlimited information, but they are also offered the ability to control the direction of their own learning.

Traditionally, research in the field of Human-Computer interaction has focused on the user's abilities and cognitive processes, and only studied their rational behaviour, thus leaving aside their emotional behavior (Djajadiningrat et al., 2000; Dillon, 2001; Brave & Nass, 2002; Picard & Klein, 2002).

In the search for more integrative and inclusive design solutions, references to "User Experience" (UX), as a new approach for the development of interactive products, have become popular in the last few years, mainly in the professional field of web development. According to D'Hertefelt (2000), the User Experience represents an emerging change of the usability concept, where the objective is not to merely improve the user's performance in the interaction -effectiveness, efficiency and easiness to learn- but also to try to solve the strategic problem of the product's utility and the psychological problem of the pleasure and entertainment derived from its use.

Furthermore, Dillon (2001) proposes a simple model that defines the User Experience as the sum of three levels: Action, what the user does; Result, what the user obtains; and Emotion, what the user feels. The difference from other definitions is that the author decomposes the triggering phenomenon (interaction) into two levels, Action and Result, and then emphasises the emotional aspect of the resulting experience.

According to Feidakis et al. (2010), there are two predominant trends as regards emotion when we talk about the design of learning systems and environments. The first trend is based on recognising, decoding and exporting emotion/affection patterns in the user-computer interaction. What the user/student really wants and how he or she is feeling at a certain time and in a specific place is considered valuable information that can really lead to personalised computer systems. The possibility of monitoring students' emotions is an attractive concept (Arroyo et al., 2009). The second approach questions not only the way of educating through the use of emotion/affection, but also the way of educating emotions/affection. Substantial theories have been established, that recognise the existence of emotions related to learning (Kort & Reilly, 2002; Goleman, 1995; Csikszentmihalyi, 1990; Gardner, 2006).

According to Fitzgerald (1998), the new generation of technological software applied to education will have a great power as it will include characteristics of Artificial Intelligence (AI), 3D interactive elements in an immersion environment, animated intelligent agents and support animations (Laureano-Cruces, 2004; Laureano-Cruces et al., 2005). Animated pedagogical agents are the state of the art in the design of Human-Computer interfaces. The credibility of these agents generates trust, a trust that will be based on the personalisation and capacity of adaptation of the agents to the student's learning style, to the attitudes and preferences as regards the agent's visual quality and its aptitudes regarding the behaviours that emulate those of humans during its intervention (Lester & Stone, 1997, Jaques & Vicari, 2007).

The new technological advances and the development of new tools for virtual teaching environments must take into consideration the fact that cognition and emotion are inseparable in the teaching-learning processes. The emotions that are detected in the virtual environment during cognitive processes can be positive or negative. However, our research focuses on detecting and interpreting the emotions that students experience through their learning processes, which the teacher can subsequently use to make students aware of what they are going through and thus improve learning. The ultimate aim of our research is to develop a human-computer interaction system that will facilitate the expression and evaluation of those emotions in the communication carried out in the virtual classroom by means of specific discourse analysis methods. This evaluation will be further completed by examining both the students' and the teacher's degree of knowledge of the system, the difficulty to use it, the scaffolding tools that are available to solve the problems that may arise, as well as the alternative media which, although they may seem redundant, may allow the actors in the classroom to consider alternative ways when faced with different difficulties that are not easy to predict. This should be done in a way that allows students to have access to all necessary resources and alternative means in the classroom so they are not forced to look for technological tools outside it.

OUR SOLUTION AND ITS APPLICATION IN A CASE STUDY

In today's constructivist learning environments centred on the student, where students develop their learning processes over time, teachers' work is highly demanding. From a theoretical perspective, we need to construct a solid conceptual framework that integrates and expands on existing ideas and methods to build a new integrated approach. From a technological point of view, we need to translate this framework into a robust system that captures and integrates all the theoretical ideas and serves as an important means to test and evaluate the entire process in real virtual learning situations.

At a theoretical level, our approach is partially based on the Activity Theory (AT) (Engeström et al., 1999), a theory that has been particularly useful in methodologies of qualitative research (e.g., in etnography case studies). It provides a method to understand and analyse a phenomenon, find patterns and make inferences through interactions that describe those phenomena. A particular activity is a goal-oriented or intentional interaction of an individual with an object through the use of tools. These tools externalise the shapes mental processes take as they manifest in constructions, whether they are physical or psychological. AT recognises the internalisation and externalisation of cognitive processes implied in the use of tools, as well as the transformation or development that results from the interaction (Fjeld et al., 2002). In our case, the application of AT consists in making several participants (students) collaborate and interact with specific objects (such as text and dialogue) through the use of specific tools (a wiki and a chat respectively) to carry out goal-oriented activities. These activities presented through language can incorporate a non-intrusive approach for the detection of emotion through exploring different possibilities that aim at the automatic extraction of emotions in student-created texts. In addition, this approach can provide dynamic recommendations for activities as well as adaptation of content according to the emotions, at each given moment, thus offering affective and effective feedback to students (Rodríguez et al., 2012).

To achieve this, we used questionnaires at the beginning of the learning activity to extract students' learning style profile, which provides initial information about the cognitive level, skills, emotional status, attitudes and expectations of each student for the learning process. This also functions as a reference to the teacher when it comes to determining the prerequisites, the format of the learning content and the development of activities using methods such as Project-based Learning, Problem-based Learning or Case-based Learning, within the paradigm of Computer Supported Collaborative Learning (CSCL).

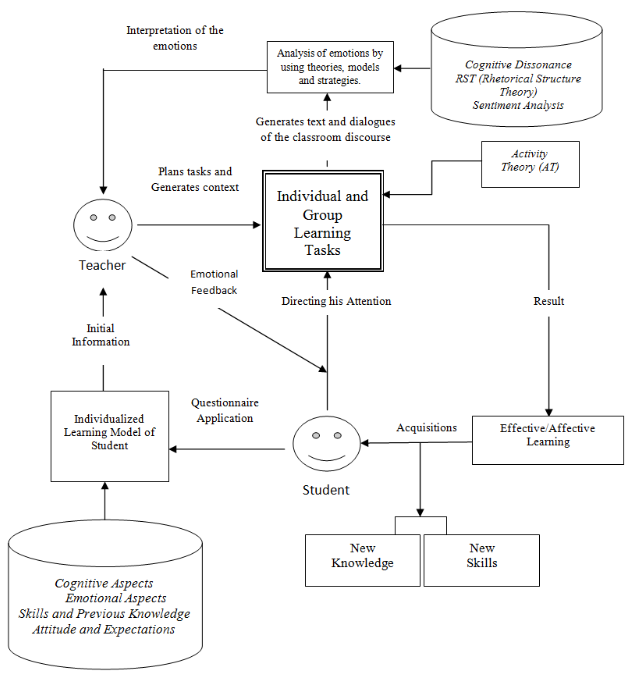
To complete the theoretical framework of our approach we also used, on the one hand, constructivist strategies such as *cognitive dissonance* to detect which emotions were produced in the interactions between the different individuals within the environment (teacher-student or student-student) during the phases of knowledge exchange. The use of this strategy allows us to identify possible activating or inhibiting emotional causes and consequences of the dissonance, as well as its influence both on students' emotional situations and behaviours and on habit and behaviour modification. It also allows us to anticipate possible situations that may generate dissonance to try to avoid them minimise their impact or use their presence as an advantage for a more effective learning. Lastly, the emotional impact of dissonance on the experience can be significant (in a positive or a negative way), when contrasting opinions in a group, whereas member participation could be conditioned by the intensity of the dissonance which is present among its members. The reduction of dissonance or a part of it may improve the participation of the less favoured members.

On the other hand, the analysis of the emotions is completed by applying an extension of the RST (Rhetorical Structure Theory) that is based on the use of *coherent relationships* between two adjacent text units to conduct discourse analysis (texts and dialogues) in the areas of Processing of Natural Language (Mann & Thompson, 1988). The extension of the theory centres on finding *emotional relationships* between two text or dialogue units, with the objective of constructing the emotional structure of the discourse (text or dialogue). The application of the integrated approach helps the system (and as a consequence, the teacher, too) to induce the dissonant elements and their emotional relationship in a controlled manner, both in collaborative tasks that the students are asked to carry out and in the conversations that students participate. Thus, we know when specific emotions arise and what causes them, and we are able to provide the appropriate feedback.

Finally, our approach also includes elements from the analysis of feelings (Pang & Lee, 2008; Liu, 2012) to detect emotions both in students' individual tasks and groupwork (i.e. wiki elaboration). The objective is to detect problems/weak points (or strong points) in different aspects of the teaching-learning process that may require immediate formative action. We can also discover positive or negative opinions that may allow us, for example, to prevent student abandonment, to measure their satisfaction, to analyse their opinions and to predict the evolution of an action. The spontaneity and immediacy of social media, combined with the permanent access to them that latest technologies offer, allow us to eliminate the delay between the generation and the publication of an opinion. Our model is represented in Figure 1.

To summarise, discourse analysis and evaluation of the cognitive process not only confirm that the new knowledge has been assimilated and new skills have been acquired but also achieve the detection, interpretation and transformation of the emotions that arose during the learning process, thus helping their development. In this sense we need to act timely. In each step of the learning process we need to evaluate not only the

Figure 1. Graphical representation of the emotion analysis model (including affective feedback)



level of the knowledge acquired but also the obtained emotional level as well as the attitude towards the learning process itself.

It is important at this point that the teacher's feedback takes time into account. Without being obsessive or abusive, the teacher will consider the duration of the student's learning process in two ways: the time needed to carry out an activity and the time the student has available. In this context, emotions can be used to initiate actions that direct the student's attention to the cognitive goal that needs to be completed. The ultimate aim is to provide an environment where students feel safe, comfortable, valued and confident that they will receive the necessary help to achieve their goals.

To demonstrate the appropriateness of our model for the analysis of emotions in an educational discourse setting, we designed the following case study which we applied to a real situation.

Application of Our Model in a Real Case Study

We designed a case study with an experimental group of twenty 3rd-year college students of Technical Engineering in Computing Systems, taking Operative Systems II in the Moodle Platform. We divided students in 5 groups of 4 members. Given this scenario and based on the Activity Theory (AT), each group worked in a collaborative way to create a Wiki page that explains how to install a content delivery platform (Moodle, Blackboard, etc) through an Apache server (Wamp, Xamp, etc). In parallel, students were expected to express their opinions, criticisms and arguments in a free way on the Wiki (in this sense they also implicitly expressed their feelings both in the text that they produced themselves and in the text their group members produced). Also, in order to take part in decision-taking processes, they had to use a chat at specific moments. To facilitate dialogue and promote an interesting and focused interaction, the teacher asked 4 questions, purposely centred to provoke an effect of *cognitive dissonance* between the group members. The effect of this strategy was to create a very active dialogue between the 4 members of each group, with diverse opinions, in several cases opposed to one another, and with a very pronounced emotional expression.

We applied our model to analyse the emotions produced among the contributions that students made during the Wiki construction, which lasted 2 weeks, and during the conversation that lasted 1 hour. Applying our extension of RST to the text/Wiki (combined with sentiment analysis) and to the dialogue (combined with the *cognitive dissonance* strategy) we achieved the construction of the emotional structure of the produced discourse, as it is shown in Figures 2 and 3.

As seen in Figure 2a, the Wiki text was split in segments (denoted by numbers in parentheses) that clearly convey a specific goal, following the paradigm of Grosz and Sidner (1986). According to their theory, discourse structure is composed of three separate but interrelated components: the structure of the sequence of utterances (called the linguistic structure), a structure of purposes (called the intentional structure), and the state of focus of attention (called the attentional state). The linguistic structure consists of segments of the discourse into which the utterances naturally aggregate. The intentional structure captures the discourse-relevant purposes, expressed in each of the linguistic segments as well as relationships among them. The attentional state is an abstraction of the focus of attention of the participants as the discourse unfolds. Upon this resulting structure we proceeded to apply our extension of RST model to obtain the emotional structure of the text, as shown in Figure 2b.

Furthermore, the conversation among group members that was carried out in the chat was split in several segments – again denoted by numbers in parentheses– which represent the linguistic structure of the conversation (i.e., the different exchange types and moves issued by each par-

Figure 2. a) Text of wiki, b) emotional structure of the text (wiki)

(1) Activity: Installation and management of a Moodle

(2) Task assignment

The group participants are, according to the color codes established by each one of us: Laura (pink), José Luis (red), Pablo (orange), Gabriel (blue). Each member has been charged with the completion of a part of the assigned activity, this way we move forward to detail each of the sections of the completed task.

Install Moodle in Apache (Gabriel says)

Activate users (Laura says) / Activate users (Pablo says)

Payment through Paypal (Jose Luis says)

(21) "Complete planning and in just one afternoon! Let's start!!! (Gabriel says)"

(3) Creation of results. Server Installation. INSTALLING MOODLE IN APACHE

"We used a Mac OS X computer as a server. To install Apache we need Mamp (the equivalent of Xampp for Windows)

Mamp is an application that allows installing our own server. In this manner we'll have Apache, MySQL, PHP and Moodle installed for Mac OS X. (Gabriel says)"

(31) "There are currently two versions, the regular and the Pro. With the regular version we can only create one server. But with the Pro version we have the option of creating unlimited virtual servers. DynDNS, Emails… the only disadvantage is that there is a charge for this version. (Laura says)" (Thank you, Laura (Gabriel says))

"The installation is just a matter of a few clicks. You download Mamp.dmg, it is a universal binary archive and since the 1.6 version the image contains both existing versions: the regular and the pro. (Gabriel says)"

(32) "Once it is installed, when you activate the application, you can see the following page from which we can "start the server", "go to the initiation page" and "preferences"; where you can select options such as start the server as soon as you initiate Mamp, the folder where we find the initiation page, port selection, the PHP version we wish to use and choose the Apache folder where we can save our webpages, blog.. (Pablo says)" (Good idea!! Pablo (Gabriel says))

"By design, the folder where we save the archives is **Applications>Mamp>Htdocs**. For example, we have the folder "Moodle 2.2" inside htdocs. And when we access Localhost (127.0.0.1) from any server, Moodle 2.2 will redirect us to index.php (moodles's starting page).

It is undoubtedly, an easy, flexible and strong solution. (Gabriel says)"

(4) Creation of results. ACTIVATING USERS.

"To activate the users in block, that is, in mass, we need to take the following steps:

From a text archive we will format it as follows:

1) every line of the archive contains a register

2) every register is a series of data separated by commas

3) The archive's first register is special and contains a list of field names.

This register defines the rest of the archive (Laura says)"

"Necessary fields: every user that we want to activate need to have (username, password, first name, last name, email)

Optional fields: (institution, department, city, country, language, timezone)

(41) <u>Example: (Attention!!!! Make sure all the fields are in the right order, otherwise it comes up with a bunch of errors)</u>

username, password, firstname, lastname, email, language, idnumber, maildisplay, course1,group1

juanb, secreto, Juan, Benítez, janb@algo.edu, en, 3663737, 1, Intro101, Seccion1

Saraf, sercreta, Sara, Fernández, sarara@alomas.edu, es, 6736733, 0, Avanzado202, Seccion3 (Pablo says)"

(5) Creation of results. PAYMENT THROUGH PAYPAL

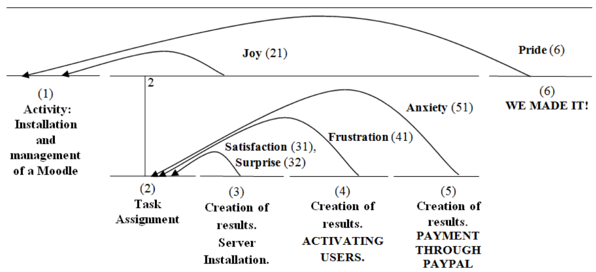
"The first thing we need to do is to activate our account in the official page for Paypal www.paypal.com, the details to include in this page is the email, password and credit card information.

Once registered we can activate Paypal in Moodle, for that we need to choose "administration>registration" and select Paypal as the main payment method.

Once here we need to decide how much we want to charge for the course, information to the students, teachers…. After that we can go to "cost" to be able to insert the amount we have specified for the course, that way it is visible for all users.

(51) Careful!! It is absolutely necessary that all users that want access to the course open an account with Paypal, since this is the only payment option. (Jose Luis says)"

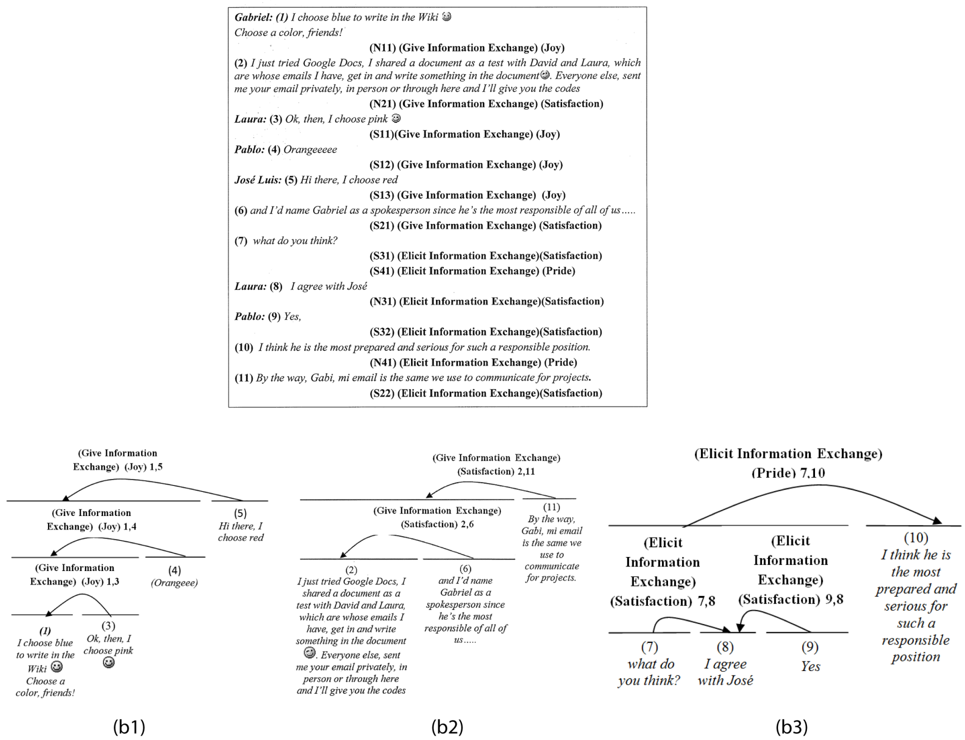
(6) WE MADE IT!! (Gabriel says)



ticipant in the conversation), as shown in Figure 3a. According to Clark and Schaefer (1989), each move is seen as a contribution to discourse and carries a specific goal. The combination of different moves forms the so-called Exchange Structure (Martin, 1992). Again, upon this structure we first applied the dialogic RST model of Daradoumis (2005) to annotate the role (nucleus or satellite) that each move plays in the exchange structure (Figure 3a). Then we applied a further extension of RST to obtain the emotional structure of the conversation, as shown in Figure 3b.

To carry out the analysis of discourse we based our work on the latest implementation of the RST tool (O'Donnell, 2000) which we extended in order to cover and supply additional relations of emotional type. Due to space restrictions we cannot provide the details of the tool application,

Figure 3. a) Chat conversation with linguistic structure and RST analysis, b) emotional structure of the conversation (b1, b2 and b3)



but only some application guidelines on both the text and the dialogue as well as the interpretation of the analysis results.

Application Guidelines and Interpretation of the Analysis Results

Our discourse analysis method was applied in several phases:

First phase: Both the text and the conversation were divided into segments in order to discover and show one or more emotions in them. With regard to the Wiki text, division was carried out according to the intentional structure of the text (Grosz & Sidner, 1986), that is, of the contribution goals as issued by each group member. With regard to the chat dialogue, division was carried out at two levels, first at the exchange level and then at the move level inside each exchange (Martin, 1992). Doing so, we create a clear association between the intentional and the emotional structure of discourse in both modes (text and dialogue).

Second phase: All segments were numbered sequentially and we refer to them as units of analysis.

Third phase: Both the Wiki text and the conversation were analysed segment by segment by the extended RST Tool and all emotions detected in each segment were tagged.

Fourth phase: Deployment of the RST Tool results in constructing the emotional structure of both the text and the conversation as shown in

Figures 2b and 3b. The emotional structure of discourse provides a nice graphical representation of how and which emotions appear as the discourse expands during an interaction as well as the way these emotions evolve and affect the intentional structure of discourse.

Fifth phase: In this phase it is important to associate the emotional to the intentional structure of discourse to explore how participants' emotions affect their goals and vice-versa. This phase is currently under research and more work is needed to find and describe solid results.

We now turn to provide a brief discussion and interpretation of the results of our analysis. First, during the construction of the wiki, our analysis showed that positive emotions such as *satisfaction, joy, surprise* and *pride* predominated, especially when the activity was in its planning phase and when it was completed. Negative emotions, such as *frustration* or *anxiety*, appeared while the activity was under construction, but they disappeared due to constant support among members. Then, during the conversation, our analysis showed only positive emotions in all exchange types. In the two "give information exchange" types (Figures 3b1 and 3b2), *joy* and *satisfaction* are relations that dominate the participants' moves, whereas in the "elicit information exchange" type (Figure 3b3) *satisfaction* and *pride* relations appear.

Both discourse types (and especially the conversation one) convey a good harmony among group members, and thus a smooth and effective collaboration among them, which facilitated the expression of their emotions and contributed to carry out the activity successfully. In the general case, this approach could show the teacher how the virtual class is behaving and evolving as an on-line community, how tasks are shared and progress, whether problems or conflicts appear across time and how affect the individuals and the group as a whole. Having a graphical representation of the emotional structure of discourse gives both the teacher and the students a means to have a clear image of the individual and group affective state which, combined with the individual intentions (as we expect to investigate), will allow the teacher to critically revise the learning situation, intervene and monitor students' performance.

In addition, group members can become aware of their partners' emotional state, which allows them to become supportive when needed. Positive feelings can also liven up the group's mood, which increases self-esteem and effort, reduces abandonment and pushes the group towards the successful completion of its tasks. Finally, difficult situations such as anxiety or fear can be detected easily and supported accordingly either by the teacher or by the group partners.

Finally, the behavioural or expressive component of the emotion includes a number of external behaviours and is greatly influenced by social, cultural and educational factors that can modulate the expression of the emotion. The social norms modulate the expression of the emotion because they ease or inhibit its manifestation depending on the context in which the emotional experience unfolds. This is still under further investigation.

FUTURE RESEARCH DIRECTIONS

At this stage of our research we have built an initial prototype that we applied for experimentation in an exploratory case study (that included a wiki creation and discussion in the form of a chat) with an experimental group. We did not have the possibility of leading a parallel experiment with a control group. We are planning to do it in the near future. Our purpose at this stage was to test our model in a real situation and gain experience as well as get feedback so as to improve our model and build a more solid one so as to apply it in a more complex situation (involving both an experimental and a control group).

As we mentioned above, another important issue is to associate the emotional with the intentional structure of discourse in order to see how participants' emotions affect their goals and vice-versa. Moreover, to strengthen and consolidate our integrated approach of emotion detection, we would like to combine our RST approach with sentiment analysis methods, which will also verify the reliability of our current results.

Once we have completed our analysis, we need to develop the means of reaction to mediate and regulate students' e-learning processes. Affective pedagogical agents or tutors have been widely used in e-learning environments in a variety of ways (Beale & Creed, 2009; Frasson & Chalfoun, 2010). This work will lay the foundations for the design of an affective virtual agent/tutor that is able to intervene and mediate in the e-learning processes of students, providing them with an appropriate affective feedback that will guide, advise and help them according to their needs and feelings. For this purpose, we will first study how the virtual tutor should manage time with the aim of providing feedback at the right time. Therefore, we need to have clear evidence of when the tutor should appear: only when feelings are detected in the student or should the tutor wait to see the student's subsequent reactions? Knowing the moment at which the tutor should appear is the result of our analysis phase, which indicates the appropriate period of time during which the tutor should intervene to control and support the student's learning process emotionally and in an appropriate manner.

In addition to the emotional characteristics that the intelligent virtual tutor should have, thanks to which it will be able to answer students as educationally, communicatively, empathetically as possible and at the appropriate time, our future work will deal with other important aspects, characteristics and problems. Among these problems we can highlight design issues, such as the tutor's aspect, which may be as human as possible or simply take the form of an animated character. Its aspect may even change with time and it may take different forms at different times, depending on each specific situation. Even though interesting advances have been made in user interface design, there are situations that require a tutor with a particular image in order to prevent any negative effects on the students' emotional state.

In long-term virtual learning practices, it is interesting to determine the factors that lead students to remain in the same negative affective state through a certain period of time that is considered detrimental and dangerous, since this can lead to a significant reduction of the quality of learning, failure and even withdrawal from studies. In this case, it requires making students react in time, guide them and help them in an appropriate manner so that they can come out of this negative affective state and get into a more positive one. In order to do this, we need to be able to gather all the data related to the activity that is being carried out by the students (since students can participate in various learning tasks, such as debates, discussion forums sending questions and problems, class workspaces working on a task, etc.). In this line, it requires the study of how students manage time in their learning processes. It is necessary to know if they feel that they have enough time to carry out a learning activity or whether they feel stressed and frustrated by the lack of time as well as what kind of emotions they express and how these emotions evolve over this period of time.

CONCLUSION

In this work, the focus of interest of our research is the discourse analysis of the educational process, in which our concern is the appropriate detection and interpretation of students' behaviours and moods and how they influence their learning. As we have seen, there are as many ways of learning as there are human beings, and in the same way we believe that there are as many ways of feeling as there are individuals, and our concern focuses on the combination of both to favour an affective-effective learning process. As a consequence, as we have already explained, emotion and cognition cannot be separated when designing teaching-learning processes in a virtual environment.

In short, our proposal is giving an important added value to the field of distance learning by trying to provide solutions to a problem (the management of students' emotions) that has not been well addressed and valued until now and that has an enormous influence on the students' participation and performance in their learning. Furthermore, it will help teachers to better understand the role and influences of emotions in teaching processes and will guide them so they can plan these processes in a better and more effective way.

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KEY TERMS AND DEFINITIONS

Cognitive Dissonance: A discomfort caused by holding conflicting cognitions (e.g. ideas, beliefs, values, emotional reactions) simultaneously.

Computer-Mediated Educational Discourse: A sociopsychological approach to CMC by examining how humans use "computers" (or digital media) to manage interpersonal interaction and to study of teacher response and to support to pupils' learning.

Constructivist Theory: Learning theory focuses on how students build their knowledge and skills.

Conversation Analysis: An approach to the study of social interaction, embracing both verbal -and non-verbal conduct, in situations of everyday life.

Discourse Analysis Methods: A general term for a number of approaches to analysing written, vocal, or sign language use or any significant semiotic event.

Effective Learning: Effective learning taking into account the student's emotional state.

Emotions: The various bodily feelings associated with mood, temperament, personality, disposition, and motivation and also with hormones and neurotransmitters.

Sentiment Analysis: The application of natural language processing, computational linguistics, and text analytics to identify and extract subjective information in source materials.

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