Personalized software tutoring and Affective Human-Computer Interaction in Social Networking-based language and open learning

A Dissertation submitted for the Degree of

Doctor of Philosophy

at the Department of Informatics,
School of Information and Communication Technologies,
University of Piraeus
by

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Under the supervision of

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Christos Troussas

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Abstract

This Ph.D. Dissertation presents a novel approach of web-based tutoring, offering personalization to students' needs. The implemented intelligent tutoring system, called POLYGLOT, incorporates social media characteristics in the user interface of the learning environment. These features include posting on a wall, tagging a classmate, instant and asynchronous text messaging, reaction buttons (liking and disliking) on questions and declaring the affective state. Also, POLYGLOT offers an authoring tool to the instructors in order to change the learning content and observe students' performance.

Given that POLYGLOT's learning content concerns the tutoring of foreign languages, namely English and French grammatical concepts, it uses the Stephen Krashen's Theory of Second Language Acquisition, consisting of five hypotheses: the Acquisition-Learning hypothesis, the Monitor hypothesis, the Input hypothesis, the Natural Order hypothesis and the Affective Filter hypothesis. As such, POLYGLOT's tutoring coincides fully with the aforementioned theory in terms of the way of instruction, means of collaboration, time constraints in learning, holding students' records, logical gradation of learning concepts and response on negative affective state (frustration) in the form of motivational messages.

To the direction of individualized instruction, POLYGLOT's student model automatically detects the learning style of students. The students' learning styles are based on the Felder and Silverman model and POLYGLOT classifies students as active or reflective, and sequential or global. Active learners prefer to communicate with their peers and to learn by working with a classmate so that they can discuss about the taught material. In contrast, reflective learners prefer to work alone. Sequential learners prefer to learn progressively and incrementally, having a linear tutoring progress. On the other side, global learners prefer to navigate through the learning material from chapter to chapter randomly. The automatic detection of students' learning style is conducted by a supervised machine learning algorithm, namely the k-nearest neighbors algorithm, which takes as input several students' features, such as their age, gender, educational level, computer knowledge level, number of languages spoken and their grade on preliminary test.

Furthermore, the presented student model incorporates an error detection and diagnosis mechanism which combined two algorithmic techniques into a hybrid approach in order to infer the reason of students' misconceptions. The first technique is the approximate string matching which finds approximate substring matching a pattern and diagnoses misconceptions such as accidental slips, pronoun mistakes, spelling mistakes and verb tense mistakes. The second technique is the string meaning similarity which diagnoses misconceptions owing to language transfer interference.

Moreover, POLYGLOT employs a model for collaboration between students. This model recommends win-win collaboration between students. The recommendation for collaboration concerns two situations. In the first situation, the recommendation for collaboration concerns

two students having complementary knowledge, namely student 1 has a high knowledge level on concept A but poor knowledge level on concept B and student 2 has a high knowledge level on concept B but poor knowledge level on concept A. In the second situation, student 1 conducts misconception A but not B while student 2 conducts misconception B but not A. This rationale can enhance students in the learning process and ameliorate the degrees of knowledge acquisition and knowledge restitution.

In POLYGLOT, students can declare their affective state among “happy”, “frustrated” and “neutral”. However, their interaction with the tutoring system, i.e. experiencing difficulty in a test or receiving a bad grade, can be a blockage of their goal and as such the reason of feeling a negative emotion, such as frustration. POLYGLOT can detect students’ frustration by using the linear regression model. The relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data.

Finally, the POLYGLOT’s response on frustration is the delivery of motivational messages based on the attribution theory, involving a three-stage process underlying that behavior must be observed/perceived, must be determined to be intentional and is attributed to internal or external causes. With the use of motivational messages, the students are assisted in the educational process and are not willing to quit learning.

All the aforementioned approaches are fully implemented and POLYGLOT is evaluated. The system was used by students of a private school of foreign languages in Athens in order to learn the grammatical concepts in both foreign languages. For the evaluation of all the modules of POLYGLOT, the Kirkpatrick's Four-Level Evaluation Model was used. The results of the evaluation were very encouraging. They demonstrated that the system effectively adapts the learning process to the students’ learning style while assisting them by diagnosing their misconceptions, recommending win-win collaborations, detecting their frustration and responding to this negative emotion.

Περίληψη

Η παρούσα διδακτορική διατριβή παρουσιάζει μία καινοτόμο προσέγγιση διαδικτυακής και εξ αποστάσεως εκπαίδευσης, προσφέροντας εξατομίκευση στις ανάγκες των μαθητών. Το υλοποιημένο ευφυές σύστημα διδασκαλίας, που ονομάζεται POLYGLOT, ενσωματώνει χαρακτηριστικά κοινωνικών δικτύων στο εκπαιδευτικό περιβάλλον διεπαφής. Αυτά τα χαρακτηριστικά περιλαμβάνουν την ανάρτηση σε «τοίχο», αναφορά ονόματος χρήστη στον «τοίχο» με χρήση ετικέτας, σύγχρονη και ασύγχρονη επικοινωνία με χρήση κειμένου, κουμπιά αντίδρασης («Μου αρέσει», «Δε μου αρέσει») σε ερωτήσεις και δήλωση συναισθηματικής κατάστασης. Επιπλέον, το σύστημα POLYGLOT προσφέρει και ένα εργαλείο συγγραφής με το οποίο οι διδάσκοντες μπορούν να αλλάζουν το εκπαιδευτικό υλικό και να ελέγχουν την πρόοδο των μαθητών.

Δεδομένου ότι το πεδίο γνώσης του συστήματος POLYGLOT είναι η εκμάθηση γραμματικών φαινομένων στην Αγγλική και Γαλλική γλώσσα, χρησιμοποιείται η θεωρία απόκτησης δεύτερης γλώσσας του Stephen Krashen, η οποία αποτελείται από τις ακόλουθες υποθέσεις: Υπόθεση Απόκτησης-Εκμάθησης, Υπόθεση Επίβλεψης, Υπόθεση Δεδομένων Εισόδου, Υπόθεση Φυσικής Πορείας και η Υπόθεση Συναισθηματικού Φίλτρου. Έτσι, η εκμάθηση μέσω του συστήματος POLYGLOT συμβαδίζει πλήρως με την προαναφερθείσα θεωρία αναφορικά με τον τρόπο διδασκαλίας, τον τρόπο συνεργασίας, τους χρονικούς περιορισμούς στην εκμάθηση, την διατήρηση αρχείων μαθητών, την λογική διαβάθμιση των εννοιών διδασκαλίας και την αντίδραση στην απογοήτευση των μαθητών με τη μορφή ενθαρρυντικών μηνυμάτων.

Προς την κατεύθυνση της εξατομικευμένης διδασκαλίας, το σύστημα POLYGLOT αυτόματα αναγνωρίζει την προτίμηση τρόπου μάθησης των σπουδαστών. Η προτίμηση του τρόπου μάθησης των σπουδαστών βασίζεται στο μοντέλο Felder-Silverman και το σύστημα POLYGLOT κατατάσσει τους μαθητές ως ενεργητικούς ή στοχαστικούς και ακολουθιακούς ή ολιστικούς. Οι ενεργητικοί μαθητές προτιμούν να επικοινωνούν με τους συμμαθητές του και να μαθαίνουν μέσα από τη συνεργασία με κάποιο συμμαθητή ώστε να συζητούν για το υλικό διδασκαλίας. Εν αντιθέσει, οι στοχαστικοί μαθητές προτιμούν να μη συνεργάζονται και να διαβάζουν μόνοι τους. Οι ακολουθιακοί χρήστες προτιμούν να διαβάζουν μόνοι. Οι ακολουθιακοί μαθητές προτιμούν να διαβάζουν σταδιακά και προοδευτικά, έχοντας μια γραμμική πορεία εκμάθησης. Από την άλλη πλευρά, οι ολιστικοί μαθητές προτιμούν να πλοηγούνται στο υλικό διδασκαλίας από κεφάλαιο σε κεφάλαιο με τυχαίο τρόπο. Η αυτόματη αναγνώριση της προτίμησης του τρόπου μάθησής τους γίνεται με τη χρήση ενός αλγορίθμου επιτηρούμενης μάθησης, του αλγορίθμου πλησιέστερου γείτονα, ο οποίος λαμβάνει σαν είσοδο χαρακτηριστικά χρηστών, όπως η ηλικία του, το φύλο τους, το μορφωτικό τους επίπεδο, το επίπεδο γνώσης υπολογιστών, τις γλώσσες που ομιλούν και το βαθμό τους σε ένα προκαταρκτικό διαγώνισμα.

Επιπρόσθετα, το παρουσιαζόμενο μοντέλο μαθητή ενσωματώνει ένα μηχανισμό εντοπισμού και διάγνωσης λαθών, το οποίο συνδυάζει δύο αλγοριθμικές προσεγγίσεις σε ένα υβριδικό μοντέλο με σκοπό να βρει την αιτία των λαθών των μαθητών. Η πρώτη τεχνική είναι η κατά προσέγγιση αντιπαραβολή συμβολοσειρών η οποία βρίσκει

προσεγγιστικά υποσυμβολοσειρές που ταιριάζουν με κάποιο μοτίβο και διαγιγνώσκει λάθη, όπως λάθη απροσεξίας, λάθη στην αντωνυμία, λάθη ορθογραφίας και λάθη στους χρόνους των ρημάτων. Η δεύτερη τεχνική είναι η σήμανση ομοιότητας συμβολοσειρών, η οποία διαγιγνώσκει λάθη που οφείλονται στη χρήση γνώσης από μία γλώσσα στην άλλη.

Επίσης, το σύστημα POLYGLOT ενσωματώνει ένα μοντέλο για τη συνεργασία των μαθητών, η οποία θα είναι ωφέλιμη και για τις δύο πλευρές. Πιο συγκεκριμένα, η πρόταση για συνεργασία αφορά δύο περιπτώσεις. Στην πρώτη περίπτωση, το σύστημα προτείνει συνεργασία μεταξύ δύο μαθητών που έχουν συμπληρωματική γνώση, δηλαδή αν ο μαθητής 1 έχει υψηλή γνώση στο αντικείμενο Α και χαμηλή γνώση στο αντικείμενο Β θα του προταθεί συνεργασία με το μαθητή 2 που έχει υψηλή γνώση στο αντικείμενο Β και χαμηλή γνώση στο αντικείμενο Α. Αντίστοιχα, στη δεύτερη περίπτωση προτείνεται συνεργασία βάσει λαθών, δηλαδή μεταξύ μαθητών εκ των οποίων ο μαθητής 1 κάνει λάθη της κατηγορίας Α αλλά όχι λάθη της κατηγορίας Β και ο μαθητής 2 κάνει λάθη της κατηγορίας αλλά όχι λάθη της κατηγορίας Α. Αυτή η λογική μπορεί να βοηθήσει τους μαθητές στην εκπαιδευτική διαδικασία και να βελτιώσει τους βαθμούς απόκτησης και αποκατάστασης γνώσης.

Στο σύστημα POLYGLOT, οι μαθητές έχουν τη δυνατότητα να δηλώσουν τη συναισθηματική τους κατάσταση μεταξύ των «Χαρούμενος», «Απογοητευμένος» και «Ουδέτερος». Παρ’ όλα αυτά, η αλληλεπίδραση με το σύστημα, δηλαδή η αντιμετώπιση δυσκολιών σε διαγώνισμα ή ένας κακός βαθμός, μπορεί να αποτελέσει εμπόδιο στην επίτευξη των στόχων του, το οποίο με τη σειρά του προκαλεί το αρνητικό συναίσθημα της απογοήτευσης. Το σύστημα POLYGLOT μπορεί να εντοπίσει την απογοήτευση του μαθητή, χρησιμοποιώντας το μοντέλο γραμμικής παλινδρόμησης. Οι σχέσεις μοντελοποιούνται χρησιμοποιώντας λειτουργίες γραμμικής πρόβλεψης των οποίων οι άγνωστες παράμετροι του μοντέλου υπολογίζονται από τα δεδομένα.

Τελικώς, η αντίδραση του συστήματος POLYGLOT στην απογοήτευση των μαθητών είναι η προβολή ενθαρρυντικών μηνυμάτων, βασισμένων στη θεωρία απόδοσης ενθαρρυντικών μηνυμάτων (θεωρία απόδοσης αιτιών), η οποία περιλαμβάνει τρία στάδια και υπογραμμίζει ότι η συμπεριφορά πρέπει να παρατηρείται, πρέπει να καθορίζεται ως σκόπιμη και να αποδίδεται σε εσωτερικές ή εξωτερικές αιτίες. Με τη χρήση των ενθαρρυντικών μηνυμάτων, οι μαθητές βοηθούνται κατά την εκπαιδευτική διαδικασία και αποθαρρύνονται από τη διακοπή της μελέτης.

Όλες οι προαναφερθείσες προσεγγίσεις έχουν υλοποιηθεί, εφαρμοστεί και αξιολογηθεί πλήρως. Το σύστημα POLYGLOT χρησιμοποιήθηκε από τους μαθητές ενός φροντιστηρίου ξένων γλωσσών στην Αθήνα, προκειμένου να διδαχθούν τα γραμματικά φαινόμενα και στις δύο γλώσσες. Για την αξιολόγηση όλων των λειτουργιών του συστήματος POLYGLOT, χρησιμοποιήθηκε το μοντέλο τεσσάρων επιπέδων του Kirkpatrick. Τα αποτελέσματα της αξιολόγησης ήταν πολύ ενθαρρυντικά. Απέδειξαν ότι το σύστημα αποτελεσματικά προσαρμόζει την εκπαιδευτική διαδικασία στην προτίμηση του τρόπου μάθησης των σπουδαστών, καθώς επίσης τους βοηθάει στη διάγνωση των λαθών τους, προτείνει συνεργασίες ωφέλιμες και για τους δύο μαθητές, εντοπίζει την απογοήτευσή τους και απαντά σε αυτή.

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Chapter 1: Introduction

1.1 Motivation of the research

The world has witnessed major improvements in the areas of transportation and telecommunications. These important changes have permitted the rise of the phenomenon of globalization by which regional economies, societies, and cultures have become integrated through a global network of people. As a result, all the emerging needs of modern life accentuate the importance of learning foreign languages (Kurata 2010). Considering the scientific area of Intelligent Tutoring Systems (ITSs), there is an increasing interest in the use of computer-assisted foreign language instruction (Virvou & Troussas 2011). In this way, students may learn a foreign language, by using a computer-assisted application. Especially, when these systems offer the possibility of multiple-language learning at the same time, the students may further benefit from this educational process (Virvou et al. 2000).

In recent years, the rapid development of high and new technology has opened new horizons in computer-assisted instruction. Intelligent Tutoring Systems are based on computer models of instructional content and support the learning, by providing personalized instruction to students. In this way, students may learn one or more foreign languages. European reality necessitates multiple language learning (European Union), so the students may further benefit from this educational process. For this reason, the need of systems that incorporate intelligence is even greater when students are taught more than one foreign language simultaneously (Virvou & Troussas 2011).

One important area of ITSs involves the specialization on language learning which is referred to as Intelligent Computer-Assisted Language Learning (ICALL). In ICALL, students are taught a language (e.g. Greek, English, French etc.) through an ITS. Nowadays, all the emerging needs of everyday life along with the phenomenon of globalization accentuate the significance of learning foreign languages. Moreover, it has to be emphasized that foreign language learning is widely promoted by many countries and clusters of countries. For example, the European Union promotes such guidance for its country members. Due to the currents global promotion of language learning, countries, such as Greece, have adopted foreign language teaching in the education curriculum of schools. Students are obliged to learn two foreign languages starting from the primary school to the secondary school. The teaching of foreign languages (English, French and German) is compulsory for all Greek pupils in all three grades. Even though the English and French languages have common characteristics so that their learning can be joint (Roberts, 1993 and Vinay and Darbelnet, 1995), there is the risk of students being confused in multiple language learning.

The need for tutoring systems that may provide user interface friendliness and also individualized support to errors via a student model are even greater when students are taught more than one foreign languages simultaneously (Virvou & Troussas 2011). A solution to this problem may be the integration of the technology of Intelligent Tutoring Systems (ITSs), so as to provide adaptive tutoring to individual students. ITSs offer intelligence and adaptivity to individual students' needs, via student modeling. The individual student model for each student contains information about the knowledge level and the error handling of the student in each concept of multiple language learning. Hence, error diagnosis is a module which supports the students while studying theory and solving exercises (Tsiriga & Virvou 2004). Socialization has important pedagogical implications in collaborative learning that support the learners' personal relationships and social interaction with their classmates (Caballé et al. 2010). Therefore, the support of collaboration in multiple language learning may promote the learning process. When adaptive personalized e-learning systems could accelerate the learning process by revealing the strengths and weaknesses of each student in a collaborative environment, they could dynamically plan lessons and personalize the communication and didactic strategy (Licchelli et al. 2004). Machine learning techniques can be used for acquiring models of individual users interacting with educational systems and group them into communities or stereotypes with common interests (Papatheodorou 2001), so that the student reap the benefits of collaboration.

Collaboration has helped humans realize shared goals, especially in cases where individual effort has been found inadequate. Over the last years we have all witnessed the power of groups working together and the electronic human networks that are changing the way we see the World Wide Web (Benevenuto et al., 2012). Correspondingly, collaboration is quite recently used in electronic learning software to help people involved in a common e-learning task achieve goals (Lichtnow et al., 2011). It is believed that humans as social beings have an endogenous tendency to create groups. Many scientists in the area of educational learning support that it would be educationally highly beneficial if these groups could consist of learners that would work complementarily (Dafoulas et al., 2009).

Social networking sites (SNSs) (e.g. Facebook, Twitter, MySpace) have become commonplace interactivity tools that bring people together through computer-based approaches. The main features of SNSs that render them very popular over other means of online communication include immediacy, interactivity, and self-identification development through continuous engagement with one another (Benson, 2001). Studies have showed that social network tools support educational activities by enhancing interaction, collaboration, active participation, information and resource sharing, and critical thinking (Mazman and Usluel, 2010, Ajjan and Hartshorne, 2008, Selwyn, 2007 and Mason, 2006). Current research on social networks has focused on identity, network structures, privacy and technological issues; therefore, there is the recognizable need for research on social networks in educational contexts (Mazman and Usluel, 2010 and Lockyer and Patterson, 2008). However, research on social networking in intelligent educational contexts is still limited.

Social networks seem particularly useful for the purposes of language learning through computer-assisted education. Troussas et al. (2013) point out that socialization has important pedagogical implications in language learning that support the learners' personal relationships and social interaction with their classmates.

SNSs can make the learning of a second language through socialization faster. The social networks offer people the facility to be surrounded by the target language, to have sufficient interaction and to actively participate in discussions (Benson, 2001). On the other hand, a very crucial element in language learning is the learner centeredness, pedagogical approach and learner's autonomy. Inevitably, learners must be at the center of teaching pedagogical practices (Li et al., 2013). Learners' autonomy has been attributed to many definitions, such as the ability to take charge of one's own learning [8], a capacity - for detachment, critical reflection, decision-making and independent action (Holec, 1979), and recognition of the rights of learners within educational systems (Benson, 2001).

In view of the above, the main goal of this research is to profit from the features of social networks and the technology of ITSs by combining them in a novel way in order to offer optimized and personalized multilingual learning. Given that Greek students are obliged to learn two foreign languages since primary school due to European regulation, the teaching of foreign languages (English and French) is integrated in the curriculum. English is compulsory for all pupils in all three grades, while pupils can choose French, as a second compulsory option[1]. Towards this direction, this work focuses on developing a prototype system for learning grammatical phenomena in English and French, as foreign languages. The system, named POLYGLOT, is a web-based intelligent tutoring system with social characteristics, such as posting on a wall, tagging a classmate, instant and asynchronous text messaging, declaration of the affective state, reaction buttons in exercises, student group collaboration. Furthermore, it involves the generation of personalized recommendation for collaboration, which is adapted to users' needs, the diagnosis of users' quiz misconceptions, the automatic detection of students' learning style assisting them in their learning experience and the automatic detection of students' frustration and a response on it in order to ameliorate the tutoring process. In particular, POLYGLOT incorporates the following:

- the Stephen Krashen's Theory of Second Language Acquisition, that involves features, such as the way of instruction, means of collaboration, time constraints in learning, holding students' records, logical gradation of learning concepts and response on negative affective state (frustration) in the form of motivational messages
- the Felder-Silverman Learning Style Model, for determining the students' learning styles
- a supervised machine learning algorithm (k-nearest neighbors algorithm) which takes as input several students' features, including their age, gender, educational level, computer knowledge level, number of languages spoken and grade on preliminary test, in order to detect their learning style
- Approximate String matching for diagnosing types of students' errors
- String meaning similarity for diagnosing errors due to language transfer interference

[1] http://www.greeceindex.com/greece-education/greek_education_foreign_languages.html

- the Linear Regression model to automatically detect students' frustration
- the Attribution Theory to deliver appropriate motivational messages to students.

1.2 Related fields and Open research questions

This study aims at answering several research questions emerging from the proliferation of technological advancements in the field of web-based instruction. All the questions follow the direction of placing the student in the center of the educational process. Hence, the research questions emerging from this study are the following:

1. Can computer science itself assist effectively on learning a new language through the use of social media features, in a way that learning autonomy is adopted?
   This question is critical because it seeks to investigate if the social features can promote the education and how they can be incorporated to benefit the students. Given that social networks have invaded the everyday life, people, and especially the younger generation, tend to devote a lot of time to communicating through posting on digital walls, sending private messages to peers, commenting and expressing their feeling using corresponding reaction buttons. Thus, this study will give insight on how the aforementioned characteristics can enhance the instruction process.

2. How can the student learning style be predicted automatically using as less characteristics as possible in order to save student's time?
   Defining the learning style model is a cumbersome process and requires answering a lot of questions from student. Hence, the student should invest much time for this purpose. In order to exceed this time restraint, the current work tries to find relationships between student characteristics and learning styles for classifying students according to their style in an algorithmic way. To this direction, it is important to specify the appropriate student characteristics, such as age, gender, educational level etc, and the proper learning style model that will identify the different way with which a student learns.

3. Based on which approach can the system recommend collaborations between users in order to provide effective learning?
   Collaboration between students is an essential module of e-learning systems that can be further promoted through the adoption of social networking features. Towards an efficient collaboration where both students can reap its benefits, the proper approach for collaboration should be identified. As such, the system will be able to recommend those peers from the learning community to students that meet the requirements for a complementary collaboration.

4. How can the error diagnosis mechanism further enhance the tutoring process?
   Error diagnosis, especially in tutoring systems for learning language, is the cornerstone of the education process because there are many different misconception categories concerning grammatical concepts. Firstly, it is necessary to define these error categories and associate them with a variety of explanations about the possible cause of the mistake. After that, the way of elaborating them should be identified for a more individualized instruction.

5. In which way does the students' characterization of the exercises affect the content adaptivity to them?
   The liking or disliking of the exercises by the students serves as an important input to the frustration detection mechanism and can promote a student-centered tutoring process.

6. How can the detection of frustration and the response to frustration in the form of motivation assist the learning process?
   The automatic detection of frustration and the response to frustration in the form of motivational messages are very important given that the frustration constitutes an impediment of the learning process that may impel student to quit learning.

Chapter 2:

Background & Literature Review

2.1 Intelligent Tutoring Systems (ITSs)

An "Intelligent Tutoring System" (ITS) can be neatly described as the application of Artificial Intelligence (AI) to an educational context. The intelligence in ITSs lies in the adaptation of its tutoring, which means offering different tutoring to the individual student (Ying et al., 1995). Over the last decades, the rapid development of high and new technology has opened new horizons in Computer-Assisted Instruction (CAI). Indeed, the intrusion of computers affected the architectures of the so-called ITSs. Broadly defined, an ITS is a computer system incorporating artificial intelligence components. Such system can aim to provide immediate and customized instruction or feedback to learners (Psotka et al., 1988) usually the lowest possible or even without intervention from a human teacher. More specifically, ITSs are trying to emulate the approaches and language of human tutors, in order to support instructional interactions in real time or upon demand, as exactly needed by individual learners. ITSs are defined as computer-based tutoring systems incorporating models of instructional content that designate what to teach, and teaching strategies that designate how to teach" (Murray, 1999). In ITS, the sequencing of the learning content is personalized to avoid a cognitive mismatch which may be caused by providing difficult learning content to low performers and providing non challenging tasks to high performers. Adapting the learning content based on the student's needs, and personalizing the learning for the student, enables ITS to work with students of different abilities.

The overall goal of an ITS is to solve the problem of over-dependency of students over teachers to the direction of offering quality education. It aims to provide access to high quality education to each and every student, thus reforming the entire education system. The aim of ITSs is to track learners' progress, tailoring feedback and hints to his/her needs. By holding information of a particular student's performance, the ITS can make inferences about his/her strengths and weaknesses, and can even suggest additional work. Implementations of ITSs incorporate computational mechanisms and knowledge representations in the fields of artificial intelligence, computational linguistics, and cognitive science. As such, there is a close relationship between intelligent tutoring, cognitive learning theories and design (Figure 1); and there is ongoing research to improve the effectiveness of ITS.

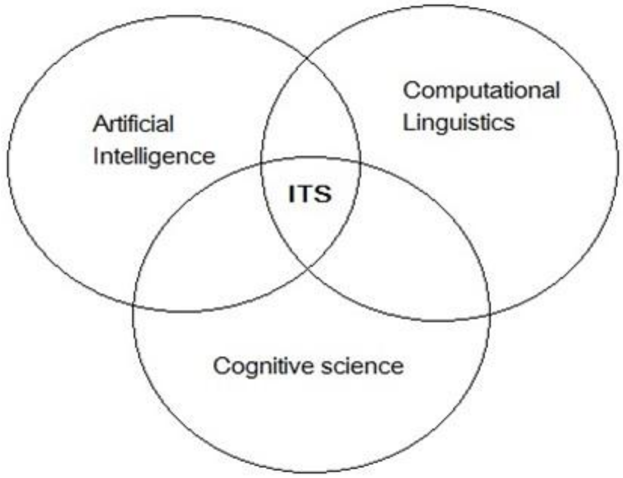

Figure 1. Domain of ITS

ITSs should involve several features as follows (Conde et al., 2009):

- To allow tutoring every task of people with disabilities, giving more autonomy in working environments.
- To have a multimodal Task Management System for data integration from different sources (speech, images, videos, and text) associated with each personalized profile.
- To be integrated into a mobile platform, i. e. a mobile telephone or PDA (Personal digital assistant).
- To contain a multimedia interface that has to be friendly, reliable, flexible, and ergonomically adapted.
- To integrate a human emotional predictive management in order to prevent risk, emergency and blockage situations that can damage these people and interfere with their integration into working and social environments.
- To be entirely configurable by stakeholders without technological knowledge in order to enable an easy and flexible access.
- To show the capability of exporting the system to other collectives, i. e. the elderly.

2.1.1 Architecture of ITS

The architecture of ITS consists of four basic and interrelated modules, namely the Learning Content, the Student Model and the Adaptation Engine and the User Interface

(Brusilovsky and Millan, 2007). The generic architecture of the ITS is shown in the Figure 2.

Learning Content

The learning content of the ITS represents a set of domain topics. Such topics are separated into learning units supporting the tutoring of a specific concept or a fact. The database of the system holds possible students' misconceptions and common wrong answers for each learning unit. The learning units can have the form of explications, instances, intimations, tests, examinations and can be utilized with the purpose of educating, presenting to or evaluating the students. The provision of a structure for the representation of the user domain knowledge constitutes the most significant function of this model.

This value can be expressed quantitatively, qualitatively or in probabilistic form.

Student Model

The student model holds several information about the students, e.g. their educational level, previous knowledge and background. Furthermore, this model also stores other type of information about students, such as:

- The skills, the goals and the plans of students
- Student's performance such as topic performance and number of questions correctly answered per session
- Learning characteristics such as the learning rate, the student's preferences and learning styles
- Affective states such as engagement, boredom, frustration and confusion

Adaptation Model

The adaptation engine is a technique or an algorithmic approach to adapt the learning content to the student based on his/her input through the user interface (e.g. response to the questions) and the information derived from the student model. An ITS adapts the learning content based on the learner's preferences such as:

- The learner's level of ability, such as, "novice" or "intermediate" or "expert" (Leung and Li, 2007).

- The learner's knowledge, such as, previous knowledge of learning content (Hong et al., 2007).
- Learning styles such as “visual", “audio", and “interactive" (Popescu, 2009).

User Interface and Log file

The user interface delivers the learning content to the student and accepts the students' responses to the questions posed by the ITS. Based on the nature of the ITS, the learning content can be delivered as text, voice, simulation or even interactive games. The user interface can be a mobile device (Tablet, Mobile, Laptop) or a desktop. The students' interaction with the ITS, such as response to questions, number of attempts and time taken for various activities (responding, reading etc.) is captured in the log file. The log file is used to serve as input of the student model.

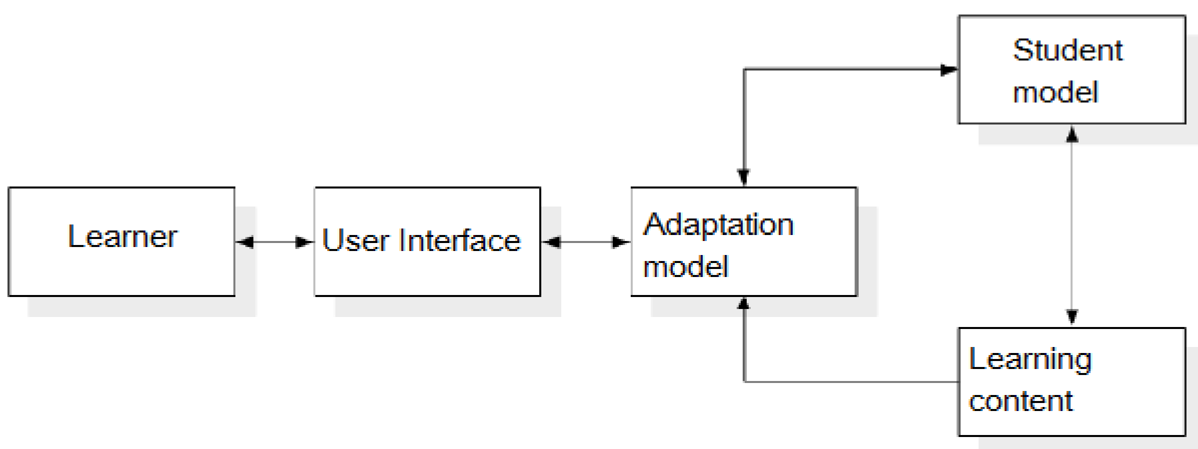

Figure 2. Generic architecture of ITS

2.1.2 Function of ITSs

The fundamental function in ITSs is the initialization of a student upon his/her registration when crucial information such as age, gender and background etc are collected and stored in the student model. The user interface supports the students based on their level and preferences. Hence, the interaction between the student and the ITS takes place for instance when the students answer questions or by other means of interaction. Every kind of interaction between the student and the ITS is stored in the student model and then is analyzed to promote the adaptation to his/her needs and preferences. Next, the adaption model of ITS tailors the learning content to students based on their request and the information from his/her profile. For instance, if a student conducts an error in a quiz, the ITS can diagnose the reason of this mistake and can support the student by giving him/her advice towards overcoming this misconception.

2.2 Intelligent Computer-Assisted Language Learning (ICALL)

Computer-assisted language learning (CALL) can be succinctly defined as “the search for and study of applications of the computer in language teaching and learning” (Levy, 1997). CALL embraces a wide range of information and communications technology applications and approaches to the direction of teaching and learning foreign languages, from the "traditional" drill-and-practice programs that characterized CALL in the 1960s and 1970s to more recent manifestations of CALL, e.g. as used in a virtual learning environment and Web-based distance learning. It also extends to the use of corpora and concordances, interactive whiteboards, computer-mediated communication (CMC), language learning in virtual worlds, and mobile-assisted language learning (MALL).

The term CALI (computer-assisted language instruction) was in use before CALL, reflecting its origins as a subset of the general term CAI (computer-assisted instruction). CALI fell out of favor among language teachers, however, as it appeared to imply a teacher-centered approach (instructional), whereas language teachers are more inclined to prefer a student-centered approach, focusing on learning rather than instruction. CALL began to replace CALI in the early 1980s (Davies and Higgins 1982) and it is now incorporated into the names of the growing number of professional associations worldwide.

The current philosophy of CALL places great emphasis on student-centered materials that allow students to study on their own. Such materials may be structured or unstructured, but they normally embody two important features: interactive learning and individualized learning. CALL is essentially a tool that assists instructors to facilitate the language learning process. It can be used to enhance what has already been taught in the traditional classroom or as a remedial tool to help learners who require additional support.

The design of CALL materials generally takes into consideration principles of language pedagogy and methodology, which may be derived from different learning theories (e.g. behaviorist, cognitive, constructivist) and second-language learning theories such as Stephen Krashen's monitor hypothesis.

During the 1980s and 1990s, several attempts were made to establish a CALL typology. A wide range of different types of CALL programs was identified by Davies & Higgins (1985), Jones & Fortescue (1987), Hardisty & Windeatt (1989) and Levy (1997). These included gap-filling and close programs, multiple-choice programs, free-format (text-entry) programs, adventures and simulations, action mazes, sentence-reordering programs, exploratory programs—and "total Cloze", a type of program in which the learner has to reconstruct a whole text. Most of these early programs still exist in modernised versions.

Since the 1990s, it has become increasingly difficult to categorise CALL as it now extends to the use of blogs, wikis, social networking, podcasting, Web 2.0 applications, language learning in virtual worlds and interactive whiteboards (Davies et al. 2010).

Warschauer (1996) and Warschauer & Healey (1998) took a different approach. Rather than focusing on the typology of CALL, they identified three historical phases of ICALL, classified according to their underlying pedagogical and methodological approaches:

- Behavioristic CALL: conceived in the 1950s and implemented in the 1960s and 1970s.
- Communicative CALL: 1970s to 1980s.
- Integrative CALL: embracing Multimedia and the Internet: 1990s.

Most CALL programs in Warschauer and Healey's first phase (1998), Behavioristic CALL (1960s to 1970s), consisted of drill-and-practice materials in which the computer presented a stimulus and the learner provided a response. At first, both could be done only through text. The computer would analyze students' input and give feedback, and more sophisticated programs would react to students' mistakes by branching to help screens and remedial activities. While such programs and their underlying pedagogy still exist today, behavioristic approaches to language learning have been rejected by most language teachers, and the increasing sophistication of computer technology has led CALL to other possibilities.

The second phase described by Warschauer and Healey (1998), Communicative CALL, is based on the communicative approach that became prominent in the late 1970s and 1980s (Underwood, 1984). In the communicative approach the focus is placed on using the language rather than analysis of the language, and grammar is taught implicitly rather than explicitly. It also allows for originality and flexibility in student output of language. The communicative approach coincided with the arrival of the PC, which made computing much more widely available and resulted in a burning issue in the development of software for foreign language learning. The first CALL software in this phase continued to provide skill practice but not in a drill format—for example: paced reading, text reconstruction and language games—but the computer remained the tutor. In this phase, computers provided context for students to use the language, such as asking for directions to a place, and programs not primarily designed for language learning were used for the tutoring of foreign languages. Criticisms of this approach include using the computer in an ad hoc and disconnected manner for more marginal aims rather than the central aims of language instruction.

The third phase of CALL described by Warschauer and Healey (1998), Integrative CALL, starting from the 1990s, tried to address criticisms of the communicative approach by integrating the teaching of language skills into tasks or projects to provide direction and coherence. It also coincided with the development of multimedia technology (providing text, graphics, sound and animation) as well as Computer-mediated communication (CMC). CALL in this period saw a definitive shift from the use of the computer for drill and tutorial purposes (the computer as a finite, authoritative base for a specific task) to a medium for extending education beyond the classroom. Multimedia CALL started with interactive laser videodiscs showing simulations of situations where the learner played a key role. Later, Warschauer (2000) renamed the Behavioristic CALL as Structural CALL and also revised the three phases, as follows:

- Structural CALL: 1970s to 1980s.
- Communicative CALL: 1980s to 1990s.
- Integrative CALL: 2000 onwards.

Bax (2003) took issue with Warschauer & Haley (1998) and Warschauer (2000) and proposed these three phases:

- Restricted CALL – mainly behaviouristic: 1960s to 1980s.
- Open CALL – i.e. open in terms of feedback given to students, software types and the role of the teacher, and including simulations and games: 1980s to 2003.
- Integrated CALL – Bax (2003) argued that at the time of writing language teachers were still in the Open CALL phase, as true integration could only be said to have been achieved when CALL had reached a state of "normalization", namely when using CALL was as normal as using a pen.

ICALL concerns the presentation of multiple challenges in all the dimensions of language learning. Such challenges include both design and implementation strategies pertaining to the use of artificial intelligence in tutoring systems for language acquisition. ICALL systems should be able primarily to enhance the learning procedure in terms of handling noisy situations. Furthermore, ICALL should incorporate language pedagogical or cognitive theories that can support students in their effort. The goals for learning that are set by the students should be clear. As such, ICALL systems should be able to model each learning case distinctively and to a proper degree of granularity. Hence, students can have the potential to figure out their progress or their weaknesses towards language learning.

Above all, careful consideration must be given to pedagogy in designing ICALL software, but publishers of ICALL software tend to follow the latest trend, regardless of its desirability. Moreover, approaches to teaching foreign languages are constantly changing, dating back to grammar-translation, through the direct method, audio-lingualism and a variety of other approaches, to the more recent communicative approach and constructivism (Decoo 2001).

Designing and creating ICALL software is an extremely demanding task, calling upon a range of skills. Major ICALL development projects are usually managed by a team of people:

- A subject specialist (also known as a content provider) – usually a language teacher – who is responsible for providing the content and pedagogical input. More than one subject specialist is required for larger ICALL projects.
- A programmer who is familiar with the chosen programming language or authoring tool.
- A graphic designer, to produce pictures and icons, and to advise on fonts, color, screen layout, etc.
- A professional photographer or. Graphic designers often have a background in photography too.
- A sound engineer and a video technician will be required if the package is to contain substantial amounts of sound and video.
- An instructional designer. Developing a CALL package is more than just putting a text book into a computer. An instructional designer will probably have a background in cognitive psychology and media technology, and will be able to advise the subject specialists in the team on the appropriate use of the chosen technology (Gimeno and Davies, 2010).

ICALL inherently supports learner autonomy, the final of the eight conditions that Egbert et al. (2007) cite as "Conditions for Optimal Language Learning Environments". Learner autonomy places the learner firmly in control so that s/he decides on learning goals.

Authoring tool seems to be a powerful idea when designing ICALL software in order to produce a set of multiple-choice and gap-filling exercises, using a simple authoring tool (Bangs, 2011), but ICALL is also related to the creation and management of an environment incorporating a constructivist and whole language philosophy (Stepp-Greany, 2002). According to constructivist theory[2], learners are active participants in tasks in which they "construct" new knowledge derived from their prior experience. Learners also assume responsibility for their learning, and the teacher is a facilitator rather than a purveyor of knowledge. Whole language theory embraces constructivism and postulates that language learning moves from the whole to the part, rather than building sub-skills to lead towards the higher abilities of comprehension, speaking, and writing. It also emphasizes that comprehending, speaking, reading, and writing

[2] https://www.learning-theories.com/constructivism.html

skills are interrelated, reinforcing each other in complex ways. Language acquisition is, therefore, an active process in which the learner focuses on cues and meaning and makes intelligent guesses. Additional demands are placed upon teachers working in a technological environment incorporating constructivist and whole language theories. The development of teachers' professional skills must include new pedagogical as well as technical and management skills. Regarding the issue of teacher facilitation in such an environment, the teacher has a key role to play, but there could be a conflict between the aim to create an atmosphere for learner independence and the teacher's natural feelings of responsibility. In order to avoid learners' negative perceptions, Stepp-Greany (2002) points out that it is especially important for the teacher to continue to address their needs, especially those of low-ability learners.

2.3 User modeling and adaptivity

A student model is the base for personalization in computer-based educational applications. It is a core component in any intelligent or adaptive tutoring system that represents many of the student's features such as knowledge and individual traits (Brusilovsky & Millan, 2007). Self (1990) has pointed out that student modeling is a process devoted to represent several cognitive issues such as analyzing the student's performance, isolating the underlying misconceptions, representing students' goals and plans, identifying prior and acquired knowledge, maintaining an episodic memory, and describing personality characteristics. Therefore, by keeping a model for every user, a system can successfully personalize its content and utilize available resources accordingly (Kyriacou, 2008).

The student model can be observed as an avatar of a real student in the virtual world, the dimensions of the student model correspond to the aspects of the physical student and the properties of the student model represent the characteristics of the real student (Yang et al., 2010). Student modeling is one of the key factors that affects automated tutoring systems in making instructional decisions (Li et al., 2011), since a student model enables understanding and identification of students' needs (Sucar & Noguez, 2008). Student modeling can be defined as the process of gathering relevant information in order to infer the current cognitive state of the student, and to represent it so as to be accessible and useful to the tutoring system for offering adaptation (Thomson & Mitrovic, 2009).

As a consequence, a crucial factor for designing an adaptive educational system is the construction of an effective student model. In order to construct a student model, it has to be considered what information and data about a student should be gathered, how it will update in order to keep it up-to-date, and how it will be used in order to provide adaptation (Millán et al., 2010). In fact, when a student model is constructed, the following three questions have to be answered: i) “What are the characteristics of the user we want to model?, ii) “How we model them?”, iii) “How we use the user model?”.

In a recent review, Self (1988) identified twenty different uses that had been found for student models in existing ITSs. From analyzing this list, he notes that the functions of student models could be generally classified into six types.

[1] Corrective: to help eradicate bugs in the student's knowledge.
[2] Elaborative: to help correct “incomplete” student knowledge.
[3] Strategic: to help initiate significant changes in the tutorial strategy other than the tactical decisions of 1 and 2 above.
[4] Diagnostic: to help diagnose bugs in the student's knowledge.
[5] Predictive: to help determine the student's likely response to tutorial actions.
[6] Evaluative: to help assess the student or the ITS.

2.3.1. Student models characteristics

2.3.1.1. Modeling students’ features

The cornerstone of building a student model is the appropriate selection of students’ characteristics, being conducted at their first interaction with the ITS. According to Gonzalez et al. (2006), the aspects of students being modeled is an initial consideration of the researchers who create an ITS. Domain dependent and independent characteristics need to be taken into account to the direction of delivering efficient personalization to students (Yang et al., 2010). Static features of students, such as email, age, prior knowledge etc., can also serve as a valuable input to the ITS and are determined before the learning process takes place (Jeremic et al., 2012). The nature of the static features is to remain unchanged throughout the learning session; however, is some cases the students may hold the capability to change them through an available options menu. Moreover, according to above researchers, dynamic features come directly from the student's interactions with the system and are those that the system constantly updates during learning sessions based on the collected data being held in the log file of the ITS.

In view of the above, the determination of the dynamic student's characteristics constituting the ground for the system's adaptation to individual student's needs is significant. These characteristics can include the level of knowledge and skills, errors and misconceptions, learning styles and preferences, affective and cognitive factors, meta-cognitive factors. The level of knowledge refers to the prior knowledge of a student on the knowledge domain as well as his/her current knowledge level. This is usually measured through tests that the student has to answer prior to the learning process. Furthermore, through these tests along with the observation of student's actions, the system can identify the misconceptions of students. Learning style refers to individual skills and preferences that affect how a student perceives, gathers and processes learning materials (Jonassen and Grabowski, 1993). According to Popescu (2009), some learners prefer graphical representations, others prefer audio materials and others prefer text representation of the learning material, some students prefer to work in groups and others learn better alone. Adapting courses to the learning preferences of the students has a positive effect on the learning process, leading to an increased efficiency, effectiveness and/or learner satisfaction (Popescu et al., 2010). A proposal for modeling learning styles, which are adopted by many ITSs, is the Felder - Silverman learning style (FSLSM). FSLSM classifies students in four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global (Felder & Silverman, 1988; Felder & Soloman, 2003). Following, the FSLM is presented and discussed thoroughly. Another method for modeling learning styles is the Myers-Briggs Type Indicator (MBTI) (Bishop & Wheeler, 1994), which identifies the following eight categories of learning styles: extrovert, introvert, sensing, intuitive, thinking, feeling, judging, perceiving.

In traditional classrooms, human tutors monitor and react to the emotional state of the students in order to motivate them and to improve their learning process; under the same rationale, an intelligent tutoring system should interpret the emotional state of students and adapt its behavior to their needs, giving an appropriate response for those emotions (Lehman et al., 2008). Therefore, affective factors are student characteristics that should be considered in order to build a student model. The affective states can be the following: happy, sad, angry, interested, frustrated, bored, distracted, focused, confused (Balakrishman, 2011). Rodrigo et al. (2007) have found that some of these emotions, like boredom or frustration, lead students to an off-task behavior. Off-task behavior means that students' attention becomes lost and they engage in activities that neither have anything to do with the tutoring system nor include any learning aim (Cetintas et al., 2010). Among typical off-task behavior examples are surfing the web, devoting time to off-topic readings, talking with order students without any learning aims (Baker et al., 2004). These behaviors are associated with deep motivational problems (Baker, 2007), and consequently, modeling affective factors can be a base for modeling students' motivation.

The cognitive features of students are important student characteristics that can be held in a student model. These features refer to aspects such as attention, knowledge, ability to learn and understand, memory, perception, concentration, collaborative skills, abilities to solve problems and making decisions, analyzing abilities, critical thinking. However, students need not only to have cognitive abilities, but they also need to be able to critically assess their knowledge in order to decide what they need to study (Mitrovic & Martin, 2006). Thereby, adaptive and/or personalized tutoring systems must consider students' meta-cognitive skills. Meta-cognition concerns to the active monitoring, regulation and orchestration of information processes in relation to cognitive objects on which they bear (Flavell, 1976). In other words, the notion of meta-cognition deals with students' ability to be aware of and control their own thinking, for example, how they select their learning goals, use prior knowledge or intentionally choose problem-solving strategies (Barak, 2010). Some meta-cognitive skills are reflection, self-awareness, self-monitoring, self-regulation, self-explanation, self-assessment, and self-management (Pena & Kayashima, 2011).

2.3.1.2. Felder-Silverman Learning Style Model

The Felder-Silverman model (FSLSM) (Felder & Silverman, 1988) is a learning style model that has its roots in traditional education but it is also used in computer-assisted instruction. This chapter will analyze in depth the aforementioned learning style model along with the characteristics of the dimensions of FSLSM. Through the description of FSLSM, it can be clearly stated how the student modeling component in any ITS can be enhanced and ameliorated. As such, the ITS can be further adapted to the students.

For example, when incorporating several characteristics of a learning style model to promote adaptivity, a student model holding information concerning such characteristics is required to support the adaptation process.

FSLSM expounds the learning style of a learner in depth, distinguishing between preferences on its dimensions. Furthermore, FSLSM is based on tendencies, indicating that learners with a high preference for certain behavior can also act sometimes differently (Graf et al., 2007).

FSLSM is used very often in research related to learning styles in advanced learning technologies. According to Carver et al. (1999), "the Felder Model is the most appropriate model for hypermedia courseware". Kuljis and Liu (2005) confirmed this by conducting a comparison of learning style models with respect to the application in e-learning and Web-based tutoring systems. Finally, Graf et al. (2007) also suggest FSLSM as the most appropriate learning style model.

FSLSM has four different dimensions. Each one of these dimensions attaches a specific trait to the student.

The first dimension differentiates between an active and a reflective way of processing information. Active learners prefer to communicate with their peers and to learn by working in groups where they can discuss about the taught material. In contrast, reflective learners prefer to work alone.

The second dimension separates sensing from intuitive learning. Learners who are interested in a sensing learning style tend to learn facts and concrete learning material. They prefer to answer questions using already known approaches and tend not to be reluctant with details as well. Moreover, sensing learners are more down to earth and use their rationale when acting. They are supposed to be more practical than intuitive learners and like to create correlations between the taught material and reality. On the other hand, intuitive learners tend to learn abstract teaching concepts, such as theoretical depictions and their subjacent meanings. They are more interested to discern associations and connections and tend to have more imagination and original ideas than sensing learners.

The third dimension distinguishes learners between visual learners who can recall concepts easily and as such they tend to learn from what they have looked at (e.g., figures, charts and graphs), and verbal learners who can understand better textual representations, no matter whether they are paper-based or oral.

The fourth dimension characterizes learners based on their preference of receiving and perceiving the learning material. Sequential learners prefer to learn progressively and incrementally, having a linear tutoring progress. They present a proneness to make logical gradual steps in understanding the learning material. On the other side, global learners use a holistic thinking process and learn in large leaps. They prefer to absorb learning material almost randomly but after they have learned enough material they suddenly get the whole picture. Because of the fact that the whole picture is important for global learners, they tend to navigate through the learning material from chapter to chapter while sequential learners prefer stepwise presentation of the learning material.

A lot of research concerns the incorporation of learning styles in adaptive tutoring systems and in general in educational technology. Furthermore, the majority of tutoring systems offering adaptivity to users and focusing on learning styles embody only some aspects of these learning style models and not all the proposed characteristics of the model. The underlying reason is the restriction of most adaptive systems to specific functions and a specific course structure (Graf et al., 2007). When conducting investigations about learning styles, it is therefore important to consider which characteristics of the learning style model are supported by the system.

According to Graf et al. (2007), there is no need to use all the dimensions in order to adapt the learning material to students. More specifically, not all characteristic behavior described in the learning style model can be mapped as well as identified from the behavior in a specific learning system. Thus, the patterns which indicate specific preferences for learning styles are adapted to the features of the systems. When indicating the learning style, it is therefore is significant to specify which characteristics can be mapped and identified, and which cannot. Having in mind the characteristics and their relevance for the learning style highlight a profound estimation of the results of the approach and therefore, to a more meaningful application of the identified information.

Thorough information about learning styles is also crucial when spotting relationships between learning styles and the performance of students in a tutoring system (see Hayes & Allinson, 1996) or other characteristics of students such as cognitive traits (Graf, Lin, & Kinshuk, in press). A detailed description of the different characteristics of each dimension and how representative they are for that specific dimension of the learning style is necessary according to Graf et al. (2007).

2.3.2. Using a student model in an ITS

According to Michaud and McCoy (2004), a well-designed tutoring system actively undertakes two tasks: that of the diagnostician, discovering the nature and extent of the student's knowledge, and that of the strategist, planning a response using its findings about the learner. This is the principal role of student model, which is the base for personalization in ITSs (Devedzic, 2006). The information of a student model is used by the system in order to adapt its responses to each individual student dynamically providing personalized instruction, help and feedback.

The student model is used for accurate student diagnosis in order to predict students' needs and adapt the learning material and process to each individual student's learning pace. It is used to produce highly accurate estimations of the student's knowledge level and cognitive state in order to deliver to them the most appropriate learning material. Furthermore, an adaptive and/or personalized tutoring system can consult the student model in order to recognize the learning style and preferences of a student and make a decision about the learning strategy that is likely to be the most effective for her/him. Moreover, an adaptive and/or personalized educational system can select appropriate learning methods in order to increase the effectiveness of tutorial interactions and improve the learning and motivation by predicting of student affective state. In addition, a student model can be used for identifying the student's strength and weaknesses in order to provide her/him individualized advice and feedback. Moreover, the system can provide the learner with more complicated tasks and proper learning methods in order to enhance deep learning and help her/him to become a better learner, by identifying her/his meta-cognitive skills.

2.4. Computer-supported collaborative learning (CSCL)

Computer-supported collaborative learning (CSCL) is a pedagogical approach where in learning takes place via social interaction using a computer or through the Internet. This kind of learning is characterized by the sharing and construction of knowledge among participants using technology as their primary means of communication or as a common resource (Stahl et al., 2006). CSCL can be implemented in online and classroom learning environments and can take place synchronously or asynchronously.

The study of computer-supported collaborative learning draws on a number of academic disciplines, including instructional technology, educational psychology, sociology, cognitive psychology, and social psychology (Hmelo-Silver, 2006).

The field of CSCL draws heavily from a number of learning theories that emphasize that knowledge is the result of learners interacting with each other, sharing knowledge, and building knowledge as a group. Since the field focuses on collaborative activity and collaborative learning, it inherently takes much from constructivist and social cognitivist learning theories (Resta and Laferriere, 2007).

2.4.1 Precursor theories

The roots of collaborative epistemology as related to CSCL can be found in Vygotsky's social learning theory (Vygotsky, 1978 and Vygotsky, 1980). Of particular importance to CSCL is the theory's notion of internalization, or the idea that knowledge is developed by one's interaction with one's surrounding culture and society (Vygotsky, 1980). The second key element is what Vygotsky (1980) called the Zone of proximal development. This refers to a range of tasks that can be too difficult for a learner to master by themselves but is rendered possible with the assistance of a more skilled individual or teacher. These ideas feed into a notion central to CSCL, namely the knowledge building is achieved through interaction with others.

Cooperative learning, though different in some ways from collaborative learning, also contributes to the success of teams in CSCL environments. The distinction can be stated as: cooperative learning focuses on the effects of group interaction on individual learning whereas collaborative learning is more concerned with the cognitive processes at the group unit of analysis such as shared meaning making and the joint problem space. The five elements for effective cooperative groups identified by the work of Johnson et al. (2002) are positive interdependence, individual accountability, promotive interaction, social skills, and group processing. Because of the inherent relationship between cooperation and collaboration, understanding what encourages successful cooperation is essential to CSCL research.

In the early 1990s, Scardamalia and Bereiter (1994) wrote seminal articles leading to the development of key CSCL concepts, namely knowledge-building communities and knowledge-building discourse, intentional learning, and expert processes. Their work led to an early collaboration-enabling technology known as the Computer Supported Intentional Learning Environment (CSILE). Characteristically for CSCL, their theories were integrated with the design, deployment, and study of the CSCL technology. CSILE later became Knowledge Forum, which is the most widely used CSCL technology worldwide to date.

Other learning theories that provide a foundation for CSCL include distributed cognition, problem-based learning, group cognition, cognitive apprenticeship, and situated learning. Each of these learning theories focuses on the social aspect of learning and knowledge building, and recognizes that learning and knowledge building involve inter-personal activities including conversation, argument, and negotiation (Resta and Laferriere, 2007).

2.4.2. Collaboration theory and group cognition

During the last two decades, researchers have explored the extent to which computer technology could enhance the collaborative learning process. While researchers, in general, have relied on learning theories developed without consideration of computer-support, some have suggested that the field needs to have a theory tailored and refined for the unique challenges that confront those trying to understand the complex interplay of technology and collaborative learning (Stahl, 2002).

Collaboration theory, suggested as a system of analysis for CSCL by Stahl (2004), postulates that knowledge is constructed in social interactions, such as discourse. The theory suggests that learning is not a matter of accepting fixed facts, but is the dynamic, on-going, and evolving result of complex interactions primarily taking place within communities of people. It also emphasizes that collaborative learning is a process of constructing meaning and that meaning creation most often takes place and can be observed at the group unit of analysis. The goal of collaboration theory is to develop an understanding of how meaning is collaboratively constructed, preserved, and re-learned through the media of language and artifacts in group interaction. There are four crucial themes in collaboration theory: collaborative knowledge building (which is seen as a more concrete term than "learning"); group and personal perspectives intertwining to create group understanding; mediation by artifacts (or the use of resources which learners can share or imprint meaning on); and interaction analysis using captured examples that can be analyzed as proof that the knowledge building occurred (Stahl, 2002)

Collaboration theory proposes that technology in support of CSCL should provide new types of media that foster the building of collaborative knowing; facilitate the comparison of knowledge built by different types and sizes of groups; and help collaborative groups with the act of negotiating the knowledge they are building. Further, these technologies and designs should strive to remove the teacher as the bottleneck in the communication process. In other words, the teacher should not have to act as the conduit for communication between students or as the avenue by which information is dispensed. Finally, collaboration theory-influenced technologies will strive to increase the quantity and quality of learning moments via computer-simulated situations (Stahl, 2002)

Stahl (2004) extended his proposals about collaboration theory during the next decade with his research on group cognition. Stahl (2006) provided a number of case studies of prototypes of collaboration technology, as well as a sample in-depth interaction analysis and several essays on theoretical issues related to re-conceptualizing cognition at the small-group unit of analysis.

2.4.3. Strategies

Currently, CSCL is used in instructional plans in classrooms both traditional and online from primary school to post-graduate institutions. Like any other instructional activity, it has its own prescribed practices and strategies which educators are encouraged to employ in order to use it effectively. Because its use is so widespread, there are innumerable scenarios in the use of CSCL, but there are several common strategies that provide a foundation for group cognition.

One of the most common approaches to CSCL is collaborative writing. Though the final product can be anything from a research paper, an entry in an online encyclopedia, or a short story, the process of planning and writing together encourages students to express their ideas and develop a group understanding of the subject matter (Heimbuch and Bodemer, 2015) Tools like blogs, interactive whiteboards, and custom spaces that combine free writing with communication tools can be used to share work, form ideas, and write synchronously (Onrubia and Engel, 2009).

Technology-mediated discourse refers to debates, discussions, and other social learning techniques involving the examination of a theme using technology. For example, wikis are a way to encourage discussion among learners, but other common tools include mind maps, survey systems, and simple message boards. Like collaborative writing, technology-mediated discourse allows participants that may be separated by time and distance to engage in conversations and build knowledge together (Asterhan and Schwar, 2010).

Group exploration refers to the shared discovery of a place, activity, environment or topic among two or more people. Students do their exploring in an online environment, use technology to better understand a physical area, or reflect on their experiences together through the Internet. Virtual worlds as well as synchronous communication tools may be used for this kind of learning (Ioannidou et al., 2010).

Problem-based learning is a popular instructional activity that lends itself well to CSCL because of the social implications of problem solving. Complex problems call for rich group interplay that encourages collaboration and creates movement toward a clear goal (Lu et al., 2010)

Project-based learning is similar to problem-based learning in that it creates impetus to establish team roles and set goals. The need for collaboration is also essential for any project and encourages team members to build experience and knowledge together. Although there are many advantages to using software that has been specifically developed to support collaborative learning or project-based learning in a particular domain, any file sharing or communication tools can be used to facilitate CSCL in problem- or project-based environments (Blumenfeld et al., 1991).

When Web 2.0 applications (wikis, blogs, RSS feed, collaborative writing, video sharing, social networks, etc.) are used for computer-supported collaborative learning specific strategies should be used for their implementation, especially regarding (Bubas et al., 2011)

- adoption by teachers and students
- usability and quality in use issues
- technology maintenance
- pedagogy and instructional design
- social interaction between students
- privacy issues
- information/system security.

2.4.4. Instructor roles in CSCL

Though the focus in CSCL is on individuals collaborating with their peers, teachers still have a vital role in facilitating learning. Most obviously, the instructor must introduce the CSCL activity in a thoughtful way that contributes to an overarching design plan for the course. The design should clearly define the learning outcomes and assessments for the activity. In order to assure that learners are aware of these objectives and that they are eventually met, proper administration of both resources and expectations is necessary to avoid learner overload. Once the activity has begun, the teacher is charged with kick-starting and monitoring discussion to facilitate learning. S/he must also be able to mitigate technical issues for the class. Lastly, the instructor must engage in assessment, in whatever form the design calls for, in order to ensure objectives have been met for all students.

Without the proper structure, any CSCL strategy can lose its effectiveness. It is the responsibility of the teacher to make students aware of what their goals are, how they should be interacting, potential technological concerns, and the time-frame for the exercise. This framework should enhance the experience for learners by supporting collaboration and creating opportunities for the construction of knowledge. Another important consideration of educators who implement online learning environments is affordance. Students who are already comfortable with online communication often choose to interact casually. Mediators should pay special attention to make students aware of their expectations for formality online.[30 While students sometime have frames of reference for online communication, they often do not have all of the skills necessary to solve problems by themselves. Ideally, teachers provide what is called "scaffolding", a platform of knowledge that they can build on. A unique benefit of CSCL is that, given proper teacher facilitation, students can use technology to build learning foundations with their peers. This allows instructors to gauge the difficulty of the tasks presented and make informed decisions about the extent of the scaffolding needed (Lu et al., 2010).

2.4.5. Effects

According to Salomon (1995), the possibility of intellectual partnerships with both peers and advanced information technology has changed the criteria for what is counted to be the effects of technology. Instead of only concentrating on the amount and quality of learning outcomes, we need to distinguish between two kinds of effects: that is, "effects with a tool and/or collaborating peers, and effects of these." He used the term called "effects with" which is to describe the changes that take place while one is engaged in intellectual partnership with peers or with a computer tool. For example, the changed quality of problem solving in a team. And he means the word "effects of" more lasting changes that take place when computer-enhanced collaboration teaches students to ask more exact and explicit questions even when not using that system.

2.4.6. Applications of CSCL

It has a number of implications for instructional designers, developers, and teachers.

- First, it revealed what technological features or functions were particularly important and useful to students in the context of writing, and how a CSCL system could be adapted for use for different subject areas, which have specific implications for instructional designers or developers to consider when designing CSCL tools.
- Second, this study also suggested the important role of a teacher in designing the scaffolds, scaffolding the collaborative learning process, and making CSCL a success. Third, it is important that a meaningful, real-world task is designed for CSCL in order to engage students in authentic learning activities of knowledge construction.
- Third, cooperative work in the classroom, using as a tool based technology devices "one to one " where the teacher has a program of classroom management, allows not only the enhancement of teamwork where each member takes responsibilities involving the group, but also a personalized and individualized instruction, adapting to the rhythms of the students, and allowing to achieve the targets set in which has been proposed for them individualized Work Plan.

Though CSCL holds promise for enhancing education, it is not without barriers or challenges to successful implementation. Obviously, students or participants need sufficient access to computer technology. Though access to computers has improved in the last 15 to 20 years, teacher attitudes about technology and sufficient access to Internet-connected computers continue to be barriers to more widespread usage of CSCL pedagogy.

Furthermore, instructors find that the time needed to monitor student discourse and review, comment on, and grade student products can be more demanding than what is necessary for traditional face-to-face classrooms. The teacher or professor also has an instructional decision to make regarding the complexity of the problem presented. To warrant collaborative work, the problem must be of sufficient complexity, otherwise teamwork is unnecessary. Also, there is risk in assuming that students instinctively know how to work collaboratively. Though the task may be collaborative by nature, students may still need training on how to work in a truly cooperative process.

Others have noted a concern with the concept of scripting as it pertains to CSCL. There is an issue with possibly over-scripting the CSCL experience and in so doing, creating "fake collaboration". Such over-scripted collaboration may fail to trigger the social, cognitive, and emotional mechanisms that are necessary to true collaborative learning (Banon, 1989).

There is also the concern that the mere availability of the technology tools can create problems. Instructors may be tempted to apply technology to a learning activity that can very adequately be handled without the intervention or support of computers. In the process of students and teachers learning how to use the "user-friendly" technology, they never get to the act of collaboration. As a result, computers become an obstacle to collaboration rather than a supporter of it (Dillenbourg, 2002).

2.4.7. CSCL for foreign language acquisition

The advent of computer-supported collaborative learning (CSCL) as an instructional strategy for second language acquisition can be traced back to the 1990s. During that time, the internet was growing rapidly, which was one of the key factors that facilitated the process. At the time, the first wikis were still undergoing early development, but the use of other tools such as electronic discussion groups allowed for equal participation amongst peers, particularly benefiting those who would normally not participate otherwise during face-to-face interactions (Ebersbach, 2008)

During the establishment of wikis in the 2000s, global research began to emerge regarding their effectiveness in promoting second language acquisition. Some of this research focused on more specific areas such as systemic-functional linguistics, humanistic education, experiential learning, and psycholinguistics. For example, Chen (2009) performed a study to determine the overall effectiveness of wikis in a class where English was taught as a second language. Another example is a a study by Kessler (2009) in which pre-service, non-native English speaker teachers in a Mexican university were given the task to collaborate on a wiki, which served as the final product for one of their courses. In this study, emphasis was placed on the level of grammatical accuracy achieved by the students throughout the course of the task.

Due to the continual development of technology, other educational tools aside from wikis are being implemented and studied to determine their potential in scaffolding second language acquisition. According to Warschauer (2010), among these are blogs, automated writing evaluation systems, and open-source netbooks. According to Schmidt (2010), the development of other recent online tools have facilitated language acquisition via member-to-member interactions, demonstrating firsthand the impact the advancement of technology has made towards meeting the varying needs of language learners.

2.4.7.1. Effectiveness and perception

Studies in the field of computer-assisted language learning (CALL) have shown that computers provide material and valuable feedback for language learners and can be an effective tool for both individual and collaborative language learning. CALL programs offer the potential for interactions between the language learners and the computer (Chapelle, 2003). Additionally, students' autonomous language learning and self-assessment can be rendered widely available through the web. In CSCL, the computer is not only seen as a potential language tutor by providing assessment for students' responses, but also as a tool to give language learners the opportunity to learn from the computer and also via collaboration with other language learners. Juan (2010) focuses on new models and systems that perform efficient evaluation of student activity in online-based education. Their findings indicate that CSCL environments organized by teachers are useful for students to develop their language skills. Additionally, CSCL increases students' confidence and encourages them to maintain active learning, reducing the passive reliance on teachers' feedback. Using CSCL as a tool in the second language learning classroom has also shown to reduce learner anxiety (Hurd, 2007).

Various case studies and projects had been conducted in order to measure the effectiveness and perception of CSCL in a language learning classroom. For example, Dooly (2007) has shown that language learners indicated that their confidence in using the language had increased and that they felt more motivated to learn and use the target language. After analyzing the results, Dooly (2007) suggests that during computer-supported collaborative language learning, students have an increased awareness of different aspects of the target language and pay increased attention to their own language learning process. Since the participants of this project were language teacher trainees, she adds that they felt prepared and willing to incorporate online interaction in their own teaching in the future.

2.5. Social Media Language Learning

Social Media Language Learning (SMLL) links interactive social media channels to language learning. This enables students to develop communication and language skills. Social media consist of interactive forms of media that allow users to interact with and publish to each other, generally by means of the internet. Daily observations and recent scholarly traditions suggest that a certain amount of learning takes place beyond the confines of the individual mind. Research has shown that language acquisition and learning is socially constructed and interactive in nature (McClanahan, 2014). According to the theory of language socialization, language learning is interwoven with cultural interaction and “mediated by linguistic and other symbolic activity” (Reinhardt and Zander, 2011). From this perspective, the use of technologies that facilitate communication and connection, particularly social media applications and programs, makes a lot of sense. Language learners are able to enhance their language skills due to the different avenues in which new social media have created. Social media provides the learner with the possibility of participating in actual, real-time, relevant conversations taking place online, and practicing the target language with or without the help of an experienced teacher by his or her side.

The Social Media Language Learning (SMLL) method consists in applying interactive social media channels to language learning, which will in turn enable the student to develop communication skills while using these social networks and became more advance in learning language.

The method provides the learner with the possibility of participating in actual, real-time, relevant conversations taking place online, and practicing the target language with the help of an experienced teacher by his or her side.

The Communicative Language Teaching (CLT) method provided the basis for the development of the SMLL method, given both emphasize the importance of teaching within a great scope of contexts with the objective of developing a functional knowledge of the language. Perfect grammar and pronunciation are not essential to the process, rather setting the focus on the communicative competence of the student and the ability to understand and make himself/herself understood.

The Social Media Language Learning is based upon three tenets:

1. Importance of live and actual communication in the target language through interaction and updated content comprehension and production based on Social Media channels.
2. Students' personal experience and interests play a defining role in learning, enabling relevant usage of language during and between classes with active participation of teacher and virtual community.
3. Fostering of social media communication skills at the same time as the language learning is taking place, in terms of editing, strategy, conceptualization, business insight, etc.

The student is therefore invited to emerge as much as possible in activities which require the use of language, given that all of them will result in learning. In-class and out-of-class communication are equally important. It combines the benefits of another method, known as Blended Learning, which allows the student to learn autonomously, whenever and wherever he wants, with all the required material available online, and at the same time have the support of an experienced teacher who eases the process and provides a professional and live explanation of the subjects at hand.

On-site classes with the teacher are intertwined with the ongoing online conversations with other relevant people. Learning is considered to be a constant, ever-flowing, indivisible part of everyday life, thus making the target language a part of it.

E-learning with social characteristics reflects many different features of social networking services, such as Facebook. Furthermore, they can be highly considered as an educational tool because of several beneficial features, such as either enabling peer feedback and collaboration or interactivity and active participation. They can enhance informal learning and support social connections within groups of learners and with those involved in the support of learning. The adoption of platform holding social characteristics can provide:

- Familiarization: The ease of use of such platforms is accentuated because of the similar User Interface to widely used and commonly accepted Social Networking Sites (e.g. Facebook).
- Usefulness: E-learning platforms holding social characteristics can enhance the individuals' productivity. Moreover, various opportunities, among which information sharing, collaboration and entertainment, influence their adoption.
- Social influence: Given the social character of such platforms, students can keep the communication with their classmates or meet new friends. Hence, this fact accentuates the perception that social influence plays a crucial role in people's decision to take part in social e-learning.
- Peer feedback: The enabling of communication among users/students is important. As such, they stay aware about significant information shared by others related to the curriculum being taught.
- Cooperation: The idea of collaborative learning can undoubtedly be expressed through the use of such platforms. In this way, students can exchange ideas,

help their peers and work together in order to enhance the educational experience.

- Knowledge sharing: A crucial aspect incorporated in the educational usage of Facebook is the exchange of resources, documents and useful knowledge concerning the curriculum being taught. Furthermore, they may provide the additional possibility of multimedia sharing so that students can share audio, video, images, and other materials related to their curriculum, with their peers.

2.5.1. Related literature for Social e-learning

This section presents the related scientific literature for social e-learning systems using a novel ISO-based framework.

2.5.1.1. Methodology and model used

The literature review that is presented and discussed in this paper proceeded from a searching study of relevant papers being published in the last few years. The main criterion for a paper to be listed in the literature review was the presented e-learning system to be implemented with a social networking perspective or to be embedded in/developed using an existing social networking site. Moreover, the search engine used in this research was the Scopus, selecting articles published in qualitative research journals or papers presented at significant international conferences. Scopus was preferred since it is the largest abstract and citation database of peer-reviewed literature and it is considered as one of the most valid search engine for research papers[3]. Another criterion for the inclusion of papers was the system to be tested by their respective authors, as the evaluation was based on their system attributes description and testing results. Towards a qualitative review of the systems, ISO/IEC 25010:2011 was used. ISO 25010 is an international standard for evaluating software quality. This standard defines a quality model which is applicable to every kind of software. This model is composed of characteristics which further subdivided into sub-characteristics. A novel framework in the context of ISO 25010 Software Product

[3] https://www.scopus.com/

Quality model is established, comprising the characteristics and sub-characteristics that have high dependency on the application domain (e-learning) and evaluate systems' capabilities regarding standard e-learning software. For each selected sub-characteristic, domain specific capabilities are defined corresponding to social e-learning system requirements.

After the review of social media-based learning systems and software quality models, a quality analysis of selected systems was conducted using the proposed approach. To this end, the evaluation is relied on the system description and the testing results of their creators, as reported in their papers. The results of the evaluation have been tabulated and a comparative discussion has been conducted. Figure 3 illustrates the research methodology used in this paper.

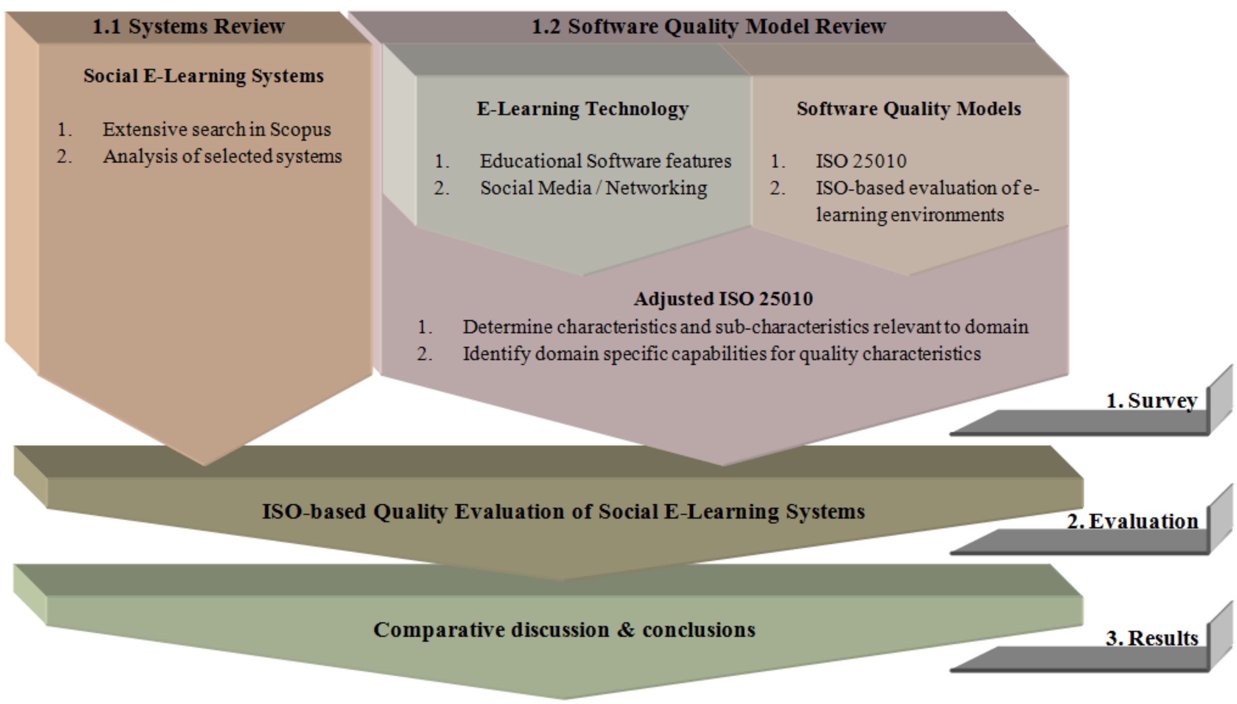

Figure 3. Research methodology

2.5.1.2. Selected Systems in the review

The current paper focuses on the evaluation of innovative educational systems that adopt social media and networking technologies. As this research area is in its infancy and growing day by day, the development of such systems is limited. Thus, after an extensive search of literature, the number of forty-one papers has been chosen, in which applications have been developed since 2010 to present. Moreover, they include a system testing section, essential for the evaluation.

With regard to papers' publication type, 65.85% of the selected systems have been published in qualitative research journals, and the rest ones have been presented at significant international conferences and have been published either as lecture notes or conference paper. Moreover, in 56.1% of the papers, the authors have developed an entire system with social networking and e-learning features, whereas in the rest papers the systems have been developed using well-known Web 2.0 technologies and LMS/CMS. In particular, almost halves of such systems exploit the capabilities of Facebook, the most popular social networking site, in order to establish a social e-learning application. Other Web 2.0 tools that have been used in the selected papers are Twitter – the most famous social networking microblogging site, Elgg – an open source social networking engine for developing social environments, Diigo – a collaboratively social annotation tool, Edu 2.0 – a powerful e-learning platform with LMS and social networking features. In addition, there are systems implemented in Moodle – an open-source course management system, and Drupal – an open-source content management system. Finally, there are some cases where the system developed by the researches is related to Web 2.0 tools, either as Moodle plug-ins or Facebook apps.

Table I and II show the statistics of the evaluated systems regarding the publication type and the platforms used for their development.

Table 1. Statistics of the evaluated systems regarding the publication type and platform used

Publication type	**System development using existing platforms**		**Total**
	Yes	*No*	
Journal papers	13	14	27

Lecture Notes	2	3	5
Conference papers	3	6	9
Total	18	23	41

Table 2. Statistics of the evaluated systems regarding the technology used (Web 2.0/LMS/CMS)

Platforms	**Publication type**			**Total**
	Journal	*Lect. Notes*	*Conf. paper*	
Facebook	7	–	1	8
Twitter	1	–	1	2
Elgg	1	1	1	3
Diigo	1	–	–	1
Edu 2.0	1	–	–	1
Moodle	1	1	–	2
Drupal	1	–	–	1

2.5.1.3. ISO/IEC 25010 Model

The International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC) develop standards and terminology in the areas of electrical and electronic related technologies[4]. The use of standards in Software

[4] https://en.wikipedia.org/wiki/International_Organization_for_Standardization

Engineering aids the systems to be secure, reliable and of good quality and ensures that it conforms to consumers' requirements.

ISO/IEC 25010 was issued in 2011, superseding ISO/IEC 9126, in order to define quality characteristics for assessing the quality of systems and software products (Iso, 2011). The fundamental objective of this standard is to address any emerging problems that can adversely affect the delivery and perception of a software development project. Hence, it is used for Systems and Software Quality Requirements and Evaluation (SQuaRE).

ISO 25010 consists of two models: a) a *system quality in use model* which relates to the outcome of system used by stakeholders in a particular context, b) a *software product quality model* which focuses on the static system properties (internal quality attributes) that can be evaluated without executing and the dynamic properties (external quality attributes) that can be measured by the behavior of the code when executed. Each model is composed of characteristics which further subdivided into sub-characteristics.

In order to evaluate the capabilities of the selected social media systems for e-learning purposes, a novel domain specific approach based on ISO 25010 product quality model is introduced. Figure 4 shows the ISO 25010 product quality model where the (sub) characteristics included in the adjusted framework have been marked and they are analyzed below.

Figure 4. ISO 25010 product quality model with checked the (sub) characteristics used in this model

Despite the widespread use of e-learning systems, there is no a standard framework for evaluating the quality of such systems. ISO 25010 is a well-known standard for the evaluation of software quality. ISO 25010 prescribes general quality requirements for software, thus it can be applied to any system. Several researchers attempted to customize this model for evaluating e-learning environments.

In Shiratuddin (2015), the authors evaluated the quality of e-Book applications in classroom learning process based on four characteristics of ISO 25010 product quality model, namely functional suitability, reliability, usability and performance efficiency. The remaining four characteristics were excluded. A set of questionnaires was distributed to a number of schools and results indicated that e-Book applications are perceived as usable, reliable, functional and efficient in supporting the learning process.

In Acharya & Sinha (2013), the authors propose a set of metrics which measure the characteristics of M-Learning (Mobile Learning) systems following the ISO 25010 software quality model. Firstly, they developed a M-Learning framework for design requirements of such applications. Afterwards, they defined appropriate quality characteristics and metrics which are suitable to evaluate the M-Learning environment. They used the eight characteristics of ISO 25010 model with the sub-characteristics that is relevant to M-Learning. Finally, they applied the model to two M-Learning systems and illustrated the results numerically.

In Hammad et al. (2015), the authors present an evaluation approach of e-learning systems which is derived using the ISO 25010 and the ISO 25012. The proposed model relies on three main models: ISO 25010 quality in use, ISO 25010 product quality and ISO 25012 data quality models. In addition to these models characteristics, domain-specific qualities are included, such as pedagogical, semantic and process-based techniques. In order to test the effectiveness of the proposed evaluation approach, the authors applied it to five different e-learning models: Learning Object, Instructional Management System (IMS) Learning Design, Massive Online Open Courses (MOOCs), Intelligent Tutoring Systems (ITS) and Responsive Open Learning Environment (ROLE).

The literature overview confirms that the use of ISO-based quality model is a key factor for achieving a reliable and of good quality software system. In particular, ISO 25010, and its former ISO 9126, have been applied in a variety of e-learning systems, using a combination of their characteristics proper for such systems. After a thorough investigation in the related scientific literature, the proposed evaluation model is substantially different to others, concerning the ISO 25010 characteristics included, the domain-specific capabilities these characteristics extended, and the systems used for evaluation. The most suitable and up-to-date model for software systems, namely ISO 25010 product quality model, is used and it is adjusted to estimate the achievement of requirements of e-learning environments with social networking features. Social e-learning constitutes a popular research area that appears from the proliferation of Web 2.0 technologies. Nowadays, e-learning tends towards the adoption of social networking features (Manca & Ranieri, 2015). Thus, a quality evaluation model for such systems is essential to investigate if they meet the requirements including: a. capabilities derived from computer-based instruction, such as Learning Management System (LMS) (Ellis, 2009), Intelligent Tutoring System (ITS) (Padayachee, 2002) and Adaptive Educational Hypermedia System (AEHS) (Mulwa, et al., 2010), and, in general, e-learning environments, and b. social learning features (Kim & Jeong, 2009).

2.5.1.4. Adjusted ISO-based evaluation model for social e-learning systems

The emergence of Web 2.0 technologies and the proliferation of social media have drastically altered the range and capabilities of the provided web services in general and more specifically in education. A wide range of social media-based systems for learning purposes has been developed. The provision of high quality systems is essential to release all benefits of e-learning and social media technology. However, there is no a standard evaluation model for the quality of such systems. To this end, a novel framework, based on ISO 25010 Software Product Quality adjusted to social e-learning environment, is introduced.

The proposed evaluation model uses the characteristics and sub-characteristics of ISO 25010 which are relevant to e-learning technology. Thus, it consists of six quality characteristics and a set of sub-characteristics. The Performance Efficiency and Security characteristics are excluded from the model as its scope is to evaluate the capabilities in the learning field. Moreover, there would be limitations on measuring them due to the fact that these characteristics are not mentioned in the systems' evaluation by their creators. The selected sub-characteristics are expanded on domain specific capabilities to address the core requirements of a social media-based system for educational purposes. Hence, using this model, a qualitative analysis of the capabilities of such systems is performed and the question if the systems satisfy the main requirements of a social e-learning environment is identified. The included quality characteristics and their sub-characteristics customized in accordance with domain specific capabilities are described below. The identification of domain specific capabilities was based on the e-learning systems quality criteria related to selected (sub) characteristics of ISO/IEC 9126 model developed in Padayachee et al. (2010). However, the new ISO 25010 is used and its features concerning social features (Kim & Jeong, 2009) and LMS / AITS (Adaptive Intelligent Tutoring System) specifications (Mulwa, et al., 2010) is adjusted. The selected capabilities are described above, giving also examples of their implementation to evaluated systems. Table III summarizes the characteristics of proposed evaluation model.

Functional suitability includes functional completeness and the corresponding domain specific capabilities are (Table 3a):

1. *Content delivery:* the system provides the educational material to students.

   In Facebook, the educational material is delivered through the posts where any file type can be attached (text, video, image etc) (Stankov, et al., 2012; Milošević, et al., 2015; Asterhan & Rosenberg, 2015; Sharma, et al., 2016; Güler, 2015; Lin, et al., 2013; Meishar-Tal et al., 2012; Raud, et al., 2012). In the same context, using Twitter, content can be shared and conversations can be followed through appropriate hashtags in tweets (Junco, et al., 2011; Manca, et al., 2014). Diigo enables users to highlight and comment on webpages or documents and share their annotations with others (Gao, 2013). Using Moodle, the teachers can easily add their course content (Mansur & Yusof, 2013; García-Peñalvo, et al., 2015). Elgg enables tutors to deliver the course material by using components such as posts, file sharing or bookmarks (Veletsianos & Navarrete, 2012; Sousa-Vieira, et al., 2013; Di Bitonto, et al., 2011). In myCourse (Giouvanakis, et al., 2010), the users can generate their content through their blogs or groups, except from the learning content provided by the platform. In the same rationale, Omega (Dominoni, et al., 2010) provides official course managed by teachers and content sharing among students which other students can rate in order to promote useful material. Similarly, Book2U (Balakrishnan, 2014) and SaxEx (Boticki, et al., 2015) embody the function of uploading and downloading material. Fermat (Zatarain-Cabada & Barrón-Estrada, 2013) is a learning social network with an embedded ITS where the course is organized into chapters and topics in a tree structure. SoACo (Kim & Moon, 2014) transforms content from social networks, such as Facebook and Twitter, into learning objects applicable to educational support systems. Finally, Veeramanickam & Radhika (2014) proposed a smart e-learning system with LMS and SNS features, while Rožac et al. (2012) integrates Coome LMS with Facebook platform through a Facebook application.

2. *Management of student records & tracking students' progress:* the system holds the records of the students such as their grade, error proneness or either the specific section that the student is learning.

   Only few systems have the functionality of monitoring students' progress as they focus on the social aspect of learning (Zatarain-Cabada & Barrón-Estrada, 2013; Hsu, et al., 2014; Shi, et al., 2013). In platforms such as Facebook, Twitter and Diigo, monitoring students' actions is a difficult task as there is not any type of log file and the post/comment filtering option is considerably restricted. The mass of information uploaded makes the navigation through comments difficult and the holistic view of students' activity impossible. On the other hand, Moodle, as being a powerful learning platform, provides an intergraded tracking progress system, including grades, activity/course completion, course reports etc (Mansur & Yusof, 2013; García-Peñalvo, et al., 2015).

3. *Communication & collaboration:* the capability given by the system to students to collaborate with peers or their instructors.

   Facebook provides the capability to students to communicate and collaborate through posts, comments and private chat with other students and the teachers in a synchronous or an asynchronous way. Meanwhile, in Twitter, the students interact with others only by tweets and retweets (Junco, et al., 2011). Using

Diigo, the users can share annotations with others and discuss through comments (Gao, 2013). Edu 2.0 (Chunyan, et al., 2014) and Moodle (Mansur & Yusof, 2013; Garmendía & Cobos, 2013) have a variety of tools through which students can communicate and collaborate, such as forum, chat, blog, sharing bookmarks etc, likewise Elgg-based systems (Veletsianos & Navarrete, 2012; Sousa-Vieira, et al., 2013) and Drupal-based as SNAP (Kirkwood, 2010). In García-Peñalvo et al. (2015) system, the communication and collaboration are achieved using MOOC platform, Twitter and Google+, including specific hashtags in the statements. The social features of commenting, sharing, messaging, rating/liking etc are also implemented by SaxEx (Boticki, et al., 2015), Topolor (Shi, et al., 2013), Book2U (Balakrishnan, 2014), PREBOX (Rodrigues, et al., 2011) and myCourse (Giouvanakis, et al., 2010). Furthermore, systems like weSPOT (Mikroyannidis, et al., 2013), Edil-learning (Longo, et al., 2014) and ColeSN (Caballe, et al., 2014) support collaborating learning and networking functionalities.

4. *Organizing students into groups:* the possibility of the system to create groups so that students can work on common projects.

   Works where students can participate into diverse groups and exchange opinions, information etc with others are in Gao (2013), Diigo-based system; Chunyan et al. (2014), Edu 2.0-based one; SocialWire (Sousa-Vieira, et al., 2013), Elgg-based one; Stankov et al. (2012), Facebook groups organizing their members using a graph theory; and PROEDI (Coutinho & Lisbôa, 2013), an educational social networking platform for the professional development of teachers. Chuang et al. (2012) proposed a method for grouping students in order to get better learning results based on friendship, test grades, pairing algorithm and evaluation, while Arndt & Guercio (2011) proposed one based on their connectivity in social networks in order to provide common learning experience. In the same context, Hsu et al. (2014) implemented a grouping system on Facebook based on students' knowledge. Other systems using this capability are Lintend (Popescu & Ghita, 2013) and MyLearnSpace (Hubwieser & Mühling, 2012) where students can join groups depending on their interests.

5. *Conducting assessments & maintaining records of assessments:* the capability of the system to provide different kind of assessments (e.g. multiple choice or filling gap exercises etc) to test the level of students' knowledge. Furthermore, it concerns the maintenance of records of assessment to the model of each student.

   Facebook, Twitter and Diigo have no assessment tool; teachers should either use other Web 2.0 tool to conduct tests and manage their results, or upload the tests as files and manage their results manually (Junco, et al., 2011; Meishar-Tal, et al., 2012; Gao, 2013; Manca, et al., 2014; Raud, et al., 2012). Whereas tools like Moodle and Edu 2.0 provide components for generating tests and online grading (Mansur & Yusof, 2013; Chunyan, et al., 2014; García-Peñalvo, et al., 2015). In SocialWire (Sousa-Vieira, et al., 2013), an Elgg-based system, a range of plugins was implemented for this purpose: the quizzes and exams, which enabled the creation of traditional test and automatic grading of students, the e-portfolio, which gathered all the kind of material produced by students, the ranking – reputation and the gradebook. Concerning the other systems, only few of them provide an integrated assessment system, including a quiz service (Zatarain-Cabada & Barrón-Estrada, 2013; Veeramanickam & Radhika, 2014; Shi, et al., 2013).

6. *Learning outcome:* the system analyzes the student learning outcome emerged from the instructive process.

   Mansur & Yusof (2013) classifies student behavior into active, constructive and intentional, based on the activities that students had visited in Moodle platform and the learning meaningful attributes. García-Peñalvo, et al. (2015), deploying Moodle, retrieves information shared by students on social networks and uses it in MOOC platform for enhancing learning process. The proposal in SocialWire (Sousa-Vieira, et al., 2013) applies rubrics to evaluate the achievement of any learning activity. Moreover, SaxEx (Boticki, et al., 2015) adopts a badge system and rewards students based on triggered questions' answers, likes, locations and posts/comments. Likewise, weSPOT (Mikroyannidis, et al., 2013) defines badges upon reaching certain goals in inquiry process. Whereas Rampun &

Barker (2011) uses reputation points to motivate users to participate more, by uploading material, posting, creating discussions etc. Finally, Fermat (Zatarain-Cabada & Barrón-Estrada, 2013) uses ACT-R cognitive theory.

Table 3a. The domain specific capabilities of Functional Suitability characteristic

Characteristic	Sub-Characteristic	Domain Specific Capabilities
Functional Suitability *(If the provided functions meet the stated and implied needs when used under specified conditions.)*	***Functional Completeness*** *(Does the set of functions cover all the specified tasks and user objectives?)*	1. Content delivery
		2. Management of student records & tracking students' progress
		3. Communication & collaboration
		4. Organizing students into groups
		5. Conducting assessments & maintaining records of assessments
		6. Learning outcome (educationally beneficial)

Maintainability includes modifiability and the corresponding domain specific capability is (Table 3b):

7. *Authoring tool:* the system provides a tool to instructors in order to create professional, engaging and interactive educational content in an easy way, as they may not have programming skills.

   Facebook groups (Stankov, et al., 2012; Asterhan & Rosenberg, 2015; Lin, et al., 2013; Meishar-Tal, et al., 2012) provide a basic authoring tool where administrators can manage the group members and group settings like privacy, posts etc. On the other hand, in applications developed using CMS, like Moodle, teachers can manage the learning material and students by using the appropriate options through a graphical environment. In addition, there are few systems that provide an authoring tool. For instance, Hsu et al. (2014) developed a Facebook application for collaborative learning which includes an instructor management interface. SaxEx (Boticki, et al., 2015) enables teachers to manage the application data and student groups, and create location-based questions. In S-LCMS (Kim & Moon, 2013), there is a group of experts responsible for creating the learning objects using corresponding components such as content generation, import, export, publishing etc.

Table 3b. The domain specific capabilities of Maintainability characteristic

Characteristic	**Sub-Characteristic**	**Domain Specific Capabilities**
Maintainability *(If the system can be modified to improve it, correct it or adapt it to changes in environment and in requirements)*	***Modifiability*** *(Can the system be effectively and efficiently modified without introducing defects or degrading existing product quality?)*	7. Authoring tool

Compatibility includes interoperability and the corresponding domain specific capability is (Table 3c):

8. *Access content from and provide content to digital libraries & other e-learning systems:* the possibility given by the system to organize, store and retrieve the files and media contained in the library collection or other external resources.

   In Web 2.0 tools analyzed in this work, users can easily shared and upload material from other resources (e.g.(Asterhan & Rosenberg, 2015; Gao, 2013; Mansur & Yusof, 2013; García-Peñalvo, et al., 2015; Chunyan, et al., 2014; Veletsianos & Navarrete, 2012; Di Bitonto, et al., 2011), likewise in the majority of other tested systems (e.g.(Kirkwood, 2010; Veeramanickam & Radhika, 2014; Kim & Moon, 2014; Coutinho & Lisbôa, 2013).

Table 3c. The domain specific capabilities of Compatibility characteristic

Characteristic	**Sub-Characteristic**	**Domain Specific Capabilities**
Compatibility *(If the system can exchange information with other products, systems or components, and/or perform its required functions, while sharing the same*	***Interoperability*** *(Can the system exchange information and use the information that has been exchanged with other systems?)*	8. Access content from, and provide content to digital libraries & other e-learning systems

hardware or software environment)		

Reliability is subdivided into fault tolerance and recoverability. The domain specific capability for fault tolerance is (Table 3d):

9. *System response (to invalid input data):* the system interacts with the student using proper messages or providing guideline upon invalid input data given.

   This is a vital function that any system should support, especially a learning environment since the students might be not familiar enough with computers and need guideline in order to accomplish the learning process. However, the papers used in this survey make no mention of this feature because they focus on the innovative capabilities of their systems.

The domain specific capability relevant with recoverability is:

10. *Error management/handling:* the system handles and manages all kind of errors emerging from poor interaction with the students.

    This capability is essential for developing reliable systems. Nevertheless, the articles of evaluated systems describe only their innovations.

Table 3d. The domain specific capabilities of Reliability characteristic

Characteristic	**Sub-Characteristic**	**Domain Specific Capabilities**
Reliability *(If the system performs specified functions*	***Fault tolerance*** *(Does the system operate as intended despite the*	9. System response (to invalid input data)

under specified conditions for a specified period of time)	*presence of hardware or software faults?)*	
	Recoverability *(In the event of an interruption or a failure, can the system recover the data directly affected and re-establish the desired state of the system?)*	10. Error management / handling

Usability is subdivided into appropriateness recognizability, learnability, operability and user interface aesthetics. The domain specific capabilities corresponding to appropriateness recognizability are (Table 3e):

11. *Consistency of layout (user friendliness):* the system follows the same guidelines concerning several issues of layout. As an example, the log-out button should be in the same place in all the forms of the system.

    Most of the systems are developed to the principles of user interface design. Therefore, their Graphical User Interface (GUI) is simple, well-structured, user-friendly and easy to use.

12. *Clear prompts for input:* the system prompt students to input several data such as their credentials.

    The input prompt and hint make the user interface more explanatory by supplying information for the proper use of the controls. Web 2.0 tools adopt this feature in their interface, while the majority of the systems used in this work made no reference on it in their paper. Fermat (Zatarain-Cabada & Barrón-Estrada, 2013) provides the appropriate learning method and personalized assistance to students, such as when they have difficulties answering test questions. Moreover, in Topolor screenshots (Shi, et al., 2013), it is observed appropriate prompts in its input fields.

The domain specific capabilities for learnability are:

13. *Help messages:* the system helps students and protects them against making errors.

    It is important the software to provide a well-designed help system in order to facilitate the users to the system navigation and to exploit all system capabilities. Unfortunately, there is no mention of this feature in the selected systems, as they analyze other capabilities.

14. *Difficulty when learning to operate the system:* the students encounter difficulties when firstly interacting with the system.

    In general, there is no mention that the students have difficulties while operating the systems, except from SaxEx (Boticki, et al., 2015).

The domain specific capability referred to operability is:

15. *Organized information and sequence of screens:* information to students is organized and they receive them is in a systematic way.

    Many Web 2.0 tools, like Facebook, Twitter, blogs etc, organize their material mainly based on the chronological order it uploaded or using appropriate tags. Meanwhile Diigo has the capability to organize it into folders. Edu 2.0 and Moodle, as learning management systems, provide an effective and efficient way to organize the lessons. In Elgg, this feature can be achieved through different plugins which support the desirable functionality. Finally, SaxEx (Boticki, et al., 2015) displays the question prompts according to the student's location during the exploration trip.

The domain specific capability for user interface aesthetics is:

16. *Pleasantness/attractiveness of system interface:* there are properties of the system that increase the pleasure and satisfaction of the user, such as the use of color and the nature of the graphical design.

Facebook and Twitter are the most popular platforms, being widely used by people of all ages. Therefore, their interface is familiar to learners and in conjunction with their user-friendliness, they are considered pleasant and easy-to-use environments for learners. All the Web 2.0 tools have a simple and usable interface and developers generally design systems which can be used with effectiveness, efficiency, and satisfaction.

Table 3e. The domain specific capabilities of Usability characteristic

Characteristic	**Sub-Characteristic**	**Domain Specific Capabilities**
Usability *(If the system can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use)*	***Appropriateness recognizability*** *(Can users recognize whether the system is appropriate for their needs?)*	11. Consistency of layout (user friendliness)
		12. Clear prompts for input
	Learnability *(Can users learn to use the system easily?)*	13. Help messages
		14. Difficulty when learning to operate the system
	Operability *(Has the system attributes that make it easy to operate and control?)*	15. Organized information & sequence of screens
	User interface aesthetics *(Does the user interface enable pleasing and satisfying interaction for the user?)*	16. Pleasantness / Attractiveness of system interface

Portability includes adaptability as well. This characteristic/sub-characteristic is used for examining the following capabilities because, according to ISO 25010 specifications (Iso, 2011), the adaptability corresponds to suitability for individualization as defined in ISO 9241-110, which means that the system is able to be customized to suit the user. The corresponding domain specific capabilities are (Table 3f):

17. *Personalization:* the system is customized and adapted to specific user needs and preferences.

    Edu 2.0 (Chunyan, et al., 2014) and Elgg (Veletsianos & Navarrete, 2012) platforms provide the capability to users to configure their dashboard by adding or removing features. S-LCMS (Kim & Moon, 2013) provides personalized learning through learning objects which are designed based on diverse learning styles and cognitive level. The work in García-Peñalvo et al. (2015) (a Moodle application) presents a tracking process of students' conversations in social networks in order to exploit this knowledge for adapting MOOC content. Another social network, Zamna (Zatarain-Cabada, et al., 2010), adapts its content related to the identified student learning style based on Felder-Silverman model. In addition, Fermat (Zatarain-Cabada & Barrón-Estrada, 2013) is adapted based on cognitive aspects and students' recognized emotion. Whereas Chuang et al. (2012) implements an adaptive system by providing adaptive grouping and adaptive tests related to groups.

18. *System recommendations:* the system can dynamically provide advice or educational material to students appropriate to their needs.

    Di Bitonto et al. (2011), deploying Elgg, proposes a recommendation method to suggest learning objects, users and discussion groups related to learner's needs and to adjust search results in order based on learner's interests. This recommendation method was implemented using tags defined by users and a clustering algorithm. Another approach is used in Topolor (Shi, et al., 2013), where through module and Q&A center, it is provided content and peer recommendation. Moreover, Omega (Dominoni, et al., 2010) provides adaptive material suggestions and filtering, based on usefulness rating of community and student mental effort, using User-based nearest neighbor algorithms.

Table 3f. The domain specific capabilities of Portability characteristic

Characteristic	**Sub-Characteristic**	**Domain Specific Capabilities**
Portability *(If the system can be transferred from one usage environment to another)*	***Adaptability*** *(Can the system effectively and efficiently be adapted by the end user?)*	17. Personalization
		18. Advice generator

2.5.1.5. Comparative discussion

Firstly, a comparative discussion about the prevailing approaches of learning through SNSs was conducted. As mentioned above, the comparison was made using the ISO/IEC 25010 model, so that the results are qualitative. As presented in Figure 5, the most commonly used e-learning characteristic is the “Content delivery”. “Content delivery” is of great importance since it involves the way with which a student receives the learning material.

Furthermore, “Communication and Collaboration” is also widely used, as seen in the percentages of Figure 5. Computer-supported collaborative learning (CSCL) is a pedagogical approach wherein learning takes place via social interaction using a computer or through the Internet. The reason why collaboration is mostly used in such systems from 2010 until now is because SNSs offer different ways of asynchronous and synchronous communication among students.

Moreover, the years 2013 up to 2015 researchers preferred to “organize students into groups”. This characteristic is a core ingredient because of students’ participation in group work. When students are in groups, they are capable of expressing their own ideas, listen to their peers’ standpoint and thus they remain in the center of the tutoring process.

As shown in Figure 5, user friendliness and attractiveness of system interface are also characteristics which have been used by the researchers. Indeed, they play a crucial role in education as students need to have a pleasant and consistent layout so that all their attention is placed to learning.

In traditional e-learning systems, personalization to students is supposed to be the cornerstone of the educational process. Specifically, students are placed to the center of tutoring and all the learning objects and functions are adapted to them. However, in social e-learning systems, the percentage of personalization as a capability is quite low. The latter systems focus on the social aspect of learning, namely communication, collaboration and grouping. The reason why this occurs is because these systems can be regarded as a growing issue in the scientific literature and they recently incorporate widely used modules and features, such as personalization support, adaptivity and recommendation.

Another important observation is that the majority of aforementioned systems lack the adoption of a learning style model or theory. The support of a learning style model or theory is significant given that the identification of students’ way of learning is the key to introduce techniques and strategies concerning the curriculum sequencing and the method of assessment.

Concerning the way of testing students’ knowledge, it is observed that the systems offered simple tools, such as tests with static and predefined form and non-dynamic correction of students’ errors. However, the use of an assessment tool that adapts its activity to students’ model and supports error diagnosis is crucial for evaluating the achievement of learning objectives.

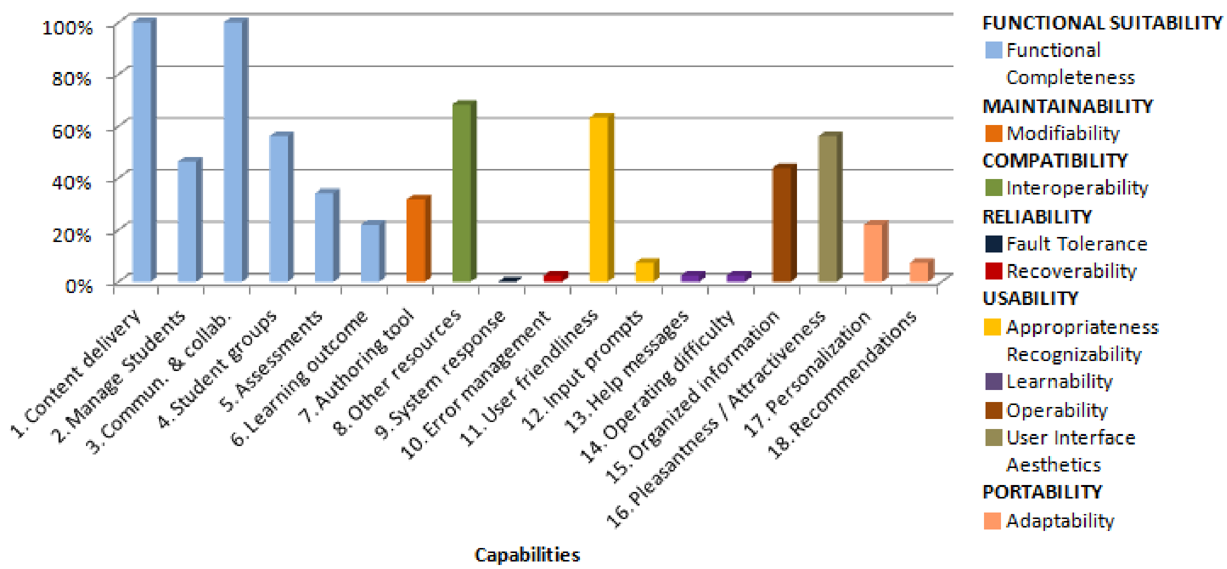

Figure 5. The percentage of each capability integrated into overall evaluated systems

Figure 6 depicts the capabilities being integrated to systems developed using well-known existing platforms, namely Web 2.0 tools, LMS and CMS, in comparison with platforms which were solely created by the authors of the papers. The first category of systems offers an easy way of creating an application through platform customization and due to the already implemented components provided freely by the platforms, such as the instant or asynchronous text messaging. Given their social aspect, these platforms offer a fertile ground for incorporating social characteristics, while there are limitations in the adoption of other modules, namely personalization and system recommendations. On the other hand, the platforms created by the researchers tend to be more educative since they implemented the systems in instructional contexts with social characteristics.

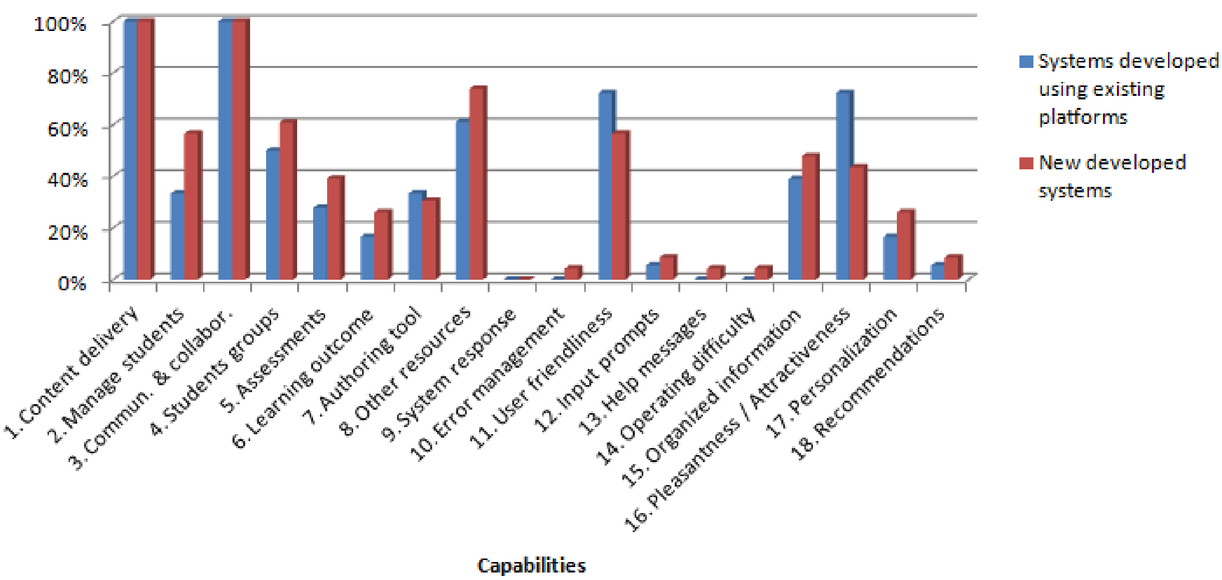

Figure 6. The percentage of each capability integrated to evaluated systems based on the kind of platform used

2.6. Affective Computing

Both in traditional and digital learning, affective states, like frustration, can be the reason of students' being disappointed or uncomfortable in the learning process (Rodrigo et al., 2007). As such, handling this problem is significant. In traditional learning, where face-to-face learning takes place, when the instructor perceives the affective states of students, s/he can positively influence them in the tutoring process. Correspondingly, in an ITS, students' affective states should be identified and motivation to them should be delivered in order to tailor the learning content to them.

Affective computing was first introduced by Picard (2000) and employed in various fields including gaming, learning, health, entertainment among others (Pinder, 2008). During the last decade, research on affective computing provoked great interest on affect detection (Calvo, D' Mello, 2010). Following, the affective states being used in affective computing are described and the definition of frustration, which is the affective state taken into account for this dissertation, is presented in detail.

2.6.1. Affective States

Although the representative affective states are related to emotions, feelings and moods, the research on affective computing research takes into consideration only the emotions (Calvo, D' Mello, 2010). Traditional emotion theories involve emotions through facial and body expressions (Darwin, 1998), (Ekman and Friesen, 2003), (Izard, 1994). Emotions were first explored scientifically by Darwin (1998). Several studies report that essential emotions, such as fear and rejection correspond to facial and body expressions (Darwin, 1998), (Calvo, D' Mello, 2010). Darwin (1998) explicated six widely recognized emotions. The six primary emotions are the anger, disgust, fear, joy, sadness and surprise (Izard, 1994), (Ekman and Friesen, 2003).

Cognitive psychologists, for instance Ortony et al. (1990), Roseman (1984) and Smith and Ellsworth (1985), have conducted further researches on emotions in order to emphasize the close connection between emotion and cognition (Marsella et al., 2010). According to cognitive psychology theories, such as the appraisal theory, emotions are determined by the people's perception of their experiences and interpretation of an event; solely the experiences and the event cannot affect the emotions. Thereby, two people with different appraisals (assessing the outcome of event) or experiences and in a different environment may feel different emotions for the same event (Roseman et al., 1990). This is the pivotal rational of appraisal theories of emotion; according to them, appraisal is seen as the cause of the cognitive changes associated with emotions (Smith and Ellsworth, 1985).

Cognitive approaches to emotions were then explored by cognitive psychologists (Ortony et al., 1990), (Roseman, 1984), (Smith and Ellsworth, 1985). The research of cognitive psychologists aimed to unveil the relationship between variable (circumstances, goal) and emotion labels (joy, fear) (Ortony et al., 1990) and the relationship between appraisal variables and cognitive responses (Smith and Ellsworth, 1985). Cognitive psychology theories report that emotions are associated with the student's experience, goal, obstruction of goal, achieving of the target etc. Following, several theories of cognitive approaches to affective states are discussed.

Roseman (1984) proposed that five appraisals influence emotions:

- Motivational state: Motivation concern the rewarding or the avoidance of punishment.
- Situational state: It is related to the presence or absence of the motivational state.
- Probability of achieving the goal.
- Legitimacy: It concerns the deserved outcome of the event.
- Agency: It concerns the outcome and who/what resulted in it.

Based on these appraisals, emotions such as joy, pride, distress, and shame are defined.

The appraisal theory, named OCC, was proposed by Ortony et al. (1990) and explains emotion as a cognitive appraisal of the current situation involving the events, agents and the objects. Also, according this theory, the emotions derived from the matching of a person's preferences or goals with the outcome of the event, namely the reaction to the events form the emotions. Similarly, the OCC theory discusses the emotions that occur due to the agents and the objects. Depending on the outcome of the event, the interference of the person, and the objects, the OCC theory defines 22 different emotions such as "Joy", "distress", "hope", "fear" and others. The cognitive emotions (fear, distress) are primarily focused on the student's goals and event outcomes. Based on the researches of (D' Mello et al., 2007), (D' Mello et al., 2009) and (Lehman et al., 2008), Calvo and D' Mello (2010) reported that the emotion occurring during the learning sessions that lasts for 30 to 120 minutes has less relevance with the basic emotions. Hence, the basic emotions might not be relevant to the students' emotions occurring during the interaction with a computer. On the other hand, learner-centered emotions, such as frustration, boredom, confusion, flow, curiosity and anxiety, are more applicable to computer learning environments (Calvo and D' Mello, 2010), based on the researches of Conati and Maclaren (2009), Baker et al. (2010), Brawner and Goldberg (2012), D' Mello et al. (2005), Hussain et al. (2011) and Sabourin et al. (2011). In learner-centered affective states, identifying and responding to the negative affective states are significant since it might render the student susceptible to quit learning (Kort et al., 2001). Concerning the educational research, there is a controversy on whether negative affective states, such as frustration and confusion, are needed for learning or should be addressed to avoid the students from quitting it (Gee, 2003).

Researches on affective computing sate that affective states, like frustration, can facilitate thinking and learning and hence they are needed while learning (Gee, 2003), (Gee, 2008). However, Gee (2008) further describes that frustration should be kept below a certain level in order to avoid high stress, powerful anger or intense fear. Moreover, frustration is a cause of student's disengagement and can eventually lead to attrition (Kappor et al., 2007). In view of the above, this dissertation focuses on the negative affective state of frustration.

2.7. Frustration

Research on frustration has been conducted for more than 80 years and concerns a common emotional response of opposition. It is related to anger, annoyance and disappointment and arises from the perceived resistance to the fulfillment of an individual's will or goal and is likely to increase when a will or goal is denied or blocked. Following, several theories about frustration are described.

2.7.1. Rosenweig's Frustration Theory

Rosenweig (1938) defines frustration as the emotion that a person feels when an ordinarily disposable need or the end-state is not available now or is removed. For instance, when a student, interacting with an ITS, needs assistance or simply a hint to provide the correct answer in a question but does not receive it, s/he is frustrated since s/he knows that it would be easily available to him/her in traditional tutoring. The theory reports that frustration can occur as a result of external factors or one's personal actions, for example the student is poorly prepared to take test. Furthermore, the theory states that "frustration tolerance tends to increase with age". Thus, the emotion of frustration is experienced more frequently by school or college students in comparison with more grown-up people.

2.7.2. Frustration Aggression Hypothesis

Dollard et al. (1939) developed the frustration aggression hypothesis which reports that the experience of frustration always can induce some form of aggression. Frustration is defined as a "condition which exists when a goal-response lacks of interference". In order to illustrate this definition, an example is given. Students A is preparing for a test by studying the theory provided by an ITS. According his/her previous interaction with the same course, s/he predicts that the goal of achieving high grades is achievable. The rationale of achieving good grades lies in several indicators, such as good preparation for the test or quitting other activities irrelevant to studying. The power of such indicators can be measured by the probability, duration and force of the occurrence of achieving high grades. An example can be a student preparing for exams. Based on previous experience, s/he predicts that the goal of getting good grades in exams is achievable. His/Her interest to achieve the goal is conveyed using several indicators, such as not playing games, spending less time on social networking activities, and his/her preparation for exam. The strength of these indicators is measured by the duration, force and probability of the occurrence of the goal-getting good grades. Since the force cannot be measured in this example, the duration of the preparation along with the probability of achieving good grades are only taken into consideration. The goal-response of this example, namely the fact which terminates the student's predicted sequence (preparing for the test will lead to good grades) is the achievement of good grades. If student A confuses the goal-response with the predicted sequence, then s/he experiences frustration. According to the frustration aggression hypothesis, "aggression is the primary and characteristic reaction to frustration". The hypothesis also states that:

- The greater the strength of the goal-response sequence involves, the greater the frustration is; it could affect the strength of the tendency to respond aggressively to frustration.
- The greater the amount of interference with the goal-response is, the greater the tendency to respond aggressively to frustration will be.
- The effect of combined frustration can induce stronger aggressive reaction than individual frustration.

In summary, the severity of frustration is determined either by the amount of the interference or by the strength of the interference or the added effect of several frustrations (cumulative).

2.7.3. Frustration and Goal-Blockage

Morgan et al. (1986) define frustration as "the blocking of behavior directed towards a goal". The main reason of frustration can be environmental factors, personal factors, or conflict. Environmental factors involve physical impediments which prevent a person achieve his/her goals. Personal factors involve the lack of ability, required to achieve a goal and the conflict is the incapability of achieving a goal because other goals have priority. This theory also supports Rosenweig's Frustration Theory; in the latter theory, frustration can occur due to external or personal factors. Spector (1978) further attests that frustration can occur when the process of maintaining one's goal is hindered. Frustration occurs when "both the interference with goal attainment or goal oriented activity and the interference with goal maintenance". In other words, if any goal or expected outcome is hindered, then a person will experience frustration. Furthermore, a person will experience frustration if s/he keeps maintaining his/her goals. The factors that affect the strength of the frustration are the importance of the hindered goal, degree of interference, and number of interferences hindering the goal achievement. Cognitive psychologists Ortony et al. (1990), Roseman (1984) and Smith and Ellsworth (1985) perceive appraisal as the reason of cognitive emotions occurring due to a person's perspective and expectation of an event. The theories of cognitive psychologists state that emotions are related to the student's experience, goal, obstruction of goal, achieving of the target etc. As such, emotions are revealed when the goal is matching with the outcome of an event.

2.7.4. Frustration and cause in computer users

Besides the theories of frustration, the following attribute of frustration has been studied in the related scientific literature and is not mentioned explicitly in frustration theories. Lazar et al. (2006) studied the causes of frustration in computer users. Their research reports that a task being of higher importance to the students spending a high amount of their time, then it is directly proportionate to a higher level of frustration. As a matter of fact, if an important goal, for the preparation which the student spent a lot of time, is not achieved, it leads to a higher level of frustration. Under this rationale, the time which is spent to achieve a goal is significant for the detection of frustration.

2.7.4.1. Definition of Frustration as used in this Dissertation

As mentioned above, the foremost and underlying reason of frustration is the impediment of the goal. Consequently, the identification of the foremost reason of frustration is vital. Apart from this, the aforementioned theories involve also more reasons about frustration except for external interference. In the field of e-learning, external factors, such as hardware problems of the computer or even connectivity problems, will not constitute a reason for frustration. In order to model the students' frustration, this dissertation takes into account the following reasons for frustration based on the researches of Dollard et al. (1939), Lazar et al. (2006), Morgan et al. (1986) and Spector, (1978):

- Frustration is the blocking of a behavior directed towards a goal.
- The distance to the goal is a factor that influences frustration.
- Frustration is cumulative in nature.
- Time spent to achieve the goal is a factor that influences frustration.
- Frustration is considered as a negative emotion, because it interferes with a student's desire to attain a goal.

2.8. Motivation Theory

Affective computing involves the detection of the student's affective state along with a responsive action to it. The way with which affective states are detected was described in depth in the previous sections. Following, the respond to the student's affective state by displaying motivational messages is presented. Motivational messages are used to urge the learner to study by using the ITS in order not to experience frustration or goal-failure. In this section, theories for motivation are described. Motivation theories are used to motivate the person to be involved in work or to keep up working. Motivation psychologists report that the desire for achievement is the cornerstone of the motivation theories. Cognitive motivational theories were developed by researching the application of the motivation theory to the event's outcome (either success or failure) (Graham et al., 1976). In this section, the motivation theories, which dominated the scientific study of motivation, are briefly presented.

2.8.1. Hull's Drive Theory

The Hull's drive theory was the first theory for motivation and is based on the energy (drive) required to motivate the person (Hull, 1943). Simultaneously, it coincides with a characteristic of the educational process, namely if the response on a stimulus (the action towards an event and the response of that event - goal-response) terminates with a satisfying result, the motivation increases; if it terminates with an annoying result, the motivation decreases. According to this theory, the habit is the strength required to increase the motivation, which is decreased due to response on the stimulus. In other words, a habit is the action which a person requires in order to proceed towards the goal. However, the habit can provide the directions required for an action, but not the drive. Hence, the mathematical relation between drive and habit for motivational behavior is given below:

- Behavior = Drive * Habit

Behavior is proportionate to Drive and Habit. This is to indicate that only Drive or Habit alone cannot motivate the person. If there is no energy (Drive = 0), the person would not act irrespective of the strength of the habit.

2.8.2. Lewin's Field Theory

Kurt Lewin's theory[5] is based on Gestalt psychology[6] in order to interpret the motivational behavior, being known as the field theory. The Gestalt psychology analyzes the behavior as a whole and is not determined by the summation of individual elements. The field theory states that behavior is determined by both the person and the environment involved:

Behavior = f(Person, environment)

The motivational force of a person is associated with three factors:

- the person's intent (need) to complete the task, known as tension (t)
- The magnitude of the goal (G), which satisfies the need and
- The psychological distance of the person from the goal (e).

The mathematical function for the motivational force of a person is: Force = f(t, G)/e. In this function, the psychological distance from the goal is inversely proportionate to the motivation force; namely, if the distance to achieve the goal is reduced (approaching zero), then the motivation to achieve the goal is increased.

2.8.3. Atkinson's theory of achievement motivation

Following the same rationale of the aforementioned theories, Atkinson also developed the mathematical function for achieving motivation; however, Atkinson focused on individual differences in motivation. Atkinson's theory[7] states that the behavior (tendency) to approach an achievement-related goal (T_t) is the product of three factors:

1. the need for achievement or motive for success (M_S),
2. the probability that a person will be successful at the task (P_S) and
3. the incentive for the success (I_S). The mathematical function is: $Ts = M_S * P_S * I_S$

[5] http://www.psychologydiscussion.net/learning/learning-theory/lewins-field-theory-of-learning-education/2525
[6] http://webspace.ship.edu/cgboer/gestalt.html
[7] https://principlesoflearning.wordpress.com/dissertation/chapter-3-literature-review-2/the-human-perspective/achievement-motivation-atkinson-mcclelland-1953/

The achievement motive M_S is developed during the early stages of life and shaped by child-reading practices. The probability of success Pi usually defined in terms of the difficulty of the task. The value of Pi ranges from 0 to 1. The third factor, which is the incentive of success I_S, is inversely related to P_I: $I_S = 1 - P_S$.

2.8.4. Rotter's Social Learning Theory

Rotter's theory[8] is also based on individual differences in behavior, like the Atkinson's theory. The motivational model by Rotter is based on the general expectancy (E) and reinforcement value (RV), and the relationship of these two factors is:

Behavior = f(E, RV)

Reinforcement value (RV) is a comparative term and is not clearly mentioned in the theory (Graham et al., 1996). The expectancy (E) of success depends on one's history of the present situation and similar circumstances. For example, one's expectancy of success in an event depends on the history of success or failure in the same event or the result of similar events. In a situation which requires one's skill, the expectancy increases after success and decreases after failure.

2.8.5. Attribution Theory

The Attribution theory attempts to explain the world and to determine the cause of an event or behavior (e.g. why people do what they do). Attribution theory, when applied to motivation, considers the person's expectation and the response from the event. This theory was constructed by Heider (1958) and subsequently developed by Weiner (1985). The attribution theory (Weiner, 1985) relates emotional behaviors to academic success and failure (cognitive). The causes of success and failure, associated with the achievement context, are analyzed. The reaction of the person is related to the outcome of an event. As such, a person feels happy if the outcome is successful and frustrated or sad if the outcome of the event is failed. This is called “outcome

[8] http://psych.fullerton.edu/jmearns/rotter.htm

dependent-attribution independent" (Weiner, 1985). The learner's attribution of success or failure is analyzed in three sets of characteristics which are the locus, stability, and controllability.

- Locus refers to the location of the cause, which deals with the cause of success or failure may be internal or external. Locus determines whether the pride and self-esteem are altered due to outcome of an event (success or failure). If the learner attributes the success to internal causes, such as, being well prepared for the exam, and doing more homework, then it will lead to pride and motivates the learner to set new goals. Whereas, if the learner attributes the failure to internal causes then it will diminish the self-esteem. Hence the learner's failure should be attributed to external factors, for example hard test or difficulty in language learning, in order to motivate the learner to give effort on future event.
- Stability refers to the learner's performance in the future. If the learner attributes the success to stable factors such as "low ability", then the outcome of the future event will be the same, given the same environment. If the learner attributes the failure to the stable factors then the future success is unlikely. If the learner attributes the failure to unstable factors such as "less effort" and "luck" then the learner's success in future events will be improved (Forsterling, 1985).
- Controllability refers to the factors which are controllable by the learner who has the ability to alter them. If the learner failed the task but can control the future outcome by altering them, such as improving math-solving ability, spending more time on homework, this will lead to self-motivation. On the other hand, if the student cannot control a failure at a task, this will lead to shame or anger.

The attribution theory states that a person's attribution towards the success or failure contributes to the person's effort on future activity. If the learner attributes the success to internal, stable and controllable factors, then it will lead to pride and motivation. If the learner attributes the failure to the internal, stable and non-controllable factors, then it will lead to diminishing the self-esteem, shame and anger. Hence, motivating the students' failure with messages which attributes the failure to external or unstable or controllable factors will help them to set a new goal with self-motivation.

2.8.6. Discussion on motivational theories

Hull's drive theory and Lewin's Field theory both explain what determines motivation using the same factors: need of a person ("drive" in Hull's and "tension" in Lewin's), the goal object, and directional value ("habit" in Hull's and "psychological distance" in Lewin's). Later, these factors are not considered in expectancy-value theories either in Atkinson's and Rotter's or in the Attribution theory. Atkinson's achievement motivation and Rotter's social learning theory focus on the individual's motivation, success rate, and history. However, these theories are addressed to the broader goals of motivation and did not provide suggestions to increase classroom performance. Hence, they are not tailored to traditional and digital learning. Graham et al. (1996) conducted a research reviewing the aforementioned theories and reported that each theory had a life span of about 20 years and major contributions to the theories were made in this time span. The theories of Hull, Lewin and Atkinson have not been used after their life span. Also, the research on Rotter's social learning theory has been reduced. Research on the Attribution theory and its application to achievement appears to be dominant in the theory of motivation (Graham et al., 1996). Also, Graham (1991) reviewed the papers related to motivation theories. This study reports that, a) there were 66 published studies in that decade and the primary conceptual framework was the attribution theory and b) "Attribution theory was proved to be a useful conceptual framework for the study of motivation in educational contexts".

More recently (1990 onwards), the motivation theory has been researched for its applications. For example, the self-determination theory (Gagne and Deci, 2005), (Deci and Ryan, 2010), (Pinder, 2008) is an application of the motivation theory in organization. The self-determination theory discusses the relevance of work motivation in the organizational behavior. The expectancy-Value theory of achievement motivation (Wigfield and Eccles, 2000) relates the children's expectancy of success, ability, and subject task to motivation. Certainly, the theory that fits perfectly in the field of education is the attribution theory (Batool et al., 2012), (Vockell, 2004).

Attribution theory is also used in affective computing, especially in ITS, to address the students' affective states (D' Mello et al., 2009), (Khan et al., 2009). Hence, the attribution theory was selected in this research in order to create motivational messages and address the affective states.

2.9. Responding to Frustration

In this section, the different approaches used to respond to frustration in computer-based learning environments are presented. Klein et al. (2002) listed the strategies to respond to students' affective states. These strategies are developed based on previous research works on active listening (Nugent and Halvorson, 1995), (Gordon, 1970). The guidelines listed in Klein et al. (2002) to respond to affective states are the following:

- The system should provide option to receive feedback from the student for their affective state. This is to show the student that the system is actively listening to their emotions. Active listening to students' emotions has shown to alter their emotions (Nugent and Halvorson, 1995).
- The students' feedback should be requested immediately whenever the student is detected frustrated. The feedback request when the student is not frustrated will be ineffective. To report the affective states, the students' should have list of option to choose from. This will provide the option to student to react on what emotion s/he is undergoing.
- The system should provide feedback messages with empathy, which should render the student capable of feeling that s/he is not alone in that affective state. Also the messages should convey the student that the emotion s/he undergoing is valid. For example the student should not feel that only s/he got wrong answers to the question given by the system or only s/he missed the goal.

The other approaches to respond to affective states include displaying the messages using agents (Prendinger and Ishizuka, 2005), (Hone, 2006). The agents are designed to show empathy, and encourage the students to continue learning. Also, the positive messages to address the students' emotion have helped them to improve their performance (Partala and Surakka, 2004). In order to create motivational messages, this dissertation is based on the researches of Dweck (1986) and Dweck (2002) on feedback messages to praise the student's effort instead of student's intelligence. In these researches, a nonverbal IQ (Intelligence Quotient) test was conducted on students and provided one of the three forms of feedback messages. One-third of the students were praised for their intelligence, one-third of the students were praised for their effort and remaining students were not praised for effort or intelligence. After providing the feedback message the students were given second set of problems which are difficult compared to first set of problems. Later, the students were interviewed to know their view on intelligence. The result shows that the students who were praised for intelligence believes that the intelligence is fixed and cannot be improved. The students, who were praised for their effort, believe that intelligence can be improved by more effort. Also, the students, who were praised for their effort, believe that failure means low effort and displayed more enjoyment in solving difficult problems. The Dweck's researches on feedback messages is a seminal work in the research area of guidelines to create feedback messages, and it had been applied to wide range of educational research (examples are motivating school students (Wigfield and Wentzel, 2007) and responding to students' affective states in computer based learning (D' Mello et al., 2007), (Baker et al., 2010)). In this research, all the above approaches to respond to frustration are adapted. The content in our motivational messages are based on attribution theory (Weiner, 1985). Based on the guidelines of Klein et al. (2002), the option to students to reflect their feedback is provided; the feedback is requested after detecting frustration and feedback messages to show empathy for students' affective state. Using the recommendation presented in (Hone, 2006) and (Prendinger and Ishizuka, 2005), the motivational messages are displayed using an agent who deliver empathy in the messages shown. Based on the research of Dweck (2002), the motivational messages are constructed to praise the students' effort and not (only) their intelligence. The strategy to respond to frustration is explained in detail in Chapter 6.

Chapter 3:

POLYGLOT Architecture & Implementation

3.1. POLYGLOT architecture

The research, presented in this dissertation, involves a full development and implementation of the novel approach of a social and adaptive tutoring system incorporating machine learning techniques for the automatic detection of the student's learning style, error diagnosis mechanism and frustration management. Specifically, an innovative integrated e-learning environment for multiple language learning (English and French languages), which is called POLYGLOT, has been developed. The technology of Adaptive ITSs was taken into account for the system's design and development. Figure 7 depicts the model of the architecture of POLYGLOT. It consists of the following components:

- **Social Media User Interface module**: This module serves as the liaison between the learner and all the modules of the system. Its major characteristics are the user friendliness and the dynamic adaptation to each learner based on his/her needs and preferences. Towards this direction, this module should hold information concerning the learners' characteristics, needs and preferences along with good feedback about what's happening and whether the user's input is being successfully processed and mendable actions. Further characteristics include clarity, concision, responsiveness, consistency, familiarity, efficiency and forgiveness. Moreover, the user interface transfers the learning content to the users. Furthermore, the user interface of POLYGLOT consists of all the characteristics that social media have. Specifically, it has a wall on which all students can post their ideas, questions and they can interact with peers. Also, the students can tag their friends on the wall so that they can address to a specific person. Apart from that, students can send messages to other students or instructors in an instant or asynchronous way. Finally, the students can express their satisfaction or dissatisfaction concerning the exercises by pressing the "Like" or “Dislike” button respectively.

- **Learning content module**: The domain model contains knowledge pertaining to the subject matter. The system utilizes its domain knowledge to reason with and solve problems, or to answer questions posed by learners. It is responsible to process the system domain knowledge to make inferences or solve problems. Moreover, it provides explanations of problem solutions and gives alternative explanations of the same concept. Also, it answers arbitrary questions from the student and holds knowledge about common misconceptions and missing concepts. Finally, it incorporates the representation of the knowledge dependencies so that the status (namely if the learner has studied the material) and the difficulty level of the concepts can be analyzed.
- **Student model**: It is considered as the core component of an ITS paying special attention to student's cognitive and affective states and their evolution as the learning process advances. As the learners work step-by-step through their exercise answering process, the ITS engages in a process called model tracing. Anytime the student model deviates from the domain model, the system identifies, or flags, that an error has occurred. The student model is responsible to maintain information about the student’s personal profile, knowledge, and current and advancing skills. Furthermore, it stores information about the student’s cognitive processes, learning preferences and/or past learning experiences. In this research, the aim is to model the cognitive states of each learner. Namely, the system has to be able to understand the learning state of each student and to recognize when a learner learns or not the learning content. To the direction of modeling the

learner's knowledge, the overlay technique is used and it recognizes the progress that the student presents in the learning content. Given that the overlay model does not hold information about learners' errors and preferences, a stereotype model is used in addition. Moreover, a hybrid model of two different algorithms is used to interpret the nature of learners' errors. Furthermore, the system classifies learners into learning styles with the use of machine learning techniques.

- **Error diagnosis module**: It is responsible for diagnosing the misconceptions of students. The error diagnosis module employs 2 different algorithms which can spot the type of error which is conducted by the student and the reason why s/he made it. POLYGLOT knowledge about how to solve an exercise correctly and in several faulty ways. The error diagnosis module uses a combination of buggy and overlay techniques to perform diagnosis of misconceptions. Buggy procedures are related to prerequisite grammatical concepts. Each one of these procedures is associated with a certain category of error. For example, a common mistake that students seem to make is the tense mistakes; namely, the student has neglected the rules of the proper use of tenses. The error diagnosis is performed by POLYGLOT in the Solving Exercises Mode (exercises where students must fill in the gap with the missing words). In multiple choice exercises error diagnosis is simple. For every erroneous answer that the student may select, there is an associated misconception. Therefore, depending on the erroneous selection that the student has made, a corresponding error message is presented, explaining the cause of the mistake. In the case of exercises where the student is asked to fill in the gap in a sentence, the error diagnosis becomes more sophisticated since in this case the student is allowed to be more creative than in multiple choice exercises. Hence, if the student’s answer differs from the system’s expectation then the system performs error diagnosis. Following, this module is further explained and described.

- **Win-Win Collaboration module**: It is responsible for recommending collaborations between learners with respect to either their learning state or the misconceptions that they conduct. By consulting win-win Collab module, the system provides advising to learners to collaborate with peers in such a way that both of them can reap the benefits of collaboration. The module offers two different approaches for collaboration. The first one is the win-win collaboration based on the already learnt language concepts and the second one is based on the types of misconceptions made by the student. For example, if a student is good at concept A but has poor knowledge on concept B, the system proposes him/her a collaboration with another learner who is complementary to the concepts. Also, under the same rationale, if a student is prone to conduct misconceptions of category A but s/he does not conduct misconception of category B, the system proposes him/her collaboration with a student who conducts misconception of category B but not of category A.
- **Frustration Recognition and Response module (Affective module)**: It is responsible for providing personalized motivational messages to students in case of frustration. The system creates and displays messages to motivate the learners according to the reasons why the student is frustrated. The prime reason for frustration is goal failure. The possible reasons for goal failure are identified from the students' goal while they interact with the ITS.

- **Learning style detection module**: This module involves the automatic detection of the student's learning style. POLYGLOT uses the Felder Silverman Learning Style Model and employs machine learning techniques in order to sophisticatedly select the right learning style of the student. This procedure does not involve traditional approaches for the detection of the learning style, such as questionnaires. In that way, the student saves a lot of time while POLYGLOT adapts the pace of tutoring to him/her based on his/her learning preferences.
- **Adaptation model**: It accepts information from the learning content and student model and makes choices about tutoring strategies and actions. At any point in the problem-solving process, the learner may request guidance on what to do next, relative to their current location in the model. In addition, the system recognizes when the learner has deviated from the production rules of the model and provides timely feedback for the learner, resulting in a shorter period of time to reach proficiency with the targeted skills. The adaptation model is aware of the progress of a learner and offers personalized tutoring and support.

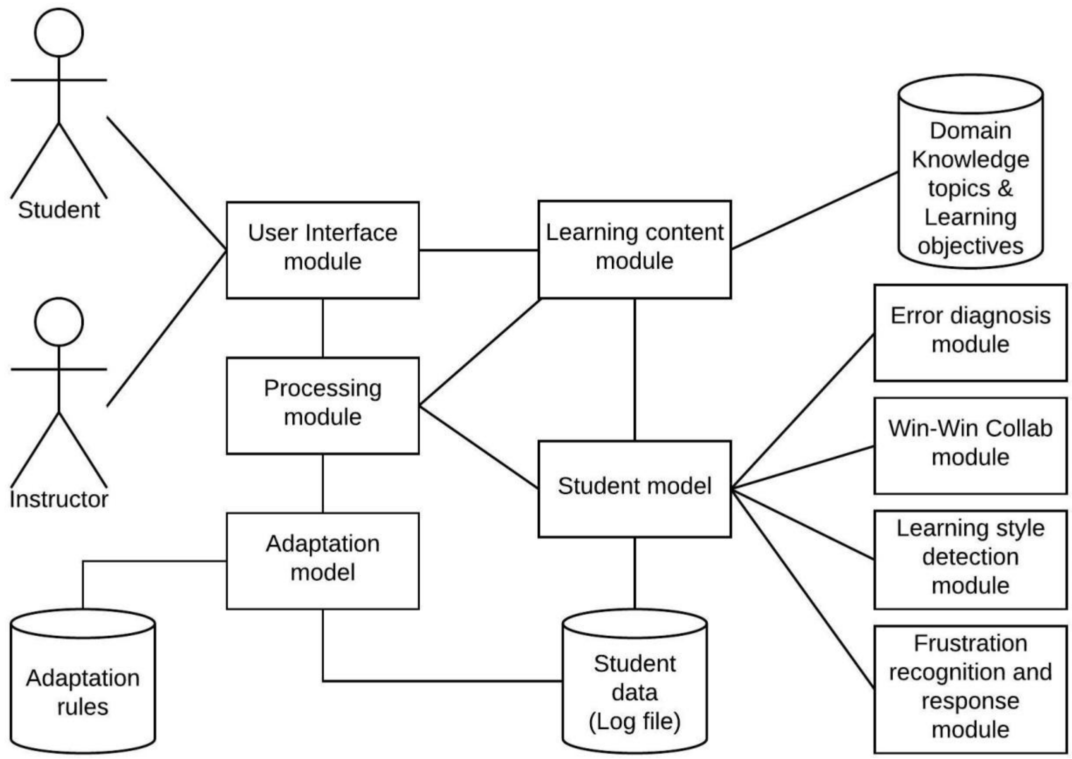

Figure 7. The architecture of POLYGLOT

3.2. POLYGLOT Implementation

POLYGLOT is a web-based adaptive and intelligent system for foreign language learning, incorporating social features. POLYGLOT is programmed using JAVA as the programming language. The following figures provide an overview of POLYGLOT.
Figures 8 and 9 show the log-in form and the registration form of POLYGLOT respectively. Figure 10 shows the start page of POLYGLOT. Figure 19 shows a start page of POLYGLOT. Figures 11 and 12 illustrate the statement of personal students' information and the preliminary test respectively. Through the preliminary test, POLYGLOT acquires information about the initial knowledge level of the student. Figure 13 illustrates the two different ways for detecting the learning style based on Felder and Silverman model; the first way is the automatic way, by simply pressing the corresponding button, while the second way is to answer the Felder and Silverman questionnaire, as shown in Figure 14. Figures 15 and 16 show a sample of the learning content of the English and French languages respectively. Figures 17 and 18 illustrate a chapter test (multiple choice test) and the results of this test respectively. Figures 19 and 20 show the final test (fill-in the gaps questions) and its results respectively.

Figure 21 illustrates the overall results, which each student can check along with charts that show graphically his/her progress in all the chapter tests and the final test. Figure 22 shows the wall on which each student can post along with the tagging activity, namely the capability of the student to tag the name of a classmate in order to address to him/her while posting on the wall. Figure 23 shows the notification message which notifies the student that a classmate tagged him/her. Figure 24 shows another way of communication between students or a student and the instructor through instant or asynchronous text messages. Figure 25 illustrates the declaration of a student's affective state, which may change after his/her interaction with POLYGLOT. Figure 26 shows a motivational message, which is delivered after the student's declaration of his/her affective state and before his/her interaction with POLYGLOT. After his/her interaction with POLYGLOT, namely taking part in an examination and liking/disliking the questions, the detection of frustration module is taking action and the motivational messages are tailored to his/her affective state. Figure 27 and 28 illustrate the two different ways of recommendation towards win-win collaboration concerning the student's knowledge level and type of conducted errors respectively. Figure 29 shows the first page of the authoring tool that the instructor can see. Figure 30 illustrates the authoring of the learning content of both foreign languages and also shows the authoring of the course quizzes. Finally, Figure 31 shows information about the progress of each student along with a chart so that the instructor has a complete overview about the progress of the students.

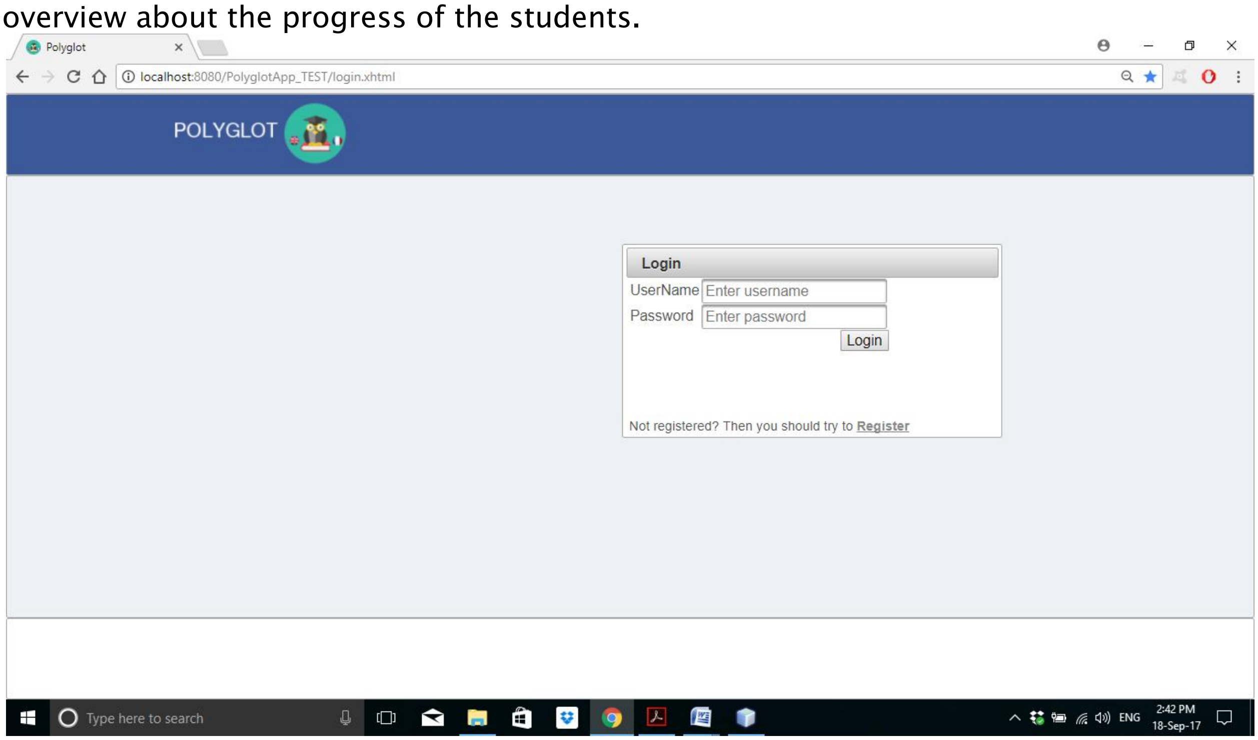

Figure 8. Log-in form

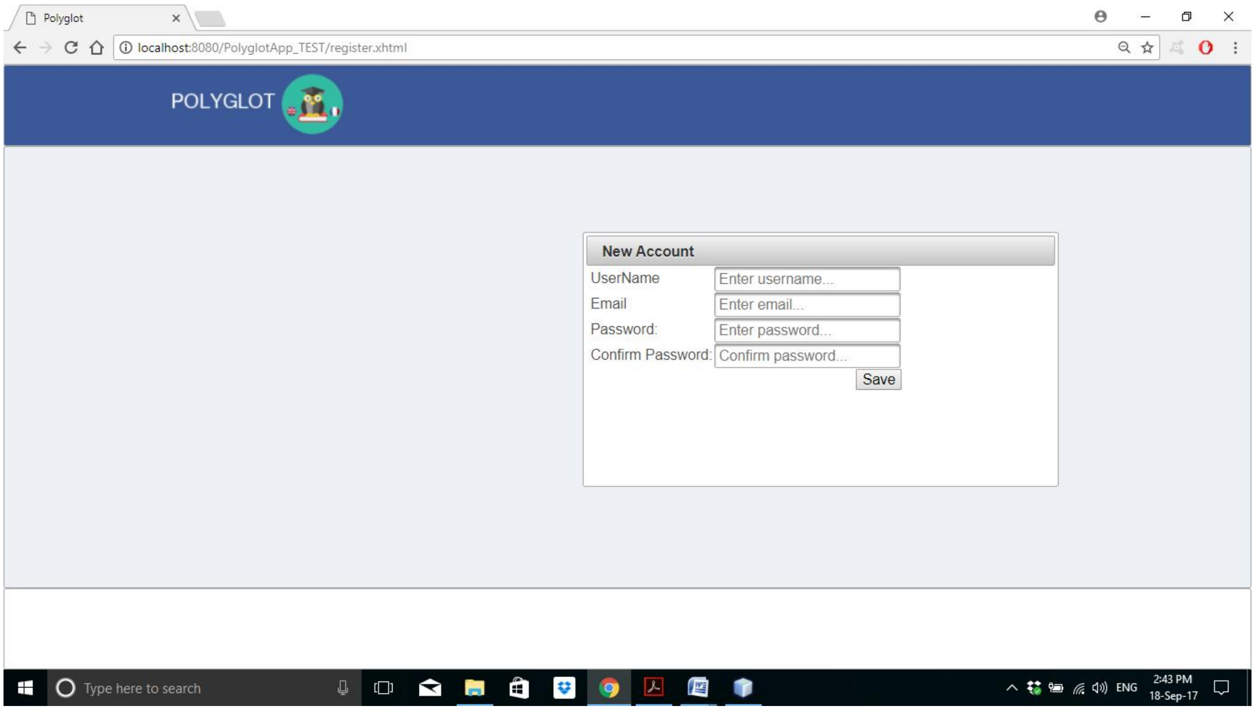

Figure 9. Registration form

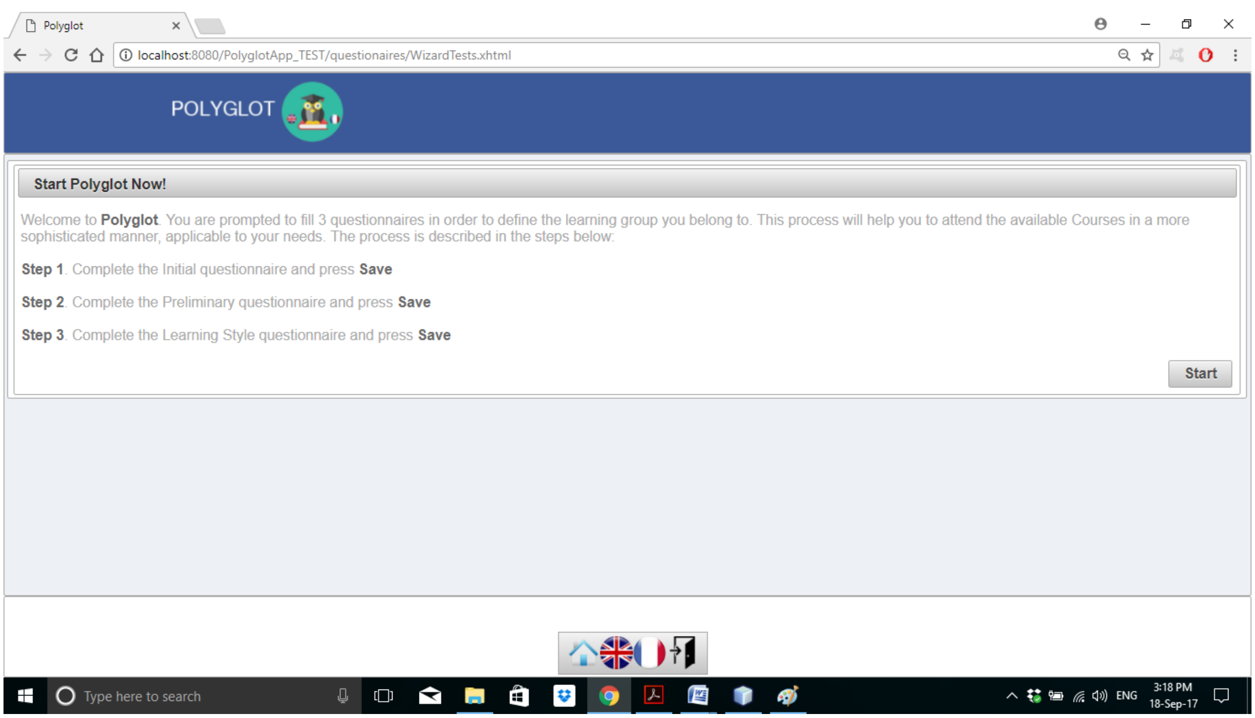

Figure 10. Start page of POLYGLOT

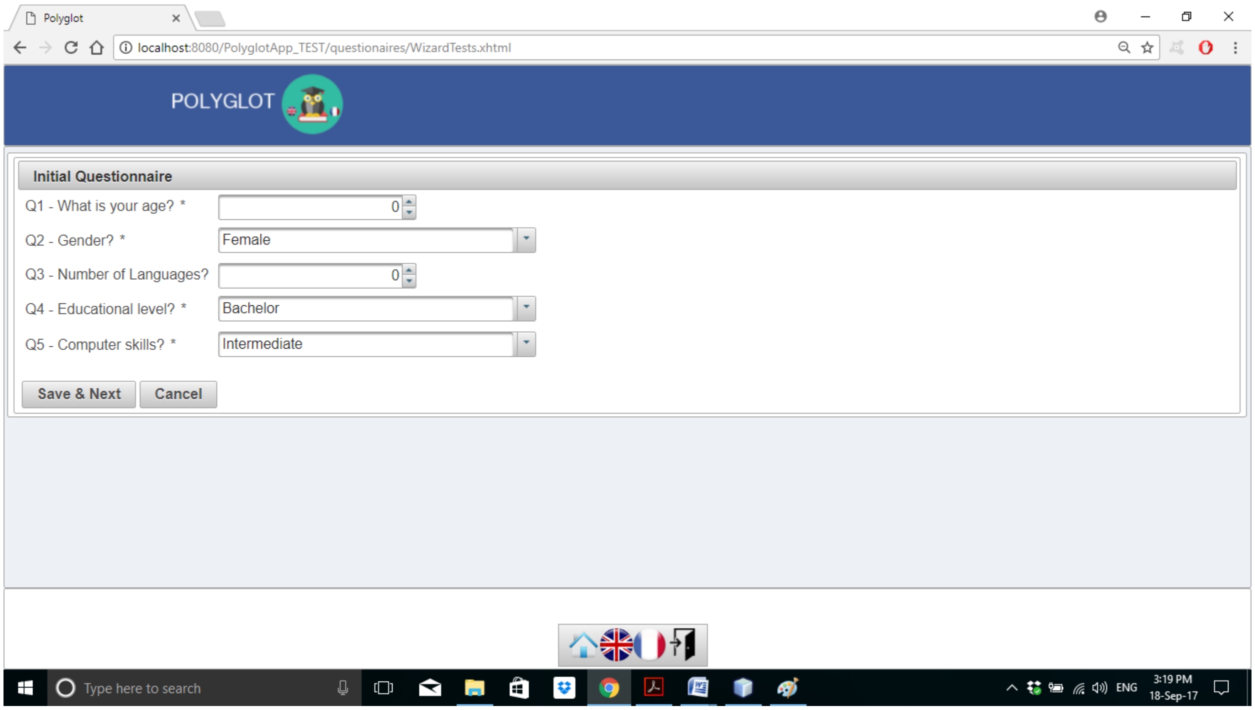

Figure 11. Initialization of POLYGLOT's student model

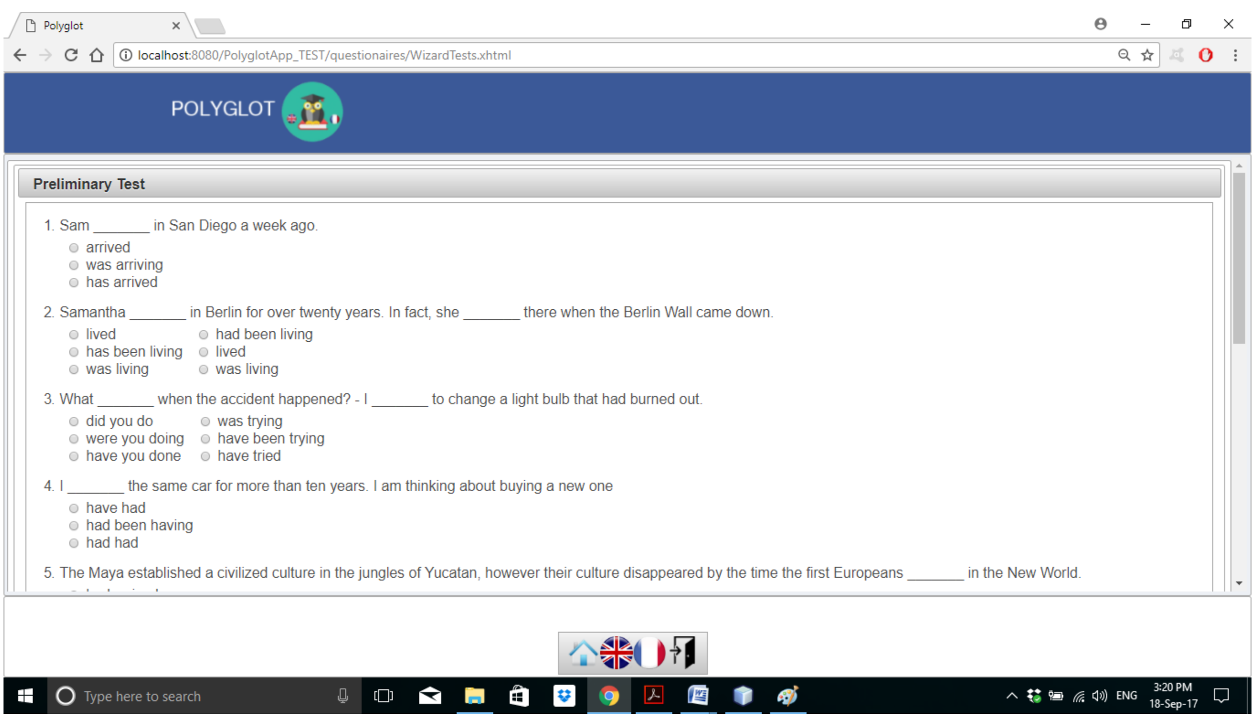

Figure 12. Preliminary Test

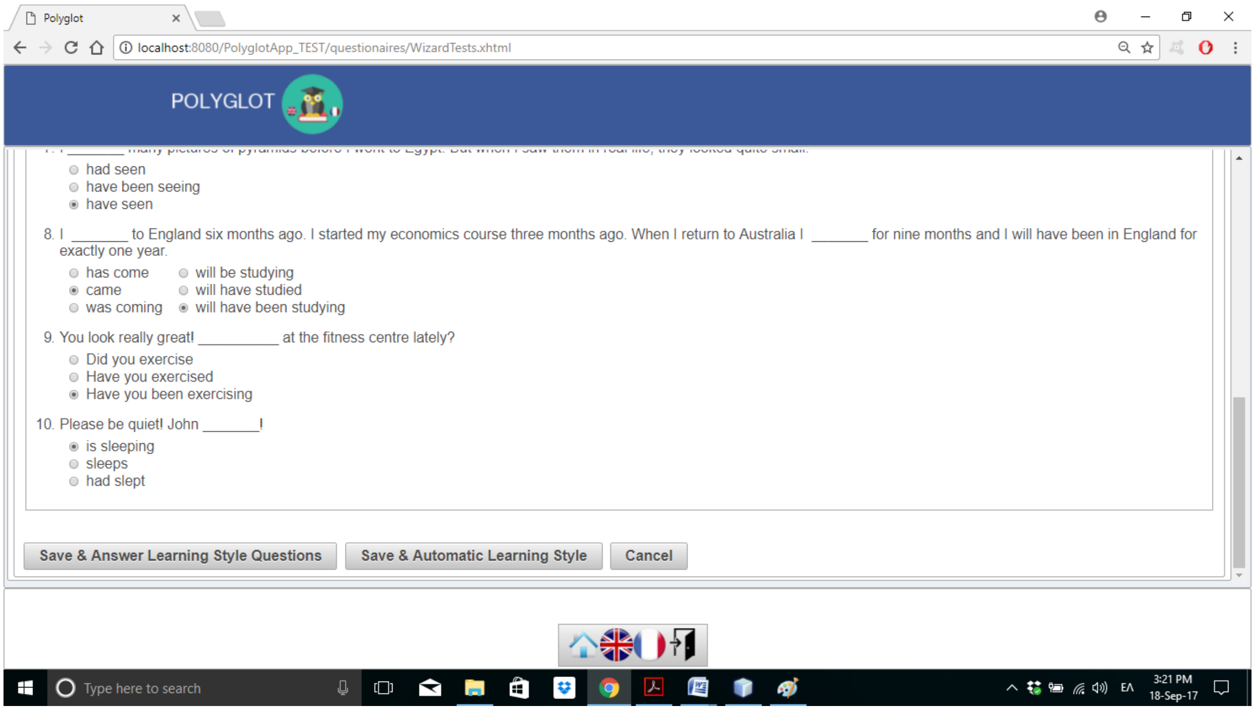

Figure 13. Two ways of detecting students' learning styles

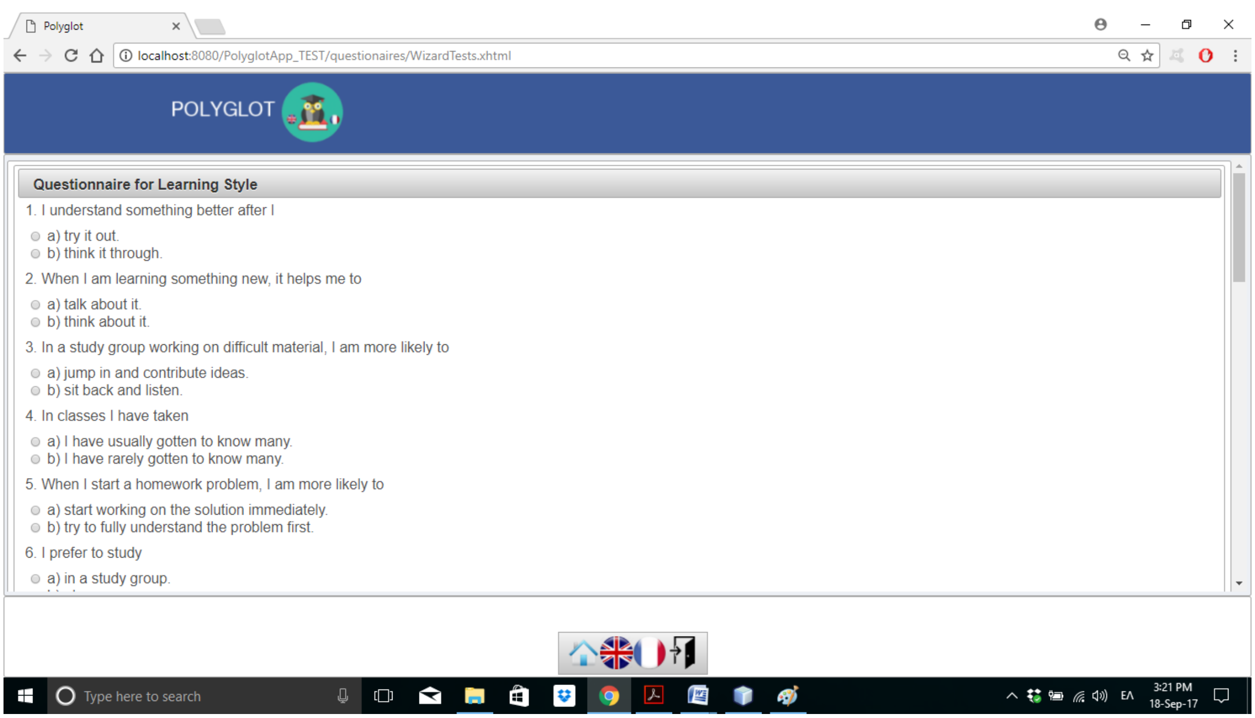

Figure 14. Questionnaire to detect learning style

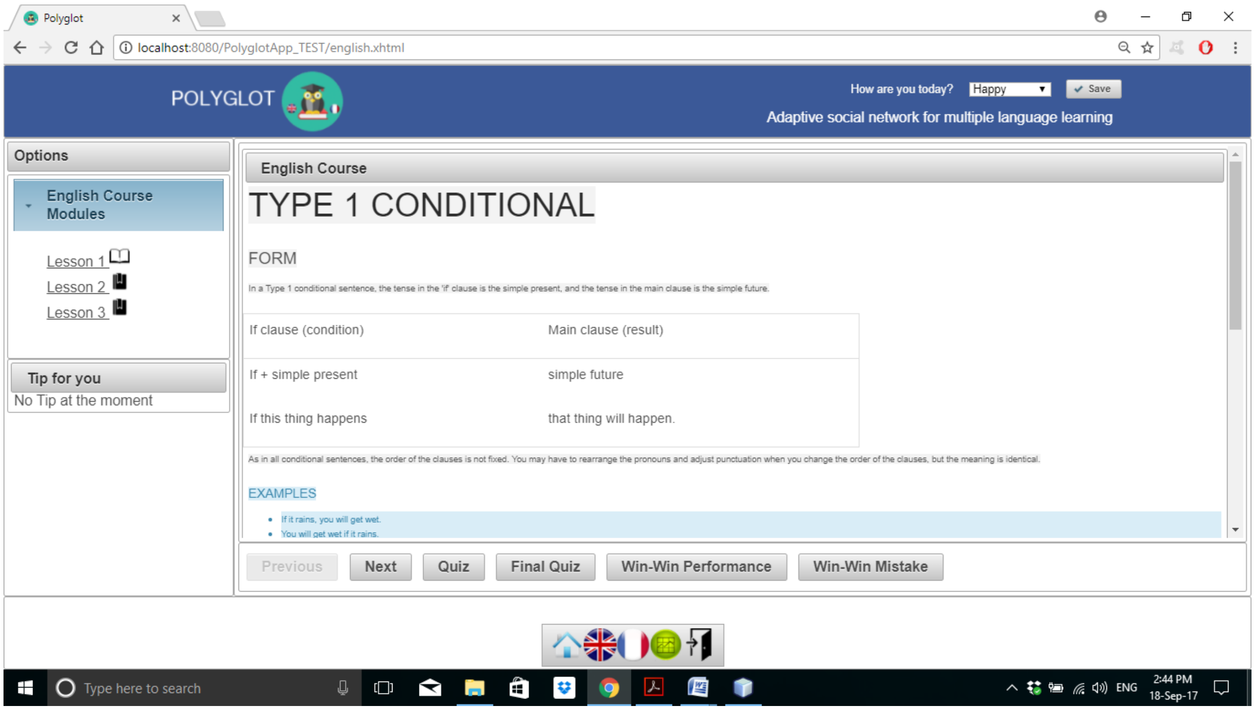

Figure 15. Learning content in the English language

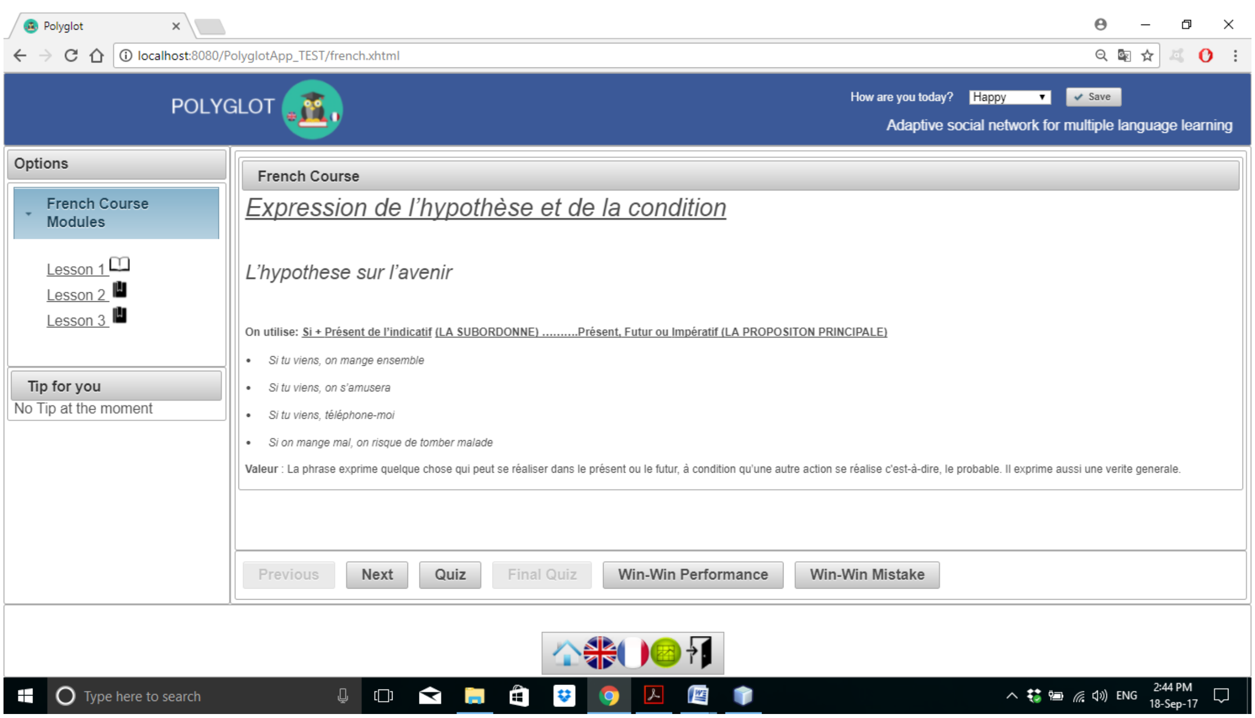

Figure 16. Learning content in the French language

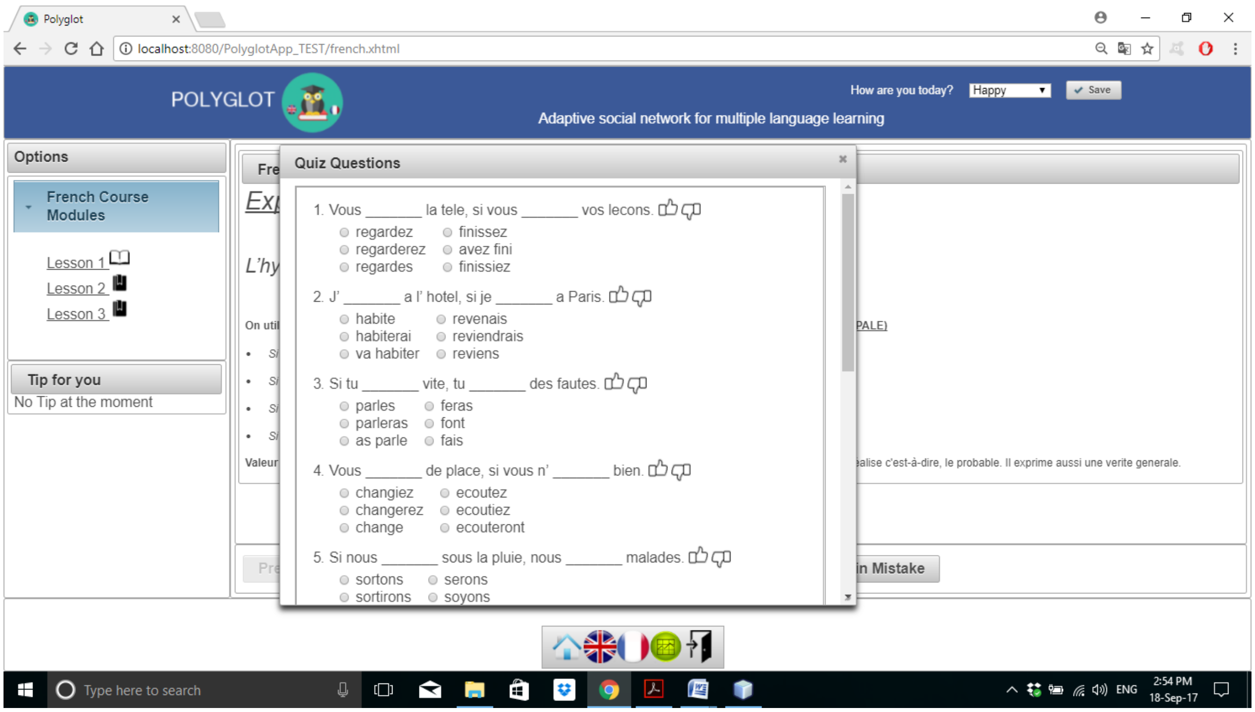

Figure 17. Sample of chapter test (multiple choice exercise)

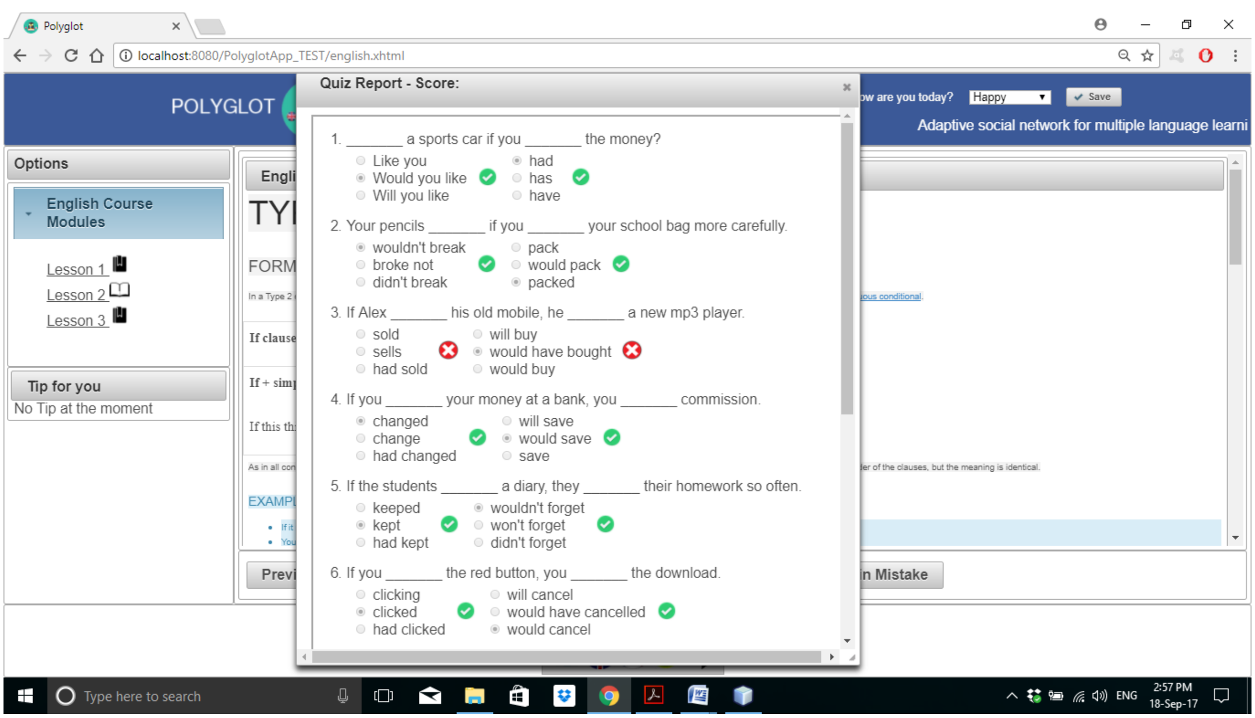

Figure 18. Results of chapter test

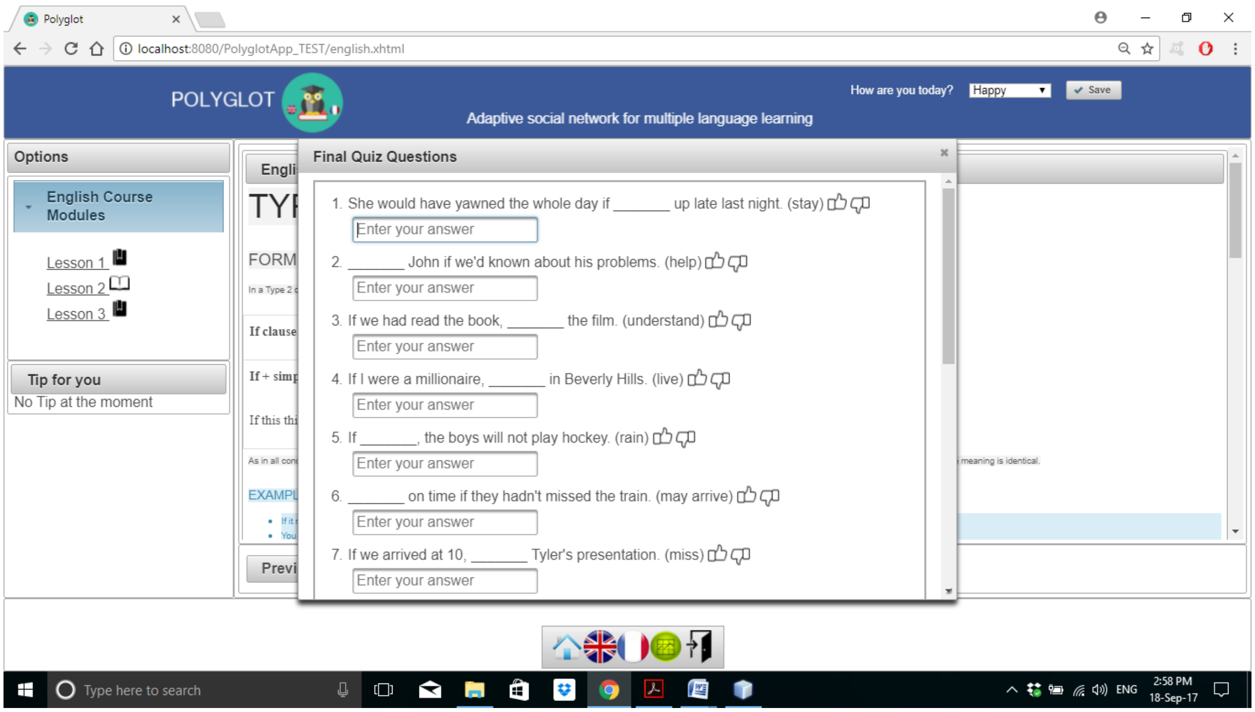

Figure 19. Sample of the final test (fill-in the gaps exercise)

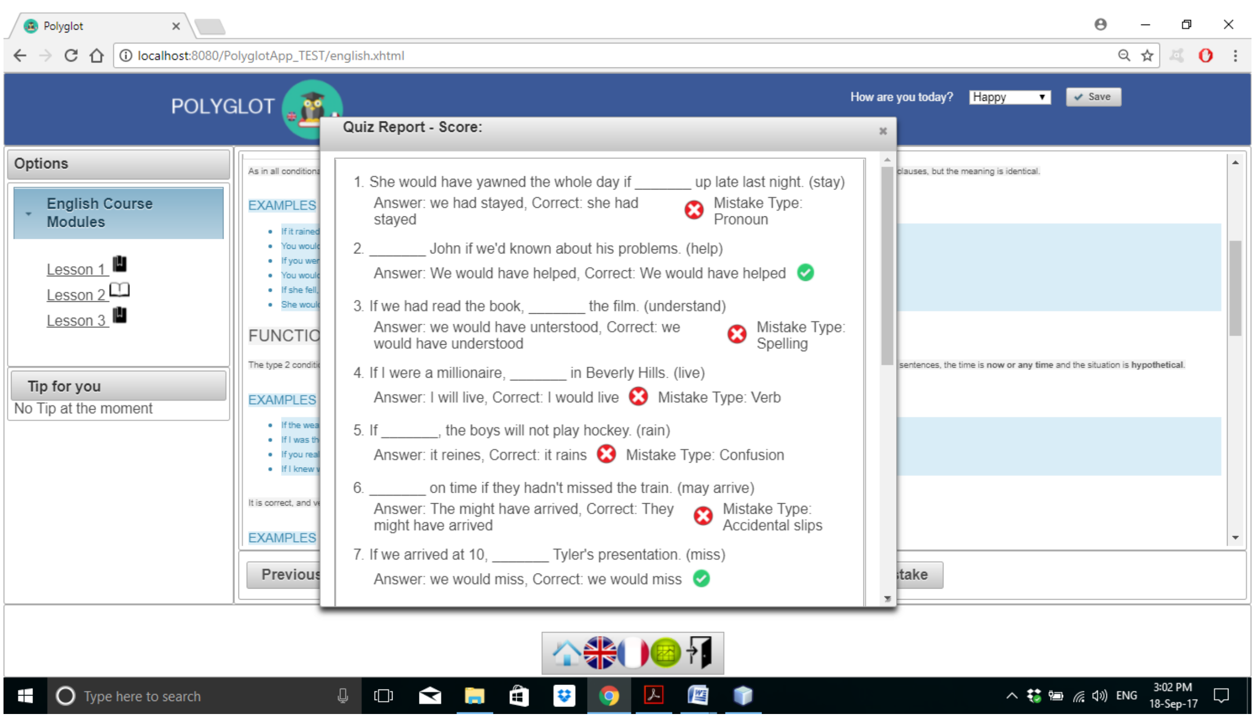

Figure 20. Results of final test

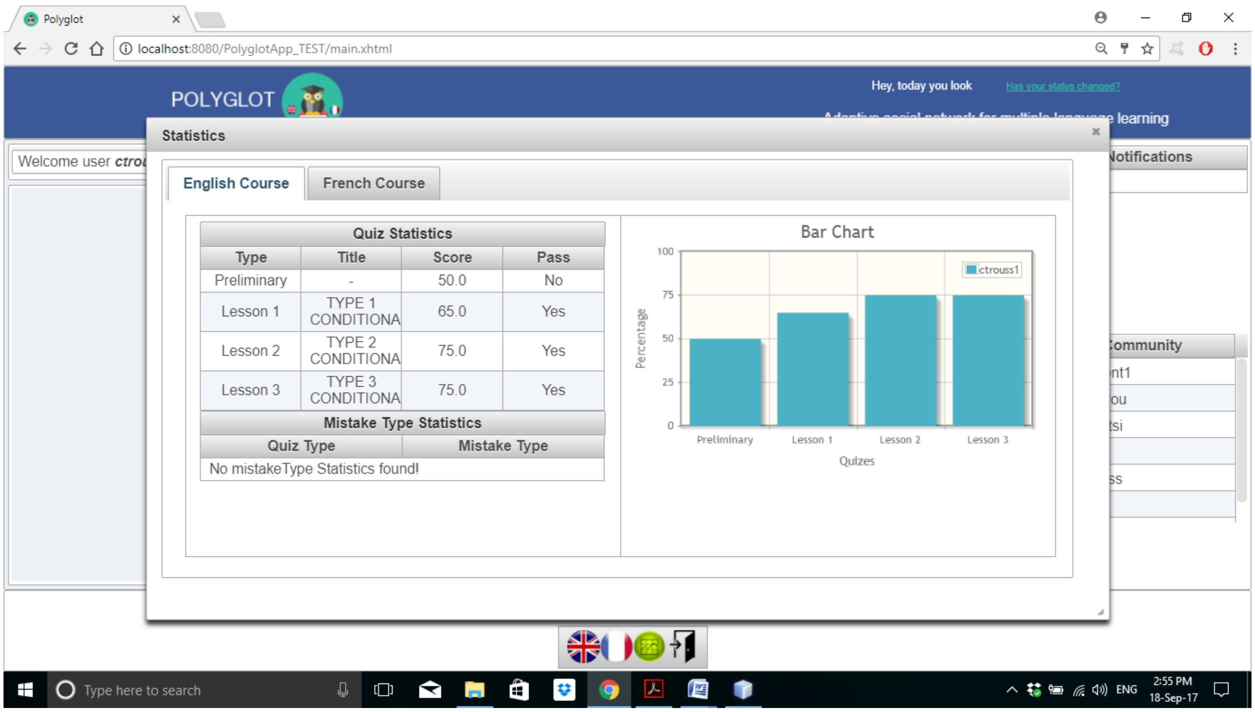

Figure 21. Overall results of the student-Progress

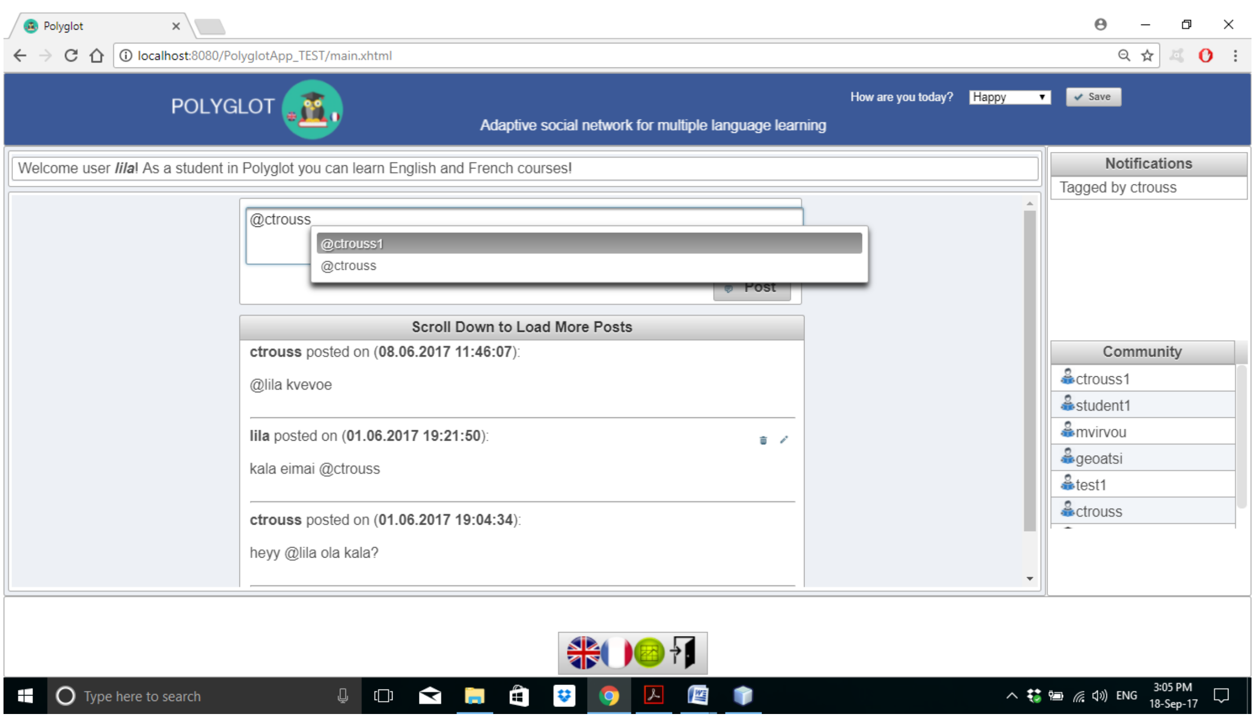

Figure 22. Posting on wall and tagging a classmate

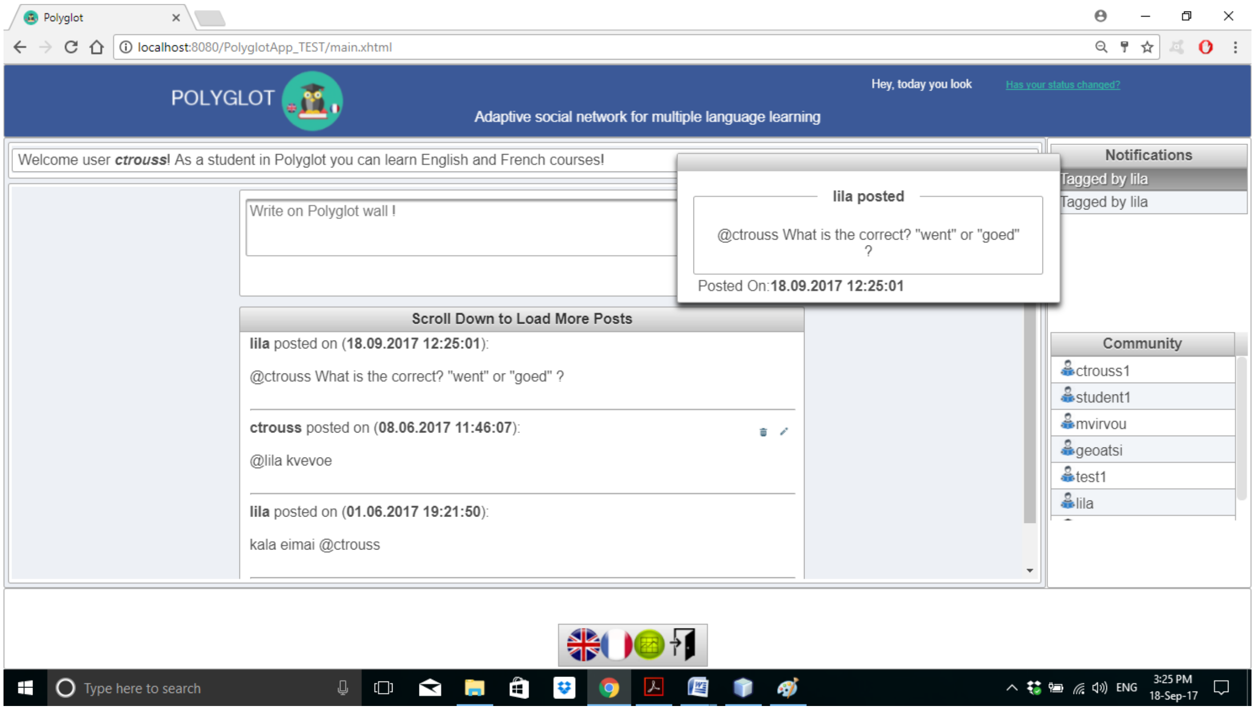

Figure 23. Notification of tagging

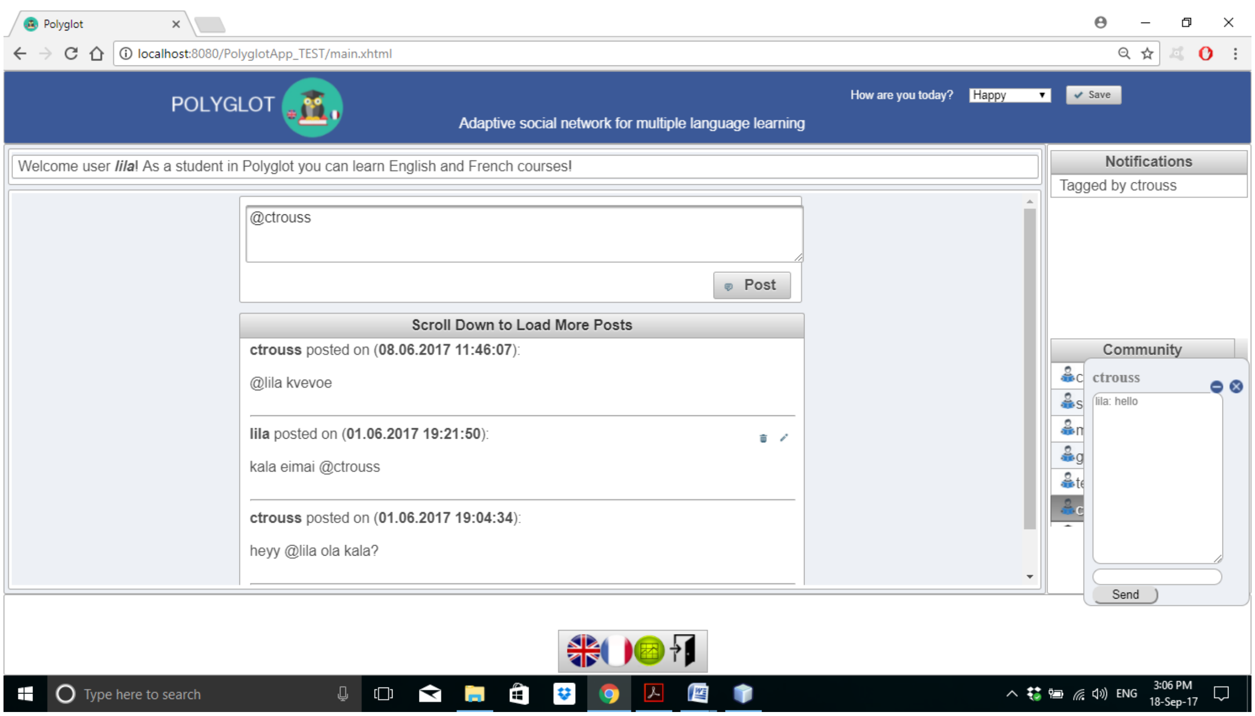

Figure 24. Instant and asynchronous text messaging

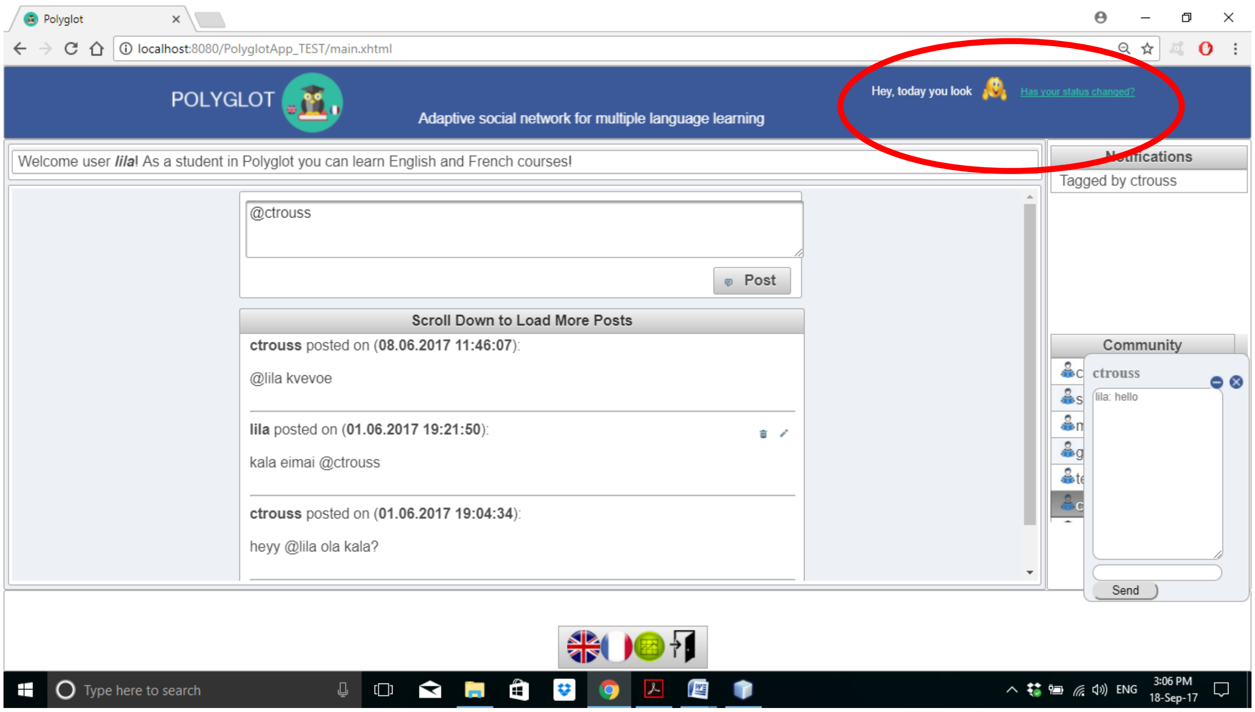

Figure 25. Student's declaration of affective state

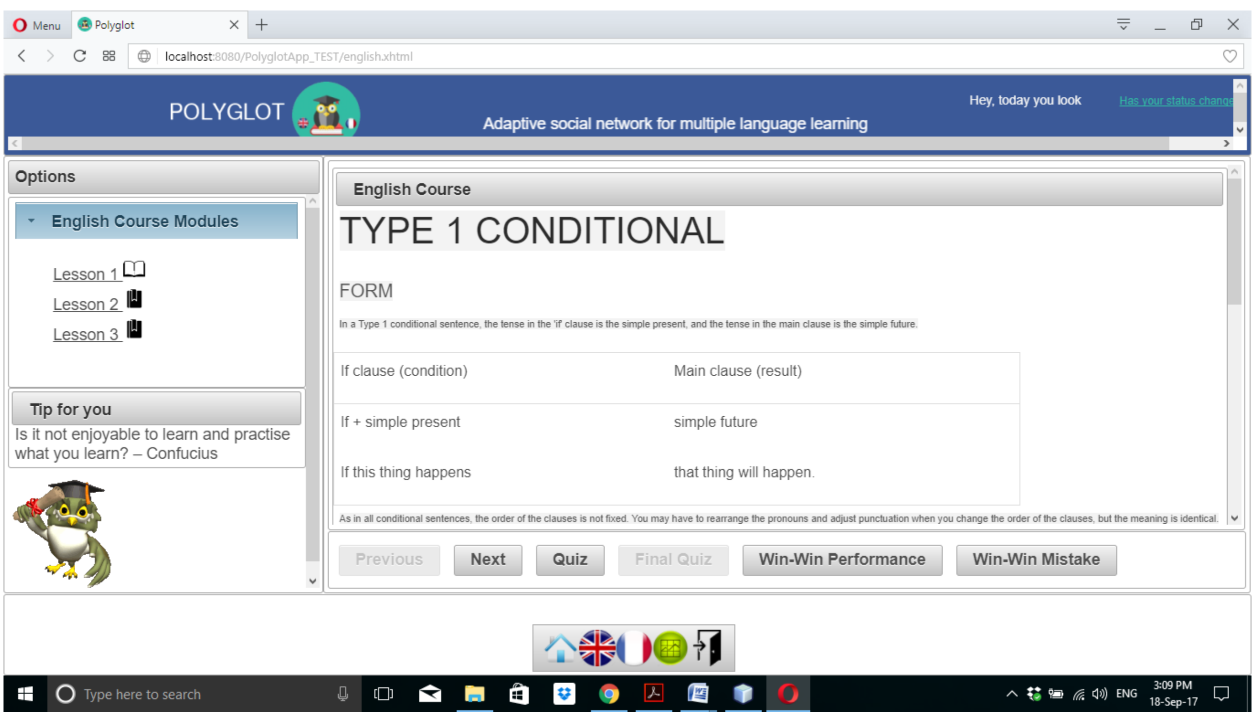

Figure 26. Motivation message after the affective state declaration (and before taking a test)

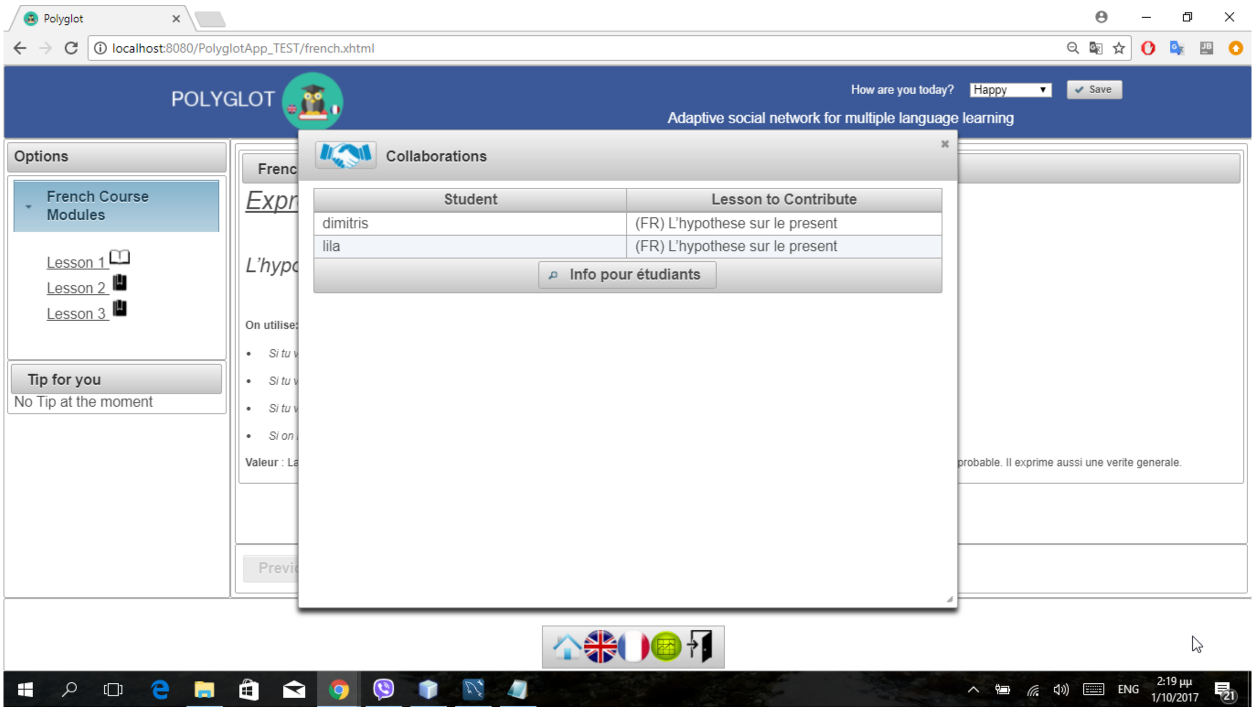

Figure 27. Win-win collaboration based on knowledge level

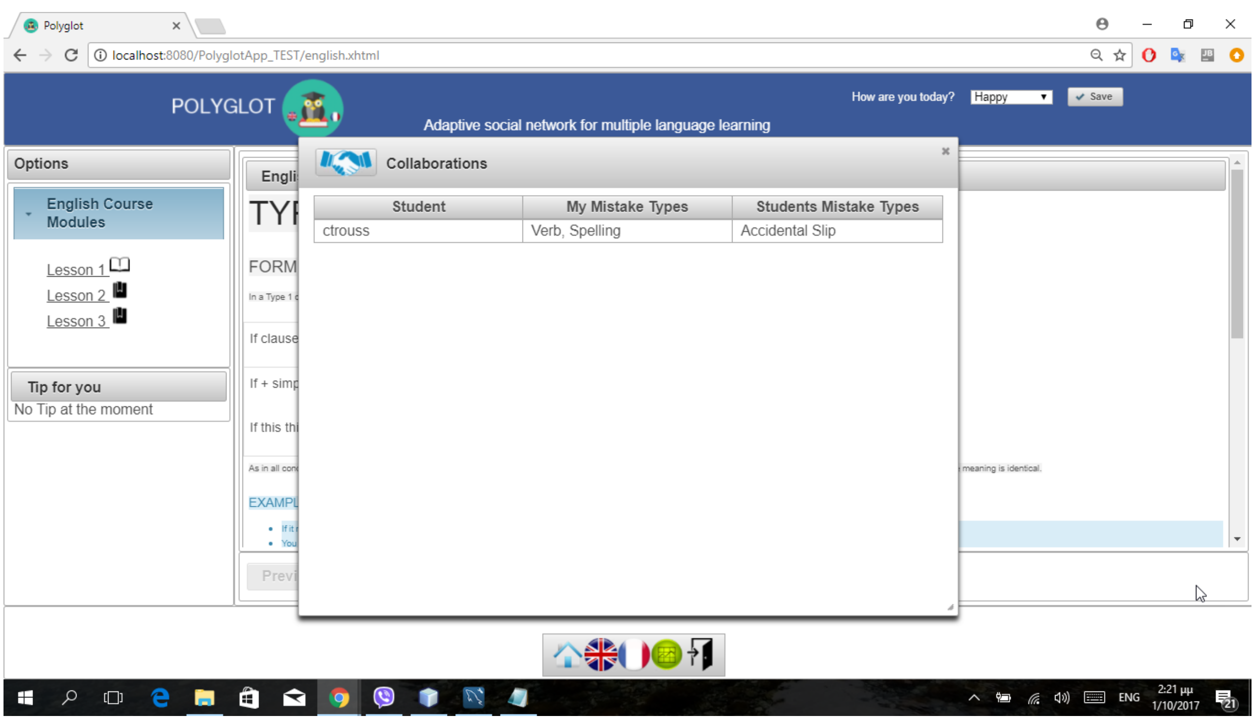

Figure 28. Win-Win collaboration based on types of mistakes

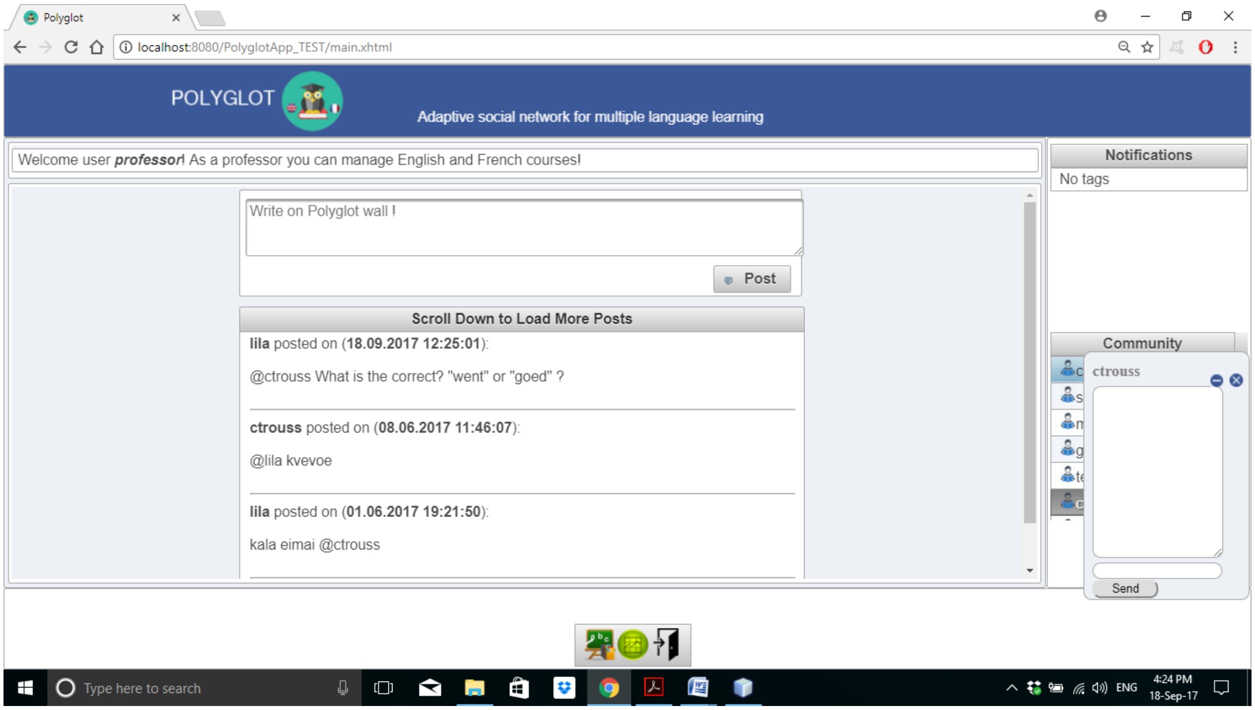

Figure 29. Authoring tool–First page of instructor

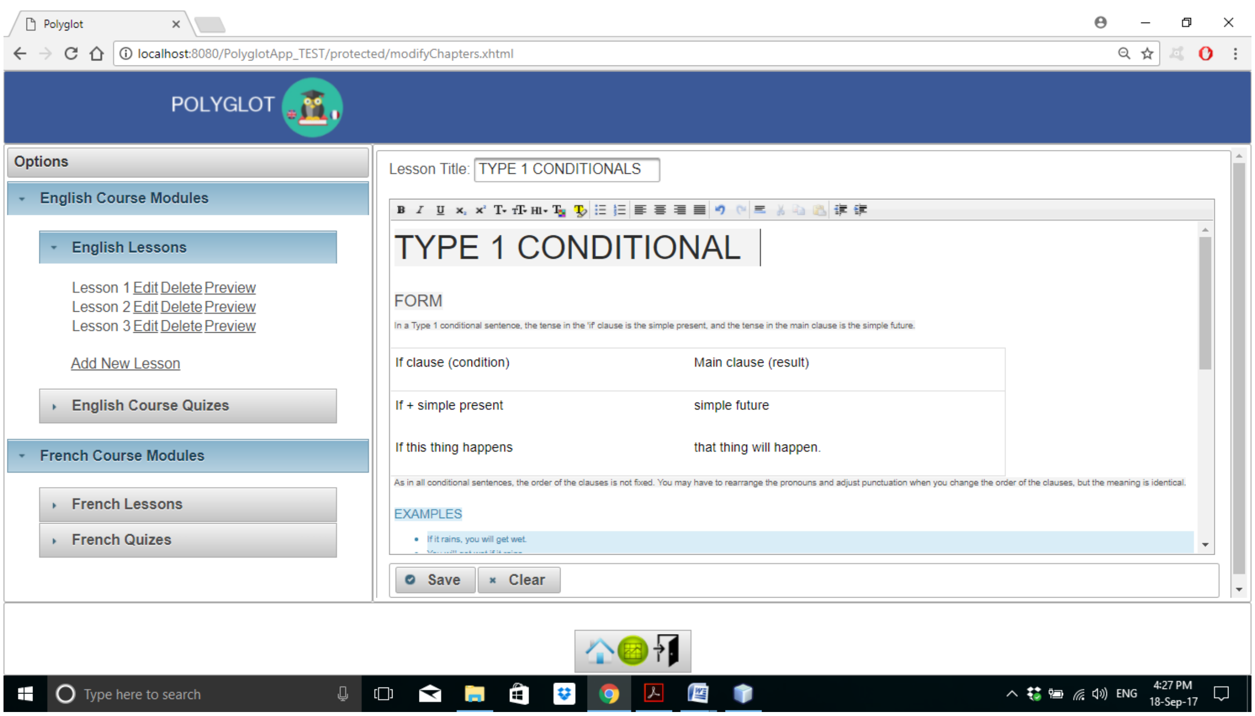

Figure 30. Authoring of the learning content and the Course tests

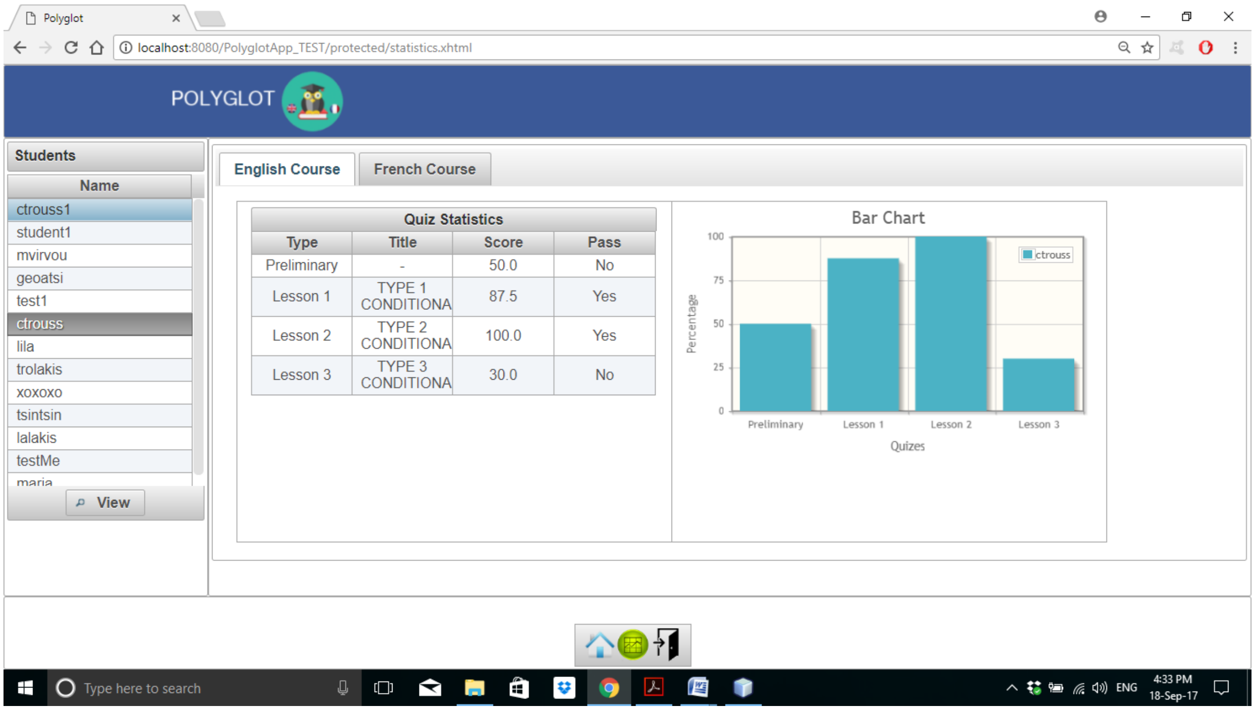

Figure 31. Information and charts for students' progress

Chapter 4:

Student modeling based on the Krashen's Theory and Felder-Silverman Model

4.1. Employing the Stephen Krashen's Theory of Second Language Acquisition in POLYGLOT

POLYGLOT is an adaptive e-learning system for the tutoring of foreign languages. As such, it is based on the Krashen's theory of second language acquisition (Krashen, 1982), consisting of five main hypotheses:

- the Acquisition-Learning hypothesis,
- the Monitor hypothesis,
- the Input hypothesis,
- the Natural Order hypothesis,
- the Affective Filter hypothesis.

The Acquisition-Learning distinction is the most fundamental of all the hypotheses in Krashen's theory. According to the theory, there are two independent systems of second language performance: 'the acquired system' and 'the learned system'. The 'acquired system' or 'acquisition' is the product of a subconscious process very similar to the process children undergo when they acquire their first language. It requires meaningful interaction in the target language - natural communication - in which students are concentrated not in the form of their utterances, but in the communicative act. The "learned system" or "learning" is the product of formal instruction and it comprises a conscious process which results in conscious knowledge 'about' the language, for example knowledge of grammar rules. Towards this direction, POLYGLOT was designed to provide the English and French language concepts and namely the three types of conditionals in both languages in a formal way of instruction, giving the theoretical and grammar rules followed by examples. Moreover, the learning material can be changed by the instructor with the use of POLYGLOT's authoring tool. Furthermore, POLYGLOT supports two different kinds of communication. The first one is the posting on a wall, where all the students can communicate and work on a project with peers or with the instructor. The second way of communication is the asynchronous and instant text messaging between two students or a student and the instructor.

The Monitor hypothesis explains the relationship between acquisition and learning and defines the influence of the latter on the former. The monitoring function is the practical result of the learned concept. According to Krashen, the acquisition process is the utterance initiator, while the learning process performs the role of the “monitor”. The “monitor” acts in a planning, editing and correcting function when a specific condition is met, namely the second language learner has sufficient time at his/her disposal in order to think about the correctness of the question provided that s/he has studied the rule. To this direction, POLYGLOT separates the acquisition process from the learning–“monitor” process, by giving to the students the opportunity to learn and be evaluated without time constraints. However, POLYGLOT keeps this information in its log file and uses it when needed. Moreover, POLYGLOT performs the monitoring function by diagnosing students’ possible misconceptions and providing assistance when needed. As shown in Chapter 5, the performance of students depicting the influence of the learning on acquisition is found to be outstanding based on the evaluation results.

The Input hypothesis in Krashen's theory explains how the learner acquires a second language, namely how the second language acquisition takes place. The Input hypothesis is only concerned with 'acquisition', not 'learning'. According to this hypothesis, the learner improves and progresses when s/he receives second language “input” that is one step beyond his/her current stage of linguistic competence. For example, if a learner is at a level “i”, then acquisition takes place when s/he is exposed to level “i + 1”. To this direction, POLYGLOT holds information about the knowledge level of the student, even from his/her first interaction with the system and performs adaptive actions in order to ensure personalization in the learning process.

The Natural Order hypothesis suggested that the acquisition of grammatical structures follows a “natural order” which is predictable. For a given language, some grammatical structures should be acquired in a proper sequence. This order seemed to be independent of the learners' age, background and conditions of exposure. Indeed, POLYGLOT has a logical gradation of the learning concepts, proceeding from the First type of conditional to the Second etc. As such, this serial presentation of the learning material presents inputs to enhance the progress of the students.

Finally, the fifth hypothesis, that is the Affective Filter hypothesis, embodies Krashen's view that a number of “affective variables” plays a facilitative role in second language acquisition. One important variable for this is the motivation. Krashen claims that learners with high motivation are better equipped for success in second language acquisition. Low motivation can "raise" the affective filter and form a "mental block" that prevents comprehensible input from being used for acquisition. In other words, when the filter is "up", it impedes language acquisition. On the other hand, positive affect is necessary for acquisition to take place. Following this rationale, POLYGLOT incorporates the delivery of motivational messages which can assist the students during their interaction with the system. Moreover, it also detects frustration that can lead to "mental block" and provides motivational messages based on the Attribution Theory, which will be described later in this chapter. Figure 32 illustrates the incorporation of the Krashen's theory in POLYGLOT.

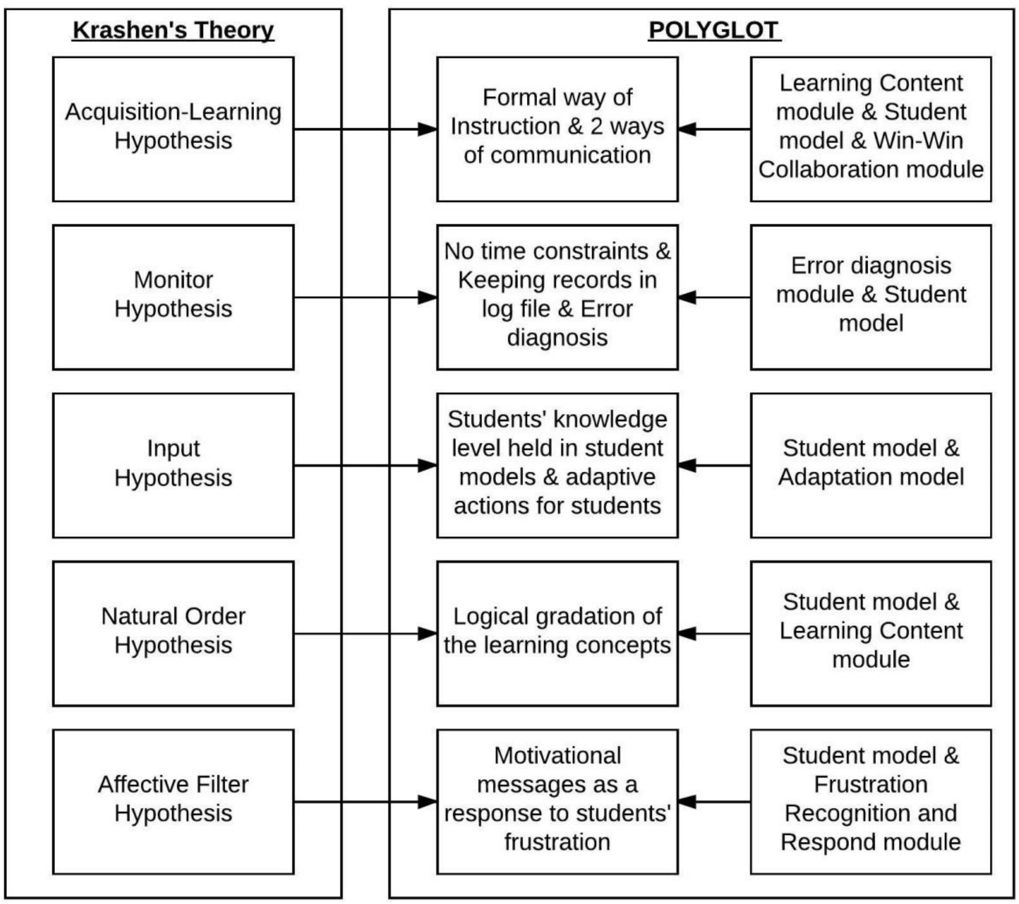

Figure 32. Incorporation of Krashen's theory in POLYGLOT

More specifically, the Learning Content module in conjunction with the Student Model and the Win-Win Collaboration module are used to support the Acquisition-Learning hypothesis and provide a formal way of instruction and two distinct ways of collaboration, namely posting on wall, instant and asynchronous text messaging and recommendation for effective collaboration. Following, the POLYGLOT Student model and Error diagnosis module are used in order to support the Monitor hypothesis, by providing no time constraints, keeping records in the log file and diagnosing students' misconceptions. The Student model and the Adaptive module are used to support the Input hypothesis by keeping the student's knowledge and performing adaptive actions to students' needs and preferences. Moreover, the Student model and the Learning Content module are used to support the Natural Order Hypothesis by offering logical gradation of the learning concepts. Finally, the Student model and the Frustration Recognition and Respond module are used to support the Affective Filter hypothesis by delivering motivational messages as a response to student's frustration. The aforementioned hypotheses are primarily presented at Chapter 3 and will be further explained afterwards.

4.2. POLYGLOT Learning Content

The domain knowledge of POLYGLOT consists of the grammar phenomenon both in the English and in French language.

The full conditional sentences in both languages consist of condition clauses specifying a condition or hypothesis, and a consequence clause or apodosis specifying what follows from that condition. The condition clause is a dependent clause, most commonly headed by the conjunction if, while the consequence is contained in the main clause of the sentence.

Different types of conditional sentences (depending largely on whether they refer to a past, present or future time frame) require the use of particular verb forms (tenses and moods) to express the condition and the consequence. In both languages teaching, the most common patterns are referred to as first conditional, second conditional and third conditional.

Each student can be taught each type of conditionals of both foreign languages in a logical row, which can be depicted in a hierarchical tree. However, as will be shown below, the way of learning is tailored to each student's preferences based on his/her learning style according to the Felder and Silverman model. Particularly, if the student is sequential, then s/he will be given each chapter after the successful completion of the former. If the student is global, then all the chapters are delivered to him/her at his/her first interaction with the system. In both cases, the serial learning can be followed. Also, the hierarchy of this tree depicts the sequencing of levels of the domain concepts of the learning material. The creation of the hierarchy is based on the aforementioned Krashen's model. For instance, the teaching of the first type of conditional precedes the teaching of the third type of conditional which presupposes the learning of the second type of conditionals.

The hierarchy of the domain concepts of the POLYGLOT's learning material is depicted in Figure 33.

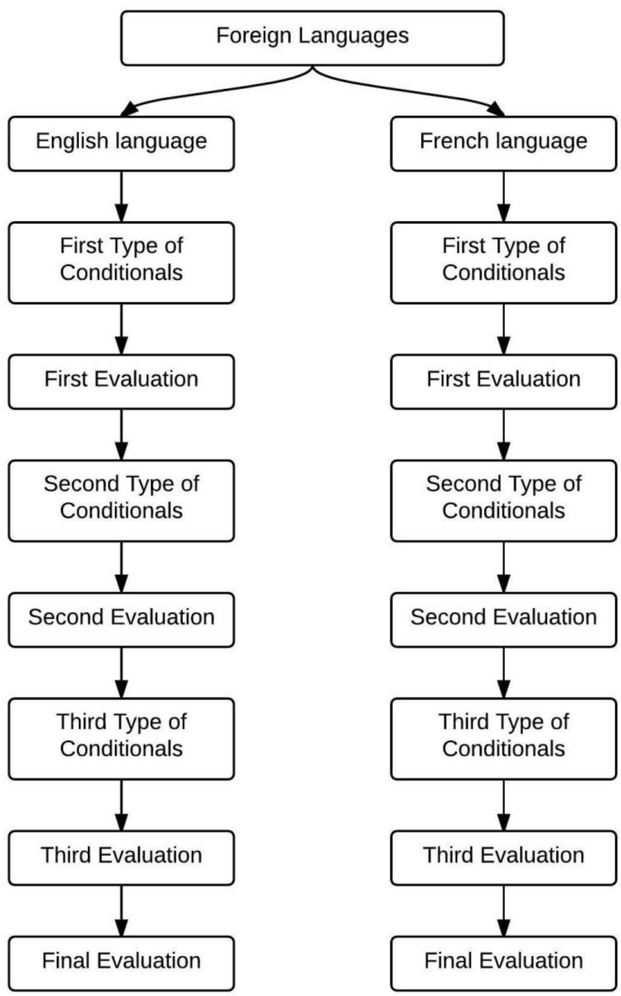

Figure 33. Hierarchy of POLYGLOT domain concepts

4.3. POLYGLOT Student model

POLYGLOT holds a student model which is responsible for adapting the learning content to the student using machine learning techniques, diagnosing the nature of student's misconceptions along with providing advice to them, when necessary.

More specifically, the student model of POLYGLOT holds static information about the students, and namely their age, gender, level of education, computer knowledge level, proneness to language learning or the foreign languages that they already know, the knowledge level of the student and the learning style in which each student belongs (Figure 34). Furthermore, it holds dynamic information such as their errors and misconceptions along with their progress, being deduced by the interaction between the student and the system. To this direction, POLYGLOT utilizes a multitier student model derived from the theory of the overlay models in conjunction with a multi-dimensional model (8 dimensions) derived from the theory of stereotypes. The overlay model represents the knowledge of the student, while the first dimension of the stereotype model represents the knowledge level of the student, the second dimension represents the type of the language learning misconceptions, the third dimension is the previous foreign language knowledge or proneness to foreign language learning, the fourth dimension is the age of the student, the fifth dimension is his/her gender, the sixth dimension is the level of education, the seventh dimension is the computer knowledge level and the eighth dimension is the learning style. Given that the representation of the student's mastery on a specific learning content is a crucial characteristic in a tutoring system, the overlay technique was chosen to model the learner's knowledge since it is appropriate for that.

The first layer of the aforementioned overlay model is related to the knowledge level of the student, as it results from his/her interaction with the system. The value of this model can be "novice", "intermediate" or "advanced", according to the ACTFL (American Council on the Teaching of Foreign Languages) Proficiency Guidelines[9] and Leung and Li (2007). Novice users are the ones who lack fundamental knowledge of the curriculum being taught. Intermediate users are the ones who have basic understanding of the curriculum while the advanced users can be seen as masters of

[9] https://www.actfl.org/publications/guidelines-and-manuals/actfl-proficiency-guidelines-2012

the curriculum. The guidelines are broken up into different proficiency levels, such as novice, intermediate and advanced. ACTFL provides a means of assessing the proficiency of a foreign language speaker.

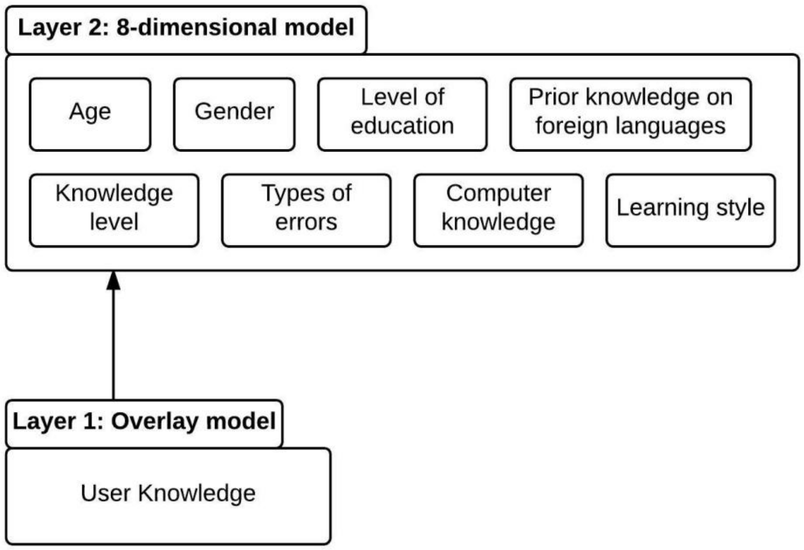

Figure 34. POLYGLOT's student model

However, defining the learner's knowledge level is not adequate in order to model individual students' needs and abilities. Towards this direction, POLYGLOT can perform misconception detection and diagnosis so that the student model can hold such kind of information. The types of misconceptions are of the following categories (Sermsook et al., 2017, Wu and Garza, 2014, Heift and Schulze, 2007 and Virvou et al., 2000):

- Accidental slips
- Pronoun mistakes
- Spelling mistakes
- Verb tense mistakes
- Language transfer interference

More specifically, accidental slips are occasional actions, which are not systematic and which the learner himself/herself can correct. For example, the student may have deleted some words and may have forgotten to complete the sentence. In the Table 4, a sample of accidental slips is shown.

Table 4. Sample of accidental slips

Accidental slips			
Answer with accidental slip	She would have had two laptops if she had digned the contract. (sign)	You would save energy if you sqitched off the lights more often. (switch)	If we had read the book, we would have unferstood the film. (understand)
Answer without accidental slip	She would have had two laptops if she had signed the contract. (sign)	You would save energy if you switched off the lights more often. (switch)	If we had read the book, we would have understood the film. (understand)

The pronoun mistakes concern the improper handling of the person. The person refers to the differences among the person speaking (first person), the person spoken to (second person), and the person or thing being spoken about. The common pronoun errors are related to the inappropriate shift in person or in number and the use of the wrong form of a pronoun or the wrong pronoun, being confused when the pronoun is part of a compound subject or object. Table 5 gives an insight to this error category.

Table 5. Sample of Pronoun mistakes

Pronoun mistakes			
Answer with pronoun mistakes	If she had worn a lighter jacket, the car driver would have seen you earlier. (wear)	You would have watched TV tonight if Peter hadn't bought the theatre tickets for us. (watch)	Them might have arrived on time if they hadn't missed the train. (might arrive)
Answer without pronoun mistakes	If you had worn a lighter jacket, the car driver would have seen you earlier. (wear)	We would have watched TV tonight if Peter hadn't bought the theatre tickets for us.	They might have arrived on time if they hadn't missed the train. (might arrive)

		(watch)	

A spelling mistake occurs when the user has typed the expected word so that one letter is redundant or missing or two neighboring letters have been interchanged. For example, the student has typed “fahter” instead of “father”. Table 6 provides examples concerning the spelling mistakes.

Table 6. Sample of spelling mistakes

Spelling mistakes			
Answer with spelling mistakes	If it rianed, we wouldn’t be in the garden. (rain)	I could scor better on the test if the teacher explained me the grammar once more. (can score)	If he greew his own vegetables, he wouldn't have to buy them. (grow)
Answer without spelling mistakes	If it rained, we wouldn’t be in the garden. (rain)	I could score better on the test if the teacher explained me the grammar once more. (can score)	If he grew his own vegetables, he wouldn't have to buy them. (grow)

The verb tense mistakes occur when using tenses in a wrong way. For example, the user may have typed “been” instead of “being”. Table 7 shows examples of this category.

Table 7. Sample of verb tense mistakes

Verb tense mistakes			
Answer with verb tense mistakes	If it rained, the boys will not play hockey. (rain)	Wouldn’t you go out more often if you have to see some friends? (have to see)	She would have yawned the whole day if she has stayed up late last night. (stay)
Answer without verb tense mistakes	If it rains, the boys will not play hockey.	Wouldn’t you go out more often if	She would have yawned the

	(rain)	you had to see some friends? (have to see)	whole day if she had stayed up late last night. (stay)

This type of errors when the student uses his/her knowledge and experience in a foreign language as a means of organizing the second language. In POLYGLOT, students can learn two foreign languages, namely English and French; as such, there is the possibility of being confused when learning these two languages at the same time. Table 8 provides example, concerning the transfer between the two languages that can lead to mistakes.

Table 8. Sample of language transfer interference mistakes

Language transfer interference			
Answer with Language transfer interference mistakes	If you sait a minute, I'll come with you. (wait)	If we arrived at 10, we would mise Tyler's presentation. (miss)	If I went anywhere, it would beau New Zealand. (to be)
Answer without Language transfer interference mistakes	If you wait a minute, I'll come with you. (wait)	If we arrived at 10, we would miss Tyler's presentation. (miss)	If I went anywhere, it would be New Zealand. (to be)

4.3.1. Approximate String Matching for error diagnosis

In order to successfully recognize one or more of the aforementioned categories of errors, POLYGLOT incorporates two algorithmic approaches, as illustrated in Figure 35. The first technique is the Approximate String Matching and tries to find string similarities by matching a student's given "exact" wrong answer with the systems correct stored answer. This technique is responsible for finding strings that match a pattern approximately. The problem of approximate string matching is typically divided into two sub-problems: finding approximate substring matches inside a given string and finding dictionary strings that match the pattern approximately. If string matching occurs in a high percentage, POLYGLOT decides whether the mistake lies among the categories of accidental slips, pronoun mistakes, spelling mistakes or verb mistakes.

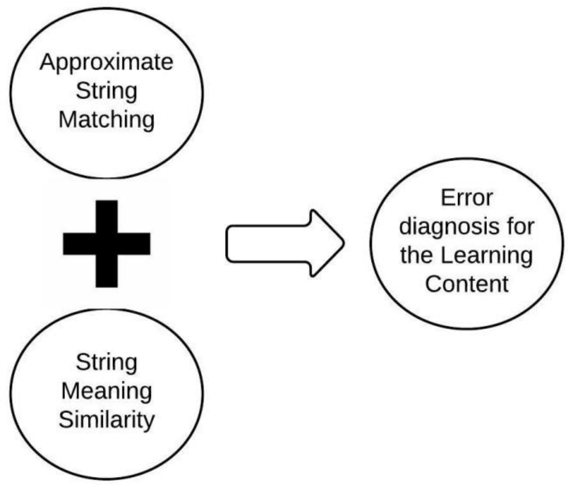

Figure 35. Hybrid model for error diagnosis

The closeness of a match is measured in terms of the number of primitive operations necessary to convert the string into an exact match. This number is called the edit distance between the string and the pattern. The usual primitive operations are:

- insertion: For example, the student may have typed cooat, instead of the coat.
- deletion: For example, the student may have typed cot, instead of coat.
- substitution: For example, the student may have typed cost, instead of coat.

POLYGLOT employs the following formulation of the problem: for each position j in the text $T = t_1 t_{2...} t_n$ and each position i in the pattern $P = P_1 P_{2...} P_m$, it computes the minimum edit distance between the i first characters of the pattern, P_i, and any substring $T_{j'j}$ of T that ends at position j.

For each position j in the text T, and each position i in the pattern P, POLYGLOT goes through all substrings of T ending at position j, and determines which one of them has the minimal edit distance E(i, j) to the i first characters of the pattern P. After computing E(i, j) for all i and j, it finds the solution, which is the substring for which E(m, j) is minimal (m being the length of the pattern P).

Computing E(m, j) coincides with the computing of the edit distance between two strings. In fact, POLYGLOT uses the Levenshtein για E(m, j); the only difference is the initialization of the first row with zeros, and saving the path of computation, that is, whether we used E(i − 1, j), E(i, j − 1) or E(i − 1, j− 1) in computing E(i, j).

In the array containing the E(x, y) values, POLYGLOT then chooses the minimal value in the last row, let it be E(x2, y2), and follow the path of computation backwards, back to the row number 0. If the field it arrived at was E(0, y_1), then $T[y_1 + {}_1]$ ... $T[y_2]$ is a substring of T with the minimal edit distance to the pattern P. Figure 36 explains graphically the aforementioned process.

		E	L	E	P	H	A	N	T
	0	1	2	3	4	5	6	7	8
R	1	1	2	3	4	5	6	7	8
E	2	1	2	2	3	4	5	6	7
L	3	2	1	2	3	4	5	6	7
E	4	3	2	1	2	3	4	5	6
V	5	4	3	2	2	3	4	5	6
A	6	5	4	3	3	3	3	4	5
N	7	6	5	4	4	4	4	3	4
T	8	7	6	5	5	5	5	4	3

Figure 36. Example of approximate string matching[10]

Furthermore, POLYGLOT knows if a learner has proneness in learning foreign languages in order to be able to distinguish if an error occurs due to non-learning or due to confusing by another language.

4.3.2. String Meaning Similarity for error diagnosis

[10] Nikita Smetanin: http://ntz-develop.blogspot.gr/

Correspondingly, using the second technique of string meaning similarity, POLYGLOT also finds meaning similarities between the given and the correct answer by translating these two answers to the system's available supported languages, namely the English and French languages. POLYGLOT follows the same rationale, as before, tailored to the meaning similarities. As such, the type of Language Transfer Inference mistake can be detected and diagnosed.

As mentioned before, the learning style of the users are detected using the Felder Silverman Learning Style Model. POLYGLOT can infer about the way with which the student prefers to process information (active and reflective learners) and the student progress towards understanding (sequential and global learners). More specifically, active learners can learn by working with others while reflective learners can learn by working alone. Hence, on the one hand active learners want to be able to collaborate with peers in an instant or asynchronous way using the POLYGLOT platform and on the other hand reflective learners do not want to collaborate. Concerning the sequential learners, they prefer to learn in a linear, orderly way in small incremental steps. This process is called "grain size instruction". In this way, the students are given the theory chapter by chapter; after they have learnt the first chapter and been examined for it, they can proceed to the next chapter and so on. On the contrary, global learners are keen on a holistic approach and learning in large leaps. Hence, POLYGLOT gives them the opportunity to have all the chapters available and learn them in the way they prefer.

4.4. Automatic detection of learning styles based on Felder-Silverman Model using the k-NN algorithm

POLYGLOT uses the Felder Silverman Learning Style Model. As mentioned before, the students can be characterized as Active or Reflective learners and Global or Sequential learners. Active learners like to collaborate with peers while reflective learners prefer working alone. Sequential learners like to be taught in linear steps, and each step should follow logically the previous one. Global learners prefer to have available all the learning material and to study in their own pace. To this direction, POLYGLOT offers the capability of collaboration and recommendation for collaboration to active students, while reflective students are given recommendation for collaboration if they ask for it. Also, sequential learners are given the learning material in a grain-size form, from chapter to chapter and they can proceed to the next chapter only if they have successfully completed the previous one. Finally, global students have the capability to navigate through the POLYGLOT's learning material in their own pace.

POLYGLOT offers two ways for the detection of students' learning style. The first one is the traditional way which is conducted by answering the questions proposed by the Felder Silverman questionnaire to detect the aforementioned dimensions. Apart from the completion of questionnaires, they give personal information and namely their age, gender, level of education, computer knowledge level, proneness to language learning/the foreign languages that they already know and to answer a preliminary test to provide their current knowledge level. The second way is the automatic one. POLYGLOT asks the student, who registers, to provide the aforementioned personal information and to answer the preliminary test. After that, POLYGLOT employs machine learning techniques to detect the learning style of the student in order to adapt the learning environment to him/her. The machine learning algorithm, that is used, is the k-nearest neighbor algorithm (k-NN). K-NN was selected for this research since it is one of the top ten data mining algorithms, according to Wu et al. (2008).

The k-nearest neighbor algorithm (k-NN) is a non-parametric method used for classification. The input consists of the k closest training examples in the feature space. In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). For example, if $k = 1$, then the object is simply assigned to the class of that single nearest neighbor. As mentioned above, POLYGLOT uses the following student characteristics in order to employ k-NN and detect his/her learning style (Figure 37):

- age
- gender
- proneness to foreign language learning/number of known languages
- educational level
- computer skills level

- preliminary test score

The aforementioned students' characteristics are used given that they are important for e-learning reasons according to Nakayama et al. (2007) and van Setersa (2012). POLYGLOT assigns a weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, as a weighting scheme, POLYGLOT gave each neighbor a weight of 1/d, where d is the distance to the neighbor. As such, students who are nearer to other students, possibly have the same preferences.

The neighbors are taken from a set of objects for which the class is known. This can be thought of as the training set for the algorithm in POLYGLOT.

POLYGLOT makes a prediction on the learning style of a given student using k-NN. The algorithm first calculates the test subjects (student being predicted) similarity to all instances in the training set and finds the k most similar ones. Similarity is calculated with a simple Euclidean distance between the features of the test subject and corresponding features of each instant in the training set. Specifically, the distance measure is given by the formula:

$d(x, y)^n = \sum_{k=1}^{n} (\mathrm{xk} - \mathrm{yk})\,\hat{}\,2$

where n is the number of dimensions (attributes) and xk and yk are the kth attributes (components) of data objects x and y, respectively.

An example of operation of the automatic detection of a student's learning style using k-NN is the following. Student A has provided to POLYGLOT static information, namely his/her age, gender, number of languages that speaks educational level, computer skills level and the score in the preliminary test. This vector is compared to the students' characteristics of the training set. As such, the student acquires the same learning style with the nearest students.

In the classification phase, k is a priori set to be equal to four. The reason is because of the fact that POLYGLOT wants to detect four distinct learning styles of students and namely:

- Active and Global learners
- Active and Sequential learners
- Reflective and Global learners
- Reflective and Sequential learners

Summarizing, POLYGLOT makes the following steps in order to detect the learning styles of the learners:

- Set K equal to 4
- Calculate the Euclidean distance
- Determine distance neighbours
- Gather category Y values of nearest neighbours
- Use simple majority of nearest neighbours to predict the value of the query distance.

Finally, it needs to be noted that POLYGLOT has used a training set, namely a vector in a multidimensional feature space, each with a class label; all these vectors where primary users of the e-learning system who served as a training way of k-NN so that it detect the learning style of the students of the private school of foreign languages. The training phase consisted only of storing the feature vectors and class labels of the training samples. The training set consisted of about 100 users, ranged from the age of 11 to 60 years old.

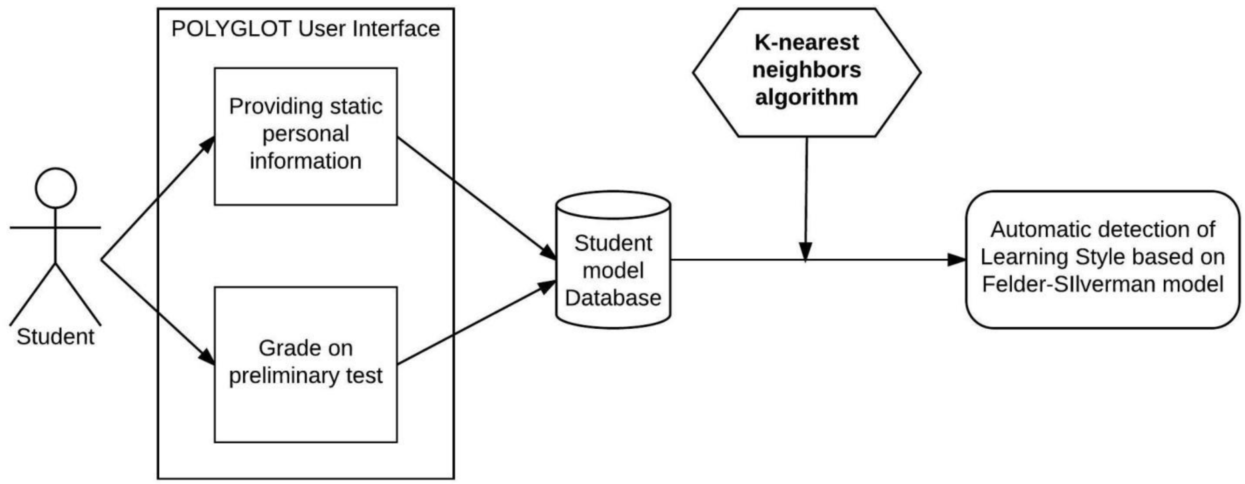

Figure 37. K-nearest neighbours algorithm for automatic learning style detection

4.5. Win-win collaboration module

Furthermore, POLYGLOT assists students concerning the collaboration with peers. As mentioned above, the student model holds information about the students' knowledge level along with the misconceptions that they conduct. To this direction, POLYGLOT supports win-win collaboration. This kind of collaboration is both advantageous and satisfactory to all parties involved. More specifically, both students, who are involved in the collaboration, benefit from the collaboration given that they gain knowledge. This happens as they offer their knowledge and at the same time they receive knowledge. As such, POLYGLOT supports two different kinds of win-win collaboration. The first one concerns the win-win collaboration based on knowledge level and the second one concerns the win-win collaboration based on the nature of misconceptions. Regarding the first kind, POLYGLOT proposes collaboration between two students of whom the student 1 is good at concept A but s/he is not good at concept B and student 2 is good at concept B but s/he is not good at concept A. As an example, if student A achieves a high mark at chapter 1 of the English language but a low mark in chapter 2 of the English or French language, POLYGLOT will propose him/her to collaborate with a student who has a low mark in chapter 1 of the English language but a high mark in chapter 2 of the English or French language respectively. By the same reasoning, regarding the second kind, POLYGLOT also proposes a collaboration between two students of whom the student 1 makes the error type A but s/he does not make the error type B and student 2 makes the error type B but s/he does not make the error type A. As an example, if student A is prone to make verb tense mistakes but not spelling mistakes, POLYGLOT will propose him/her to collaborate with a student who does not make spelling mistakes but not verb tense mistakes. Hence, win-win collaboration can provide a good result for both students involved. Figure 38 illustrates how this module works.

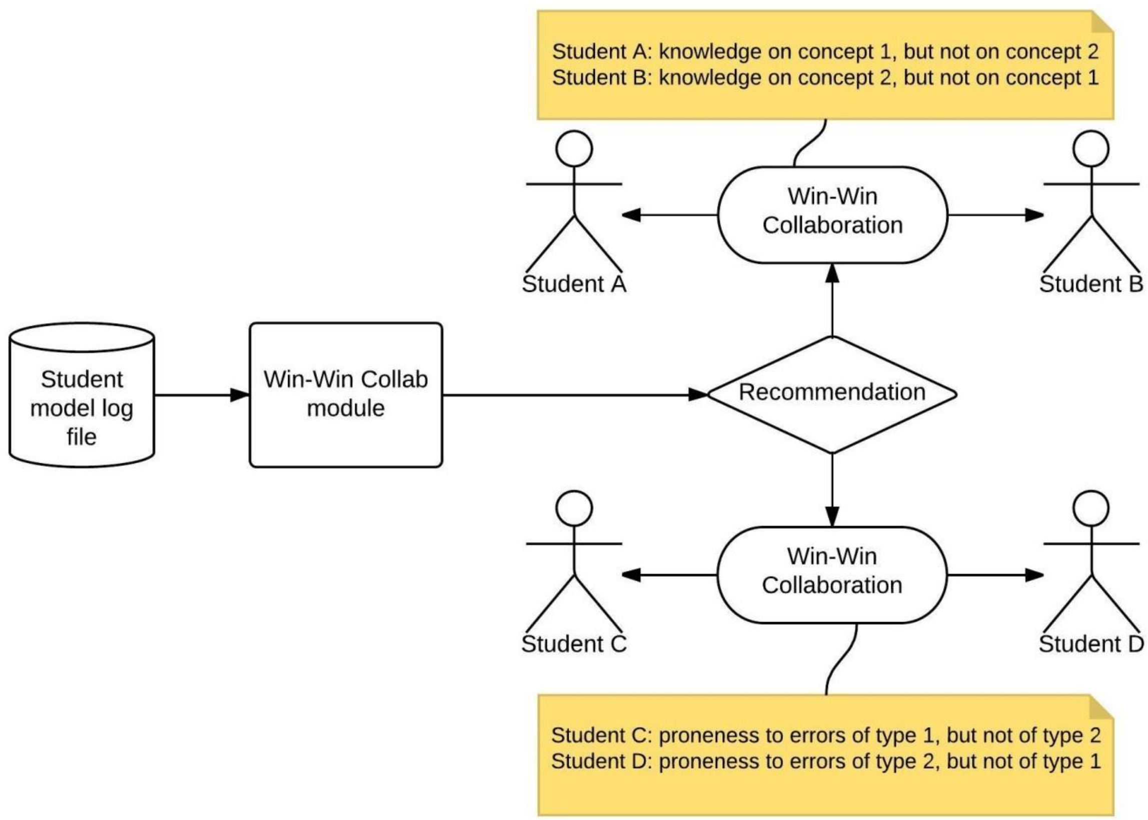

Figure 38. Win-Win collaboration module

Chapter 5:

Frustration Detection based on the Linear Regression Model

5.1. Declaration and Management of Affective states

Before the student's interaction with the system, POLYGLOT firstly asks him/her to declare his/her affective state, namely to declare if s/he is "happy", "frustrated" or "neutral". This characteristic adheres to the basic principles of social networking sites (e.g. Facebook) that tend to ask the user how s/he is feeling. This first step of affect declaration serves as the threshold to manage the affective states of students. Hence, the system can primarily support users by delivering messages, as further described in the next Chapter. To this direction, POLYGLOT can support students even before interacting with the system and can motivate them to reach their goals.

More specifically, before the student starts to study the learning content and be evaluated by POLYGLOT, s/he has the capability to declare his/her affective state. Based on this declaration, POLYGLOT takes this input and provides several messages to the students based on the declared affective state. These messages are not motivational given that there is no need to motivate students since they are not frustrated by the interaction with the ITS (Daish et al., 2012). As will be seen in the next Chapter, POLYGLOT responds to frustration when it takes information by the student model log file, such as students' poor grades, response time on exercises and liking/disliking of questions. To this direction, POLYGLOT employs conditional constructs in order to decide the appropriate message for each declared affective state. Following, Figures 39, 40 and 41 illustrate samples of messages to students before their integration with POLYGLOT. Specifically, Figure 39 shows a message to students when they are happy, Figure 40 shows a message to unhappy/frustrated students while Figure 41 shows a message to students with a neutral affective state.

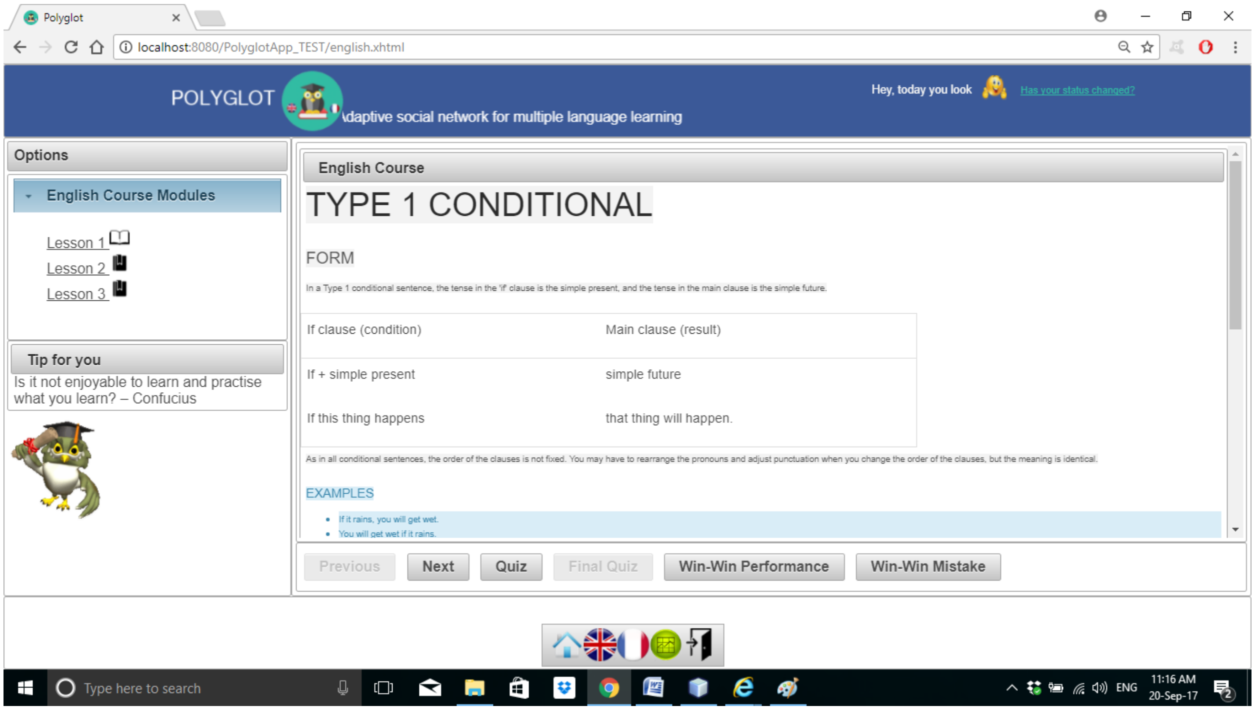

Figure 39. Message to student (before any kind of interaction), when s/he is happy

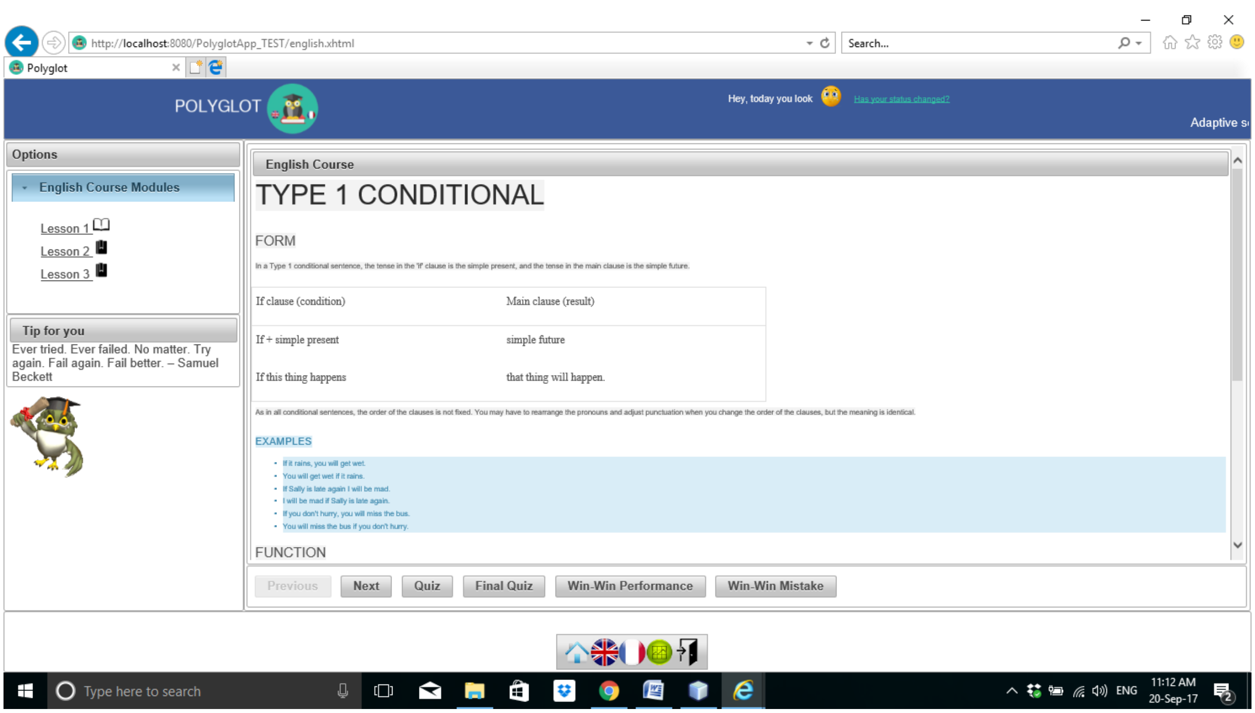

Figure 40. Message to student (before any kind of interaction), when s/he is frustrated

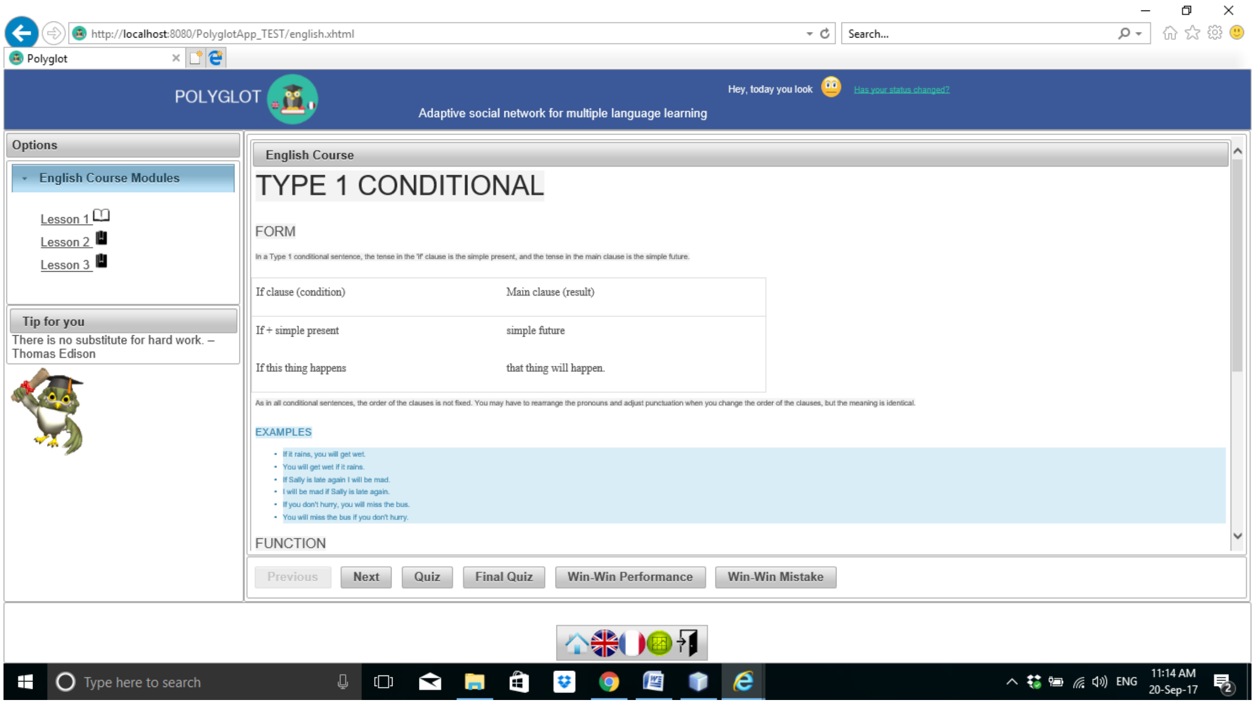

Figure 41. Message to student (before any kind of interaction), when in a neutral affective state

5.2. Automatic Detection of Frustration

After the interaction with POLYGLOT, the affective state of the student can change. Hence, POLYGLOT incorporates mechanisms to detect frustration.

Frustration of students is more applicable to computer learning environments (Calvo and D' Mello, 2010, Conati and Maclaren, 2009, Baker et al., 2010), Brawner and Goldberg, 2012, D' Mello et al., 2005, Hussain et al., 2011) and Sabourin et al., 2011). In learner-centered affective states, identifying and responding to the negative affective states are significant since it might render the student susceptible to quit learning (Kort et al., 2001). According to Gee (2008), frustration should be kept below a certain level in order to avoid high stress, powerful anger or intense fear. Moreover, frustration is a cause of student's disengagement and can eventually lead to attrition (Kappor et al., 2007). For all the above reasons, this dissertation takes into account only students' frustration and responds on this emotion.

POLYGLOT creates a model to detect and respond to frustration accurately and in real-time, when students are working with the ITS. In this chapter, the approach to detect student's frustration, when they interact with the ITS, is described. Then, the way that the approach is applied to POLYGLOT is presented. The frustration model is created by constructing features from the POLYGLOT's log data related to the frustration. The focus is placed on the instances of frustration that occur due to goal blockage. Frustration, in this case, is considered to be a negative emotion, as it interferes with a student's desire to attain his/her goals. To model the frustration, the linear regression classifier is used. The linear regression model is exible, fast and accurate. Also, the linear regression classifier models into the factors contributing to frustration. It determines which features contribute most to frustration, as well. Thus the linear regression model can be the means to respond to frustration systematically, and identify potential sources of frustration, thereby, helping students to avoid it.

5.3. Linear Regression Model to Detect Frustration

In this section, the linear approach to detect frustration is described. In order to model frustration, the following steps are used:

1. Perception of frustration as the emotion being aroused from students' confusion preventing them from achieving a goal.
2. Identification of the students' goals while they interact with the system (*goal1, goal2,..., goaln*).
3. Reporting the blocking factors of each identified goal (block.goal1, block.goal2,…, block.goaln). Operationalization for POLYGLOT, using its log data.
4. Creation of a linear regression model for frustration index (Fi) with the blocking factors identified.
5. Determination of the weights of the linear regression model using labeled human observation data.

The selection and combination of features from the POLYGLOT's log file is conducted through a systematic process based on an analysis of goal-blocking events. According to Step 1, the goals of the students are identified with respect to their interaction with the ITS, and the top n goals are selected in Step 2. Based on information from the student log files, a blocking factor (block), for each of the n goals is identified (Step 3). For example, the block.goalj represents the blocking factor for the goalj. A linear model for Fi is formulated; F_i represents the frustration index at the i_{th} question based on the blocking behaviors of student goals (Step 4). The features in the linear regression model are constructed based on the aforementioned perception of frustration. A threshold is applied to the frustration index Fi in order to detect whether the student is frustrated or not. The average of values used to represent frustration and non-frustration, during the training process, is used as threshold. The weights of the linear regression are determined during the training process (Step 5)–with labeled data from human observation–which is an independent method to identify affective states. The proposed linear regression model to detect frustration is given as follows:

$$F_i = a[w_0 + w_1 * block.goal1 + w_2 * block.goal2 + \ldots + w_n * block.goaln + w_{n+1} * t_i] + (1 - a)[F_{i-1}] \quad (5.1)$$

The weights w_0, w_1, w_2,…, w_n in the equation above are determined by the linear regression analysis, which is explained later in this chapter. As explained in the previous paragraph, the terms block.goal1, block.goal2,…, block.goaln, are the blocking factors for goals goal1, goal2,…, goaln, respectively. The term t_i symbolizes the time spent by the student to answer the question i. Lazar et al. (2006) state that the time spent to achieve the goal is an important reason of frustration. The last term in the equation, $(1-a)[F_{i-1}]$ accounts for the cumulative effect of frustration. We include this term on the basis of (Klein et al., 2002), which states that frustration is cumulative in nature. The value of a, determines the contribution of frustration at $(i-1)^{th}$ question to frustration at i_{th} question; a ranges from 0 to 1. We assume that the student is not frustrated at the beginning of their interaction with the ITS, and hence, choose $F_i = 0$ for i = 1, 2, 3. The scope of this approach is to identify frustration that occurs due to students' goal blockage (blocking factors) while interacting with the ITS. Instances of frustration, that might have occurred due to external situations unrelated to the students' interaction with the ITS, are excluded. Hence, the primary concern is the accuracy of the detection (precision), no matter how many the frustration instances are (recall).

5.4. Incorporation of the Linear Regression Model in POLYGLOT

In this section, the application of the linear regression approach to POLYGLOT log data is explained. The goal is to detect frustration of the students while they interact with POLYGLOT. The creation of the linear regression model is based on the following steps:

Step 1. Definition of frustration:

As mentioned above, the perception of frustration is important for the linear regression model and is related to the emotion being aroused from student's confusion and prevents him/her from achieving a goal. At Chapter 2, frustration was defined based on the researches of Dollard et al. (1939), Lazar et al. (2006), Morgan et al. (1986) and Spector (1978) as follows:

- Frustration is the blocking of a behavior directed towards a goal.
- The distance to the goal is a factor that influences frustration.
- Frustration is cumulative in nature.
- Time spent to achieve the goal is a factor that influences frustration.
- Frustration is considered as a negative emotion, because it interferes with a student's desire to attain a goal.

Step 2. Identification of Students' Goals:

The four most common goals of students, while interacting with POLYGLOT, are identified. According to Daish et al. (2012), McWhaw and Abrami (2001), Jacob and Rockoff (2012), Ewing (2012), the students' goal is the achievement of good grades in all the tests of the e-learning system. Based on these researches, we also asked the 80 students from the private school of foreign languages to state which their goals are before using POLYGLOT. Their answers coincide with the aforementioned researches and are the following:

- To get the correct answer to a single question
- To pass successfully the test of each chapter
- To reach the Final test (having passed successfully the tests of all chapters)
- To pass successfully the Final test

The corresponding blocking factors of each goal are discussed in the next step.

Step 3. Defining the Blocking Factors:

POLYGLOT involves the goals goal1, goal2, goal3, goal4 and their corresponding blocking factors block.goal1, block.goal2, block.goal3, block.goal4. To model the blocking factor (block) of each goal, several characteristics are taken into account, such as the students' response to questions, the time needed to answer each test and their liking/disliking in questions of chapter tests and final test; these features are being captured in the POLYGLOT's student log file.

Concerning the goal1, namely "to get the correct answer to a single question", the blocking factor is having the wrong answer to this single question. We use a_i to represent the answer of the single question. Specifically, when the answer is correct then ai = 1, and when the answer is wrong then $a_i = 0$. The blocking factor of the goal1 is captured using

block.goal1 = $(1 - a_i)$

Concerning the goal2, namely "to pass successfully the test of each chapter", the student should answer correctly all the questions of the test of each chapter. This goal can be blocked, if a student gets a grade which does not allow to successfully pass the test in order to proceed to the next chapter, as a logical sequence of the learning material (even if the student is a global student). Since the blocking factor by getting the wrong answer to the current question is partly addressed in block.goal1, we consider only the blocking factor by achieving more correct answers in order to take requested grade to pass. Hence the block.goal2 has two components. One way in which the goal2 can be blocked is when the student answers correctly some of the needed questions and the majority of them wrongly. Each test of each chapter has 10 questions and as such this is captured by the blocking factor block.goal2 as follows:

block.goal2 = $(a_{i-4} * a_{i-3} * a_{i-2} * a_{i-1} * (1 - a_i)^6)$

Concerning the goal3, namely "to reach the Final test" (having passed successfully all the tests of each chapter), the student should answer correctly the majority of the questions in each test of the three chapters for the one foreign language. The same happens correspondingly for the other foreign language. This goal can be blocked, if the student does not achieve the needed grade in any of the three tests. Namely, s/he does not answer correctly the majority of the questions in any of the three tests. This is captures by the block.goal3 as follows:

block.goal3= $(\text{block.goal2})_{T1} + (\text{block.goal2})_{T2} + (\text{block.goal2})_{T3}$

In the above formula, T_1 symbolizes the test 1, T_2 symbolizes the test 2 and T_3 symbolizes the test 3.

Concerning the goal 4, namely “to pass successfully the Final test”, the student should answer correctly the majority of the questions of the final test. Given that the final test has 30 questions, the blocking factor of goal4 is captured using:

$$\text{block.goal4} = (a_{i-12} * \ldots * a_{i-2} * a_{i-1} * (1 - a_i)^{18})$$

Step 4. Employment of the Linear Regression Model:

The mathematical model to detect frustration in POLYGLOT is given in Equation 5.1, with the individual terms block.goal1, block.goal2, block.goal3 and block.goal4, being defined in the above equations:

$$F_i = a[w_0 + w_1 * \text{block.goal1} + w_2 * \text{block.goal2} + w_3 * \text{block.goal3} + w_4 * \text{block.goal4} + w_5 * t_i] + (1 - a)[F_{i-1}]. \tag{5.1}$$

Chapter 6: Motivational messages based on the Attribution Theory

6.1. Respond to Frustration

As mentioned in Chapter 2, the followed strategy to respond to frustration consists of the following aspects:

- Create motivational message to attribute the students' failure to achieve the goal to external factors
- Create messages to praise the students' effort instead of outcome
- Create messages with empathy, which should make the student feel that s/he is not alone in that affective state
- Create message to request student's feedback
- Display messages using an agent

We create and display the messages to motivate the students based on the reasons for why the student is frustrated. The prime reason for frustration is the goal failure. The possible reasons for goal failure are due to the non-achievement of good grades (Daish et al., 2012, McWhaw and Abrami, 2001, Jacob and Rockoff,2012, Ewing, 2012) and are identified from the students' goal while they interact with the ITS. We represent these reasons as “events”. To create and display the messages we consider the events in POLYGLOT as listed in the Table 9. The frustration model is modified to identify the Reasons of Frustration (RF) as shown in equation 6.1.

$$RF = block.goal1 + block.goal2 + block.goal3 + block.goal4 \tag{6.1}$$

The values of RF and its corresponding reasons for failure are detailed in Table 10. The value of RF will be in the range of 0 to 2. For instance, if the goal1, that is getting the correct answer to a single question, is blocked then it is identified by block.goal1 which is that then answer to a single question is wrong.

Table 9. Events as reasons of goal failures

Event	RF Value	Pattern of answers
Ev1	0	Incorrect student's response to a single question a_i.
Ev2	1	Incorrect student's response a_i to the majority of questions of the test of a single chapter.
Ev3	2	Incorrect student's response a_i to the majority of questions of the tests of all the chapters.

Ev4	3	Incorrect student's response a_i to the majority of questions of the final test.

6.2. Delivery of motivational messages based on the Attribution Theory

The motivational messages are based on the Attribution Theory (presented in Chapter 2) and created using the reasons of frustration held in the log data of POLYGLOT. Attribution theory was proved to be a useful conceptual framework for the study of motivation in educational contexts (Graham, 1991).

As mentioned at Chapter 2, the Attribution Theory is a framework assuming that people try to determine why people do what they do, namely, it interpret the causes to an event or behavior. A three-stage process underlies an attribution:

- behavior must be observed/perceived
- behavior must be determined to be intentional
- behavior attributed to internal or external causes

The Attribution theory is mainly about achievement. According to it, the most important factors affecting attributions are ability, effort, task difficulty, and luck. Attributions are classified along three causal dimensions:

- locus of control (two poles: internal vs. external)
- stability (do causes change over time or not?)
- controllability (causes one can control such as skills vs. causes one cannot control such as luck, others' actions, etc.)

According to the theory, when a student succeeds, s/he attributes his/her successes internally. Namely, s/he believes that success is due to high ability and effort which s/he is confident of. When a rival succeeds, a student tends to credit external (e.g. luck). When a student fails or makes mistakes, external attribution is more likely to be used, attributing causes to situational factors rather than blaming his/her fault. Thus, failure doesn't affect their self-esteem but success builds pride and confidence. When students fail or make mistakes, internal attribution is often used, saying it is due to their internal personality factors. The main principles of the Attribution Theory are the following:

- Attribution is a three stage process: (1) behavior is observed, (2) behavior is determined to be deliberate, and (3) behavior is attributed to internal or external causes.

- Achievement can be attributed to (1) effort, (2) ability, (3) level of task difficulty, or (4) luck.
- Causal dimensions of behavior are (1) locus of control, (2) stability, and (3) controllability.

In view of the above, motivating the students' success with messages, praising their ability, can enhance students in the learning process and motivating the students' failure with messages which attribute the failure to external or unstable or controllable factors will help them to set a new goal with self-motivation. Figure 42 illustrates how the principles of the Attribution Theory are used by POLYGLOT in order to deliver motivational messages. The motivational messages in Figure 42 are a sample of the ones delivered by POLYGLOT and are in the yellow boxes.

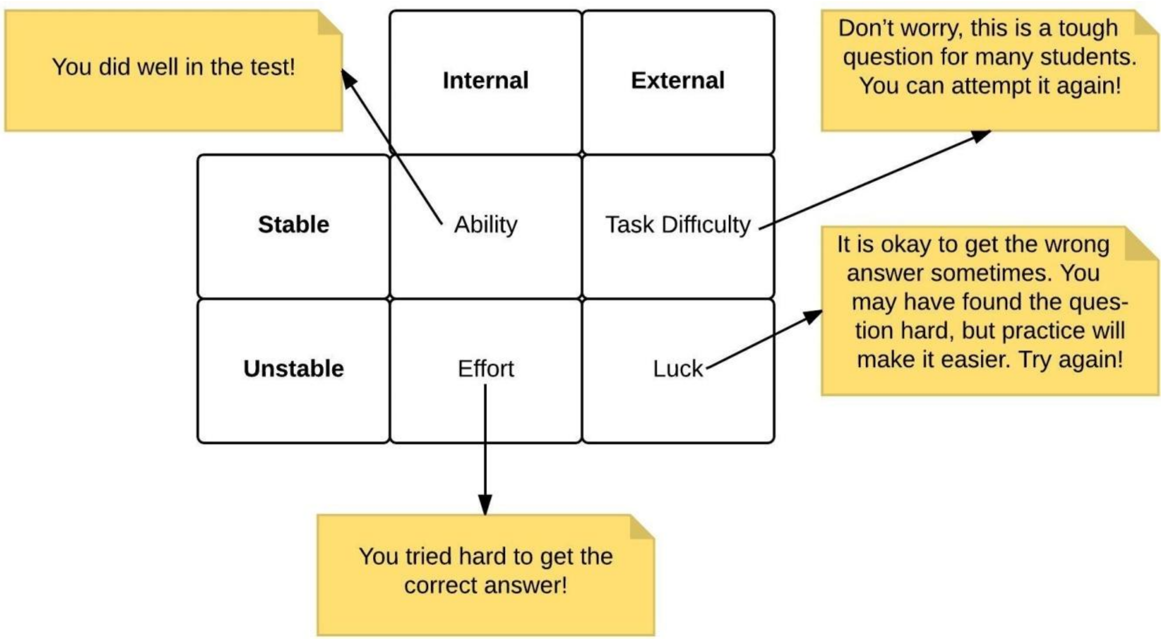

Figure 42. Sample of motivational messages based on the Attribution Theory

The following parameters are identified from the POLYGLOT log data, and are taken into account while creating the motivational messages. The messages are given in the Table 10 with condition to display the message and the reason for creating the message.

Average Response Time (Resp_T) is the average time taken to answer the questions in POLYGLOT by students. For the test of each chapter, the average response time from POLYGLOT existing log data is 50 seconds. This time coincides with the time that the teachers of the private school of foreign languages proposed as the average response time. The Response Rate is the percentage of instances when students answered the question correctly. We calculate the response rate for all questions using the POLYLGLOT's existing log data. We represent the response rate as RR. Frustration instances in a current session are represented by Fru_ins. The Fru_ins counts the number of frustration instances detected in the session, namely how many times the student has faced frustration in a current session.

Wrong answers in the majority of the questions of each chapter test or the final test are kept in the student model log file and used for the delivery of motivational messages. Liking and disliking of exercises serve as a valuable input to POLYGLOT and motivational messages are also delivered to students based on this interaction. The messages, discussed in the Table 10, are concatenated based on the conditions and displayed to the students. Each message can be appeared in a speech bubble from an agent (an owl, as shown in Chapter 3).

Table 10. Motivational messages responding to frustration

	Condition/Event	Motivational message	Explanation
Fru_ins=1	Ev1	You did well in the last question!	Stating the reason for frustration and praising the effort of the learner
	Ev2	You did well in the test!	
	Ev3	You did well in all the tests!	
	Ev4	You did well in the Final Test!	
	Resp_T > Average response time	You tried hard to get the correct answer!	Praising the effort of the learner
	Resp_T < Average response time	Try harder!	Motivating the learner
	Chapter Test	For sure, you will do well in the next questions!	
	Final Test	You may succeed next time!	
	Dislike of the majority of questions of Chapter Test	You can take a break and try again with a new state of mind!	

Fru_ins=2	Final Test	Don’t worry, this is a tough question for many students. You can attempt it again!	Attributing the failure to the difficulty of the question and motivating the learner
	Response Rate>50% in the final test	It is okay to get the wrong answer sometimes. You may have found the question hard, but practice will make it easier. Try again!	Sharing the feeling of the learner – showing empathy
	Response Rate<50% in the final test	It seems that this is a tough question for many students. Try again!	Attributing the failure to the difficulty of the question
	Dislike of the majority of questions of Final Test	It seems that this test is disliked! Try again!	Attributing the failure to the disliking of the question
Fru_ins=3	All questions	You can send a message to the instructor if you want!	Receiving student's feedback
	Dislike of questions of chapter test or Final Test	No motivational message. Automatic notice to instructor in order to decide if s/he will change the question.	

For the events listed in Table 10, that is for each goal failure, POLYGLOT shows the motivational messages (as shown in Figure 43a) based on the student's response time in answering the questions, grade, type of the question (belonging to a chapter test or final test) and liking/disliking of the questions. POLYGLOT’s frustration model takes into consideration the following factors:

- For the first instance of frustration, POLYGLOT chooses the message based on the time spent by the student to answer the question, that is, Resp_T. If the student spent more than an average response time then, based on the event, the message praising the student's effort of answering the question will be shown. If the student spent less than an average response time then, the message to motivate the student will be shown. This is to praise the students' effort to answer the question. Accordingly, POLYGLOT selects the appropriate message in case of a student's disliking of a question of the chapter test.

- For the second instance of frustration, POLYGLOT chooses the message based on the response rate. If the response rate is more than 50% of the average then the message to motivate the student will be shown. If the response rate is less than 50% of the average, then the message to attribute the failure to the difficulty of question will be shown. If the response rate is less than 50% of the average, then this question might be difficult for many of the students. This is to attribute the students' failure to difficulty of the question; hence, the student will be motivated for the next questions. Accordingly, POLYGLOT selects the appropriate message in case of a student's disliking of a question of the final test.
- For the third instance of frustration, the student's feedback is gathered either implicitly or explicitly.

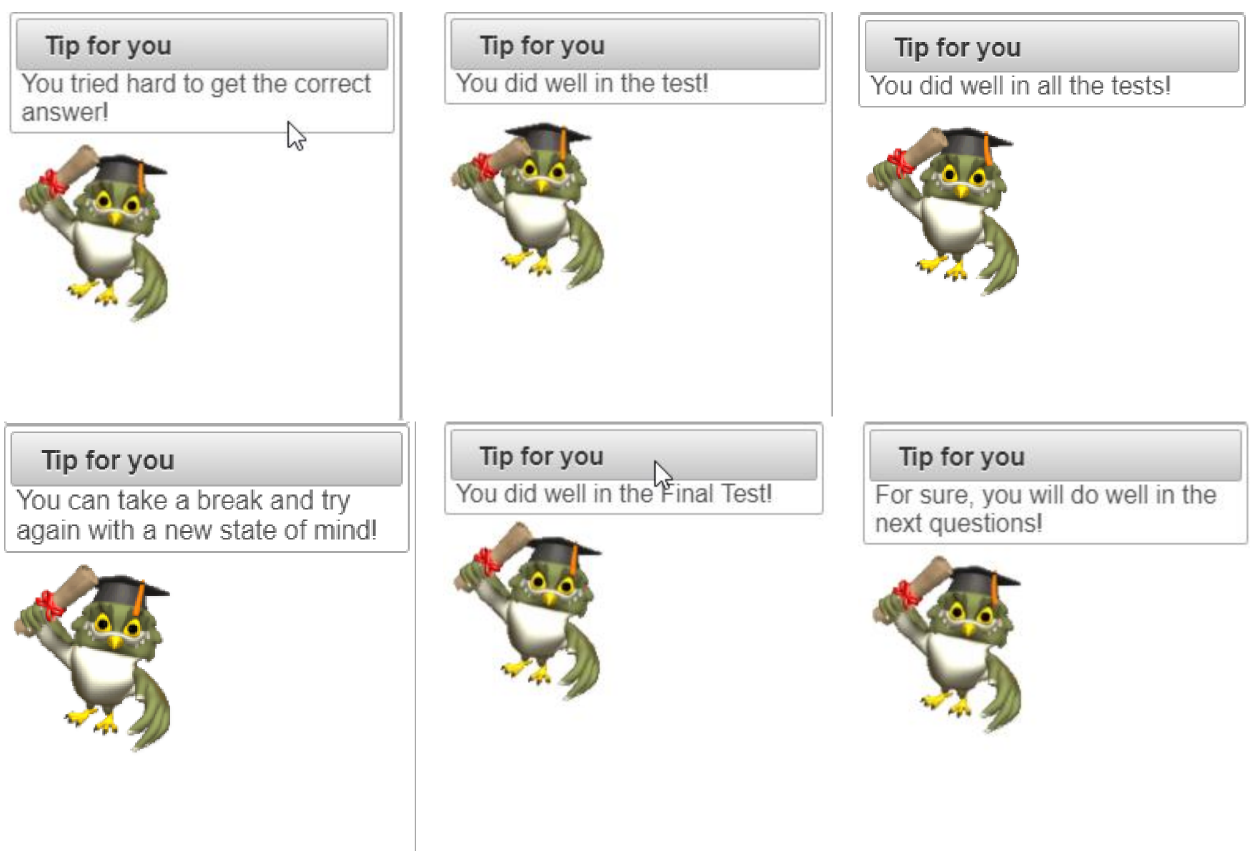

Figure 43a. Sample of motivational messages to students (after their interaction with POLYGLOT)

Figure 43b and Figure 43c illustrate examples of delivering motivational messages to students based on their interaction with POLYGLOT. For instance, student A, who is in the Final Test, needs a lot of time to answer an exercise, has poor results and has liked the majority of the questions, will receive the message “You may succeed next time!” in case s/he has faced a high number of frustration instances (motivation to the student) or the message “It is okay to get the wrong answer sometimes. You may have found the question hard, but practice will make it easier. Try again!” in case s/he has faced a low number of frustration instances (empathy to the student). As shown in Figure 44, the student's interactions with the user interface of POLYGLOT are stored in the log file. From the POLYGLOT’s log data, the features to detect frustration are constructed. The Frustration model is created based on these features, as the input from the log data. If the student's frustration instances are detected by the frustration model, then the reasons for frustration are identified. The reasons for frustration are represented as events. The appropriate motivational message based on the events and the data from log file is selected.

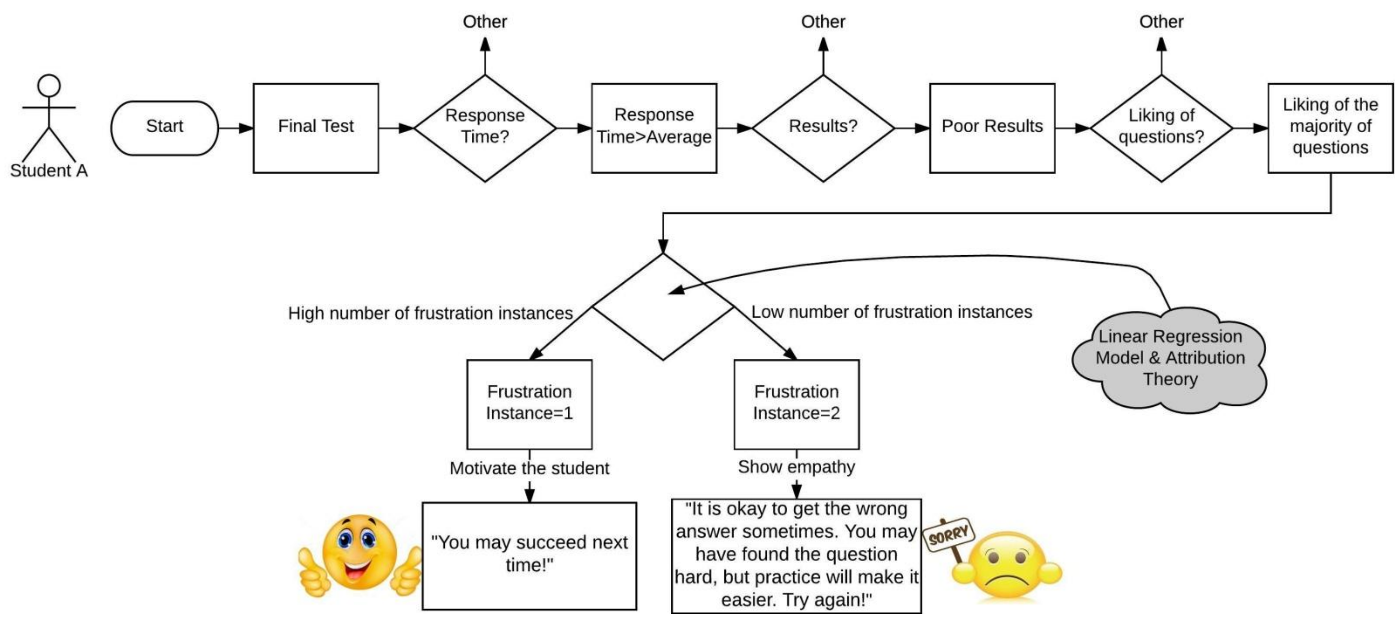

Figure 43b. First example of delivering motivational messages to students

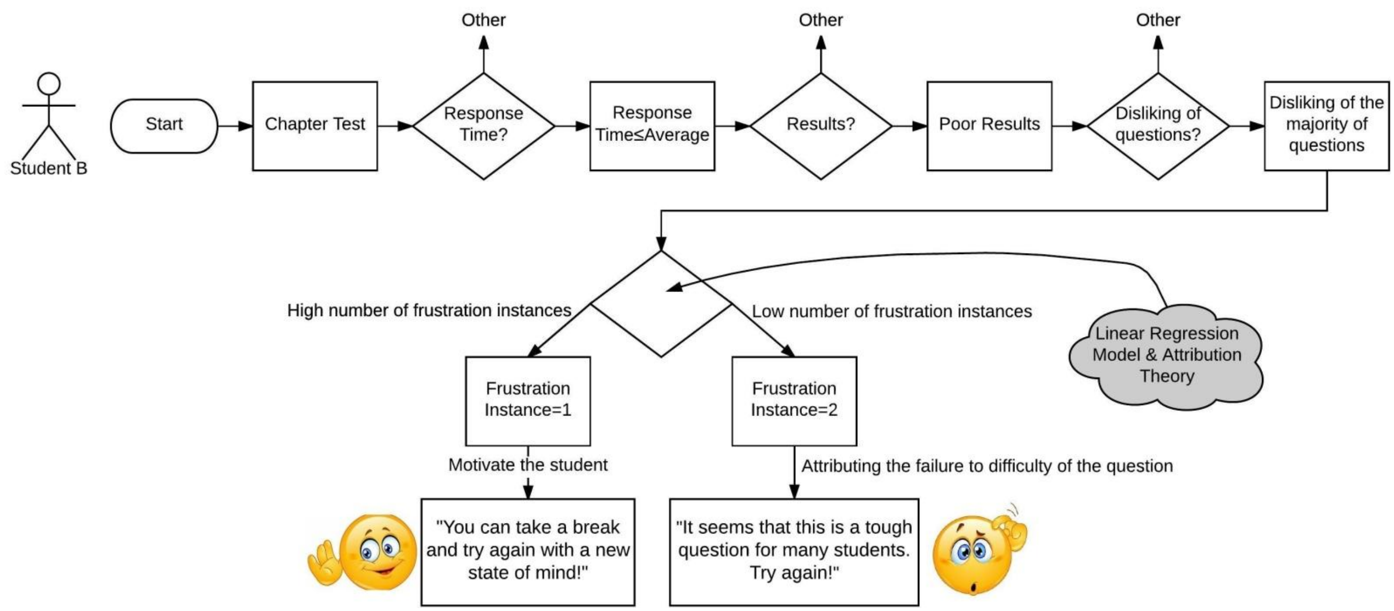

Figure 43c. Second example of delivering motivational messages to students

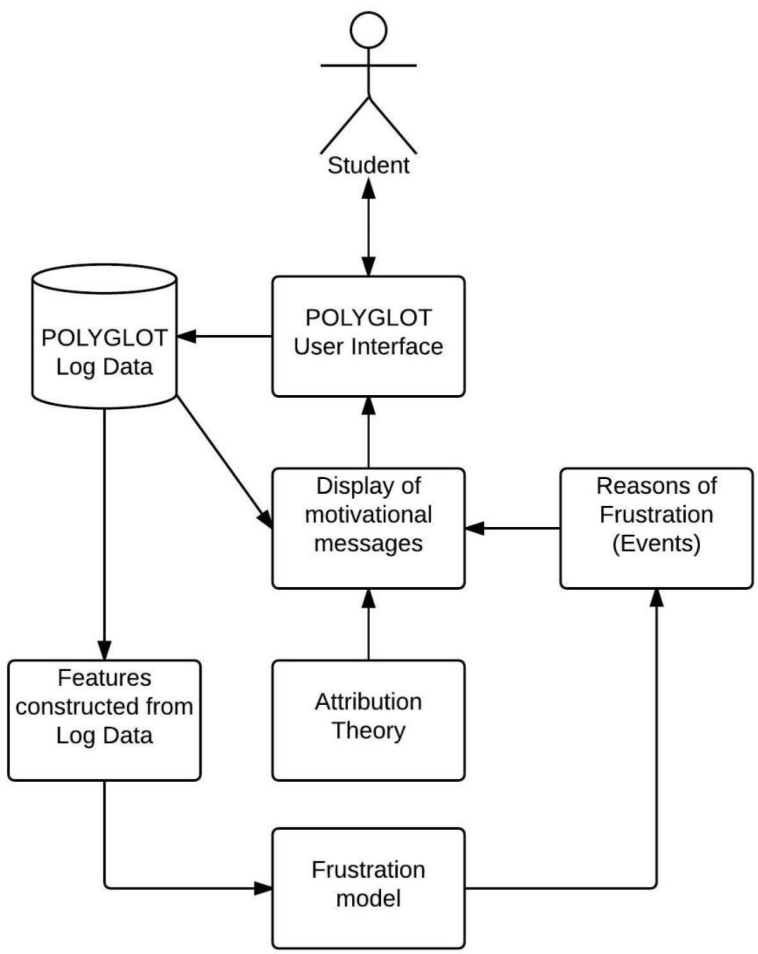

Figure 44. Methodology to Detect and Respond to Frustration in POLYGLOT

Chapter 7:

Evaluation of POLYGLOT

7.1. Evaluation process and framework used

Typically, systems evaluation is used to measure progress in achieving preset goals, ameliorate program development and provide useful feedback to instructors and learners. Posavac and Carey (2007) observed that program evaluation is a "collection of methods, skills and sensitivities necessary to determine whether a human service is needed and likely to be used, whether the services are sufficiently intensive to meet the unmet needs identified, whether the service is offered as planned and whether the service actually helps people in need". In addition, McNamara (2000) noted that improvement, in practice, implementation and reproduction is the goal of any high-quality program evaluation.

Evaluation can be valuable in different kind of software. It can either significantly assist in developing a concrete understanding of system's intended outcomes or give a clear perception of the system's efficiency. Moreover, systems evaluation does not concern solely the investigation of the relationships between expectations and outcomes; it has expanded to comprise more complex issues, such as effectiveness, efficiency, value and adequacy based on a systematic data collection and analysis (Rossi et al., 2004). Nevertheless, system evaluations should produce a fertile ground for valid comparisons between similar programs (McNamara, 2000).

There are many different types of evaluating measures depending on the objects or programs being assessed and the purpose of the evaluation (Fitzpatrick et al., 2004). The cornerstone of the evaluation is the manner in which information can be captured and used throughout the life of the program. McNamara (2000) reports that the appropriateness of an evaluative measure has a direct correlation to the specific nature of information being sought. The judgment of the evaluation method is based on a specific methodology, a deep understanding of the information needed and knowledge from personal experiences and beliefs (Fitzpatrick et al., 2004).

A system evaluation design depends on the information required in order to meet the objectives being set by the group seeking the evaluation (McNamara, 2000). As such, a focused evaluation that addresses the full set of objectives of a varied group of stakeholders will produce a qualitative result (Fitzpatrick et al., 2004). Furthermore, the overall goal to consider when selecting evaluation method is how to arrive at the most beneficial information to key stakeholders in the most realistic method.

Accordingly, evaluation is an inseparable part of tutoring systems. A teacher can do many things to collect information on the students' level of achievement. They include giving tests, assignments, oral questions, observation during the teaching-learning session, and portfolio. The activities are conducted not only to determine the students' grade but also to improve the quality of learning.

Learning evaluation should be conducted in a thorough and sustainable way, involving assessment on the learning process and outcomes. One of important factors that contribute to the achievement of educational objectives is the learning process itself.

On the other hand, evaluation and assessment (both on the learning process and on the outcomes in a continuous way) also play a role in encouraging the teaching staffs to improve the quality of learning process.

One of the main components in the education system is assessment. Assessment provides not only a description or information on the students' achievement or mastery of the learnt materials, but also a feedback to the educational program itself. Learning assessment is conducted as a part of decision-making process when it comes to the students' mastery of the materials after they are engaged in the teaching-learning process. In addition, learning assessment is also useful to figure out whether the learning strategy or approach is appropriate or not.

Accordingly, the educational system needs competent teaching staffs that are capable of not only teaching in a good way but also evaluating the learning outcome in an appropriate and effective way based on characteristics of the subject. As a part of the learning program, evaluation must be done in an optimum way. It should not rely merely upon the learning output, but also on the input, output, and quality of the learning process. In both educational sector and learning process, the role of information technology media should not be overlooked. The use of media is an element, which must be considered by the lecturers/teaching staffs in all of the learning activities. Accordingly, learning assessment should not rely merely upon the traditional tests.

Limitation of the traditional tests as the sole decision-making tool when it comes to the students' achievement is that it simply assesses the scientific knowledge. The assessment focuses only on the limited dimension of learning outcomes (knowledge and skills). It cannot be used to assess in-depth reasoning capability. In addition, it is not able to show the real competence of the students (Mokhtari et al., 1996). Another limitation of the traditional tests is that each question generally has a single, absolute answer. It does not focus on the process, but on the outcome; it neither reveals the students' thinking process nor measures all aspects of the teaching-learning process.
Mardapi (2000) suggests that there are seven elements of learning evaluation. They are 1) focusing the evaluation, 2) designing the evaluation, 3) collecting information, 4) analyzing and interpreting, 5) reporting information, 6) managing evaluation, and 7) evaluating evaluation. The definition shows that in the early phases, an evaluator must first determine focuses and design of the evaluation.

The objective of evaluation is to obtain accurate and objective information on a program, which has been planned and implemented in the previous phases. The information may come from the process of program implementation, impacts/results, and efficiency. The results of evaluation determine whether the program is successful or not, whether it is going to be continued or stopped, and whether it is going to be used as a basis for the next program or not.

POLYGLOT was assessed using two different techniques. The one evaluation model that we use is the Kirkpatrick's model (1979). It defines four levels of evaluation:

- Level 1: Reaction: It examines how the students felt, and their personal reactions to the learning experience, for example:
    - did the trainees like and enjoy the training?
    - did they consider the training relevant?
    - was it a good use of their time?
    - did they like the venue, the style, timing, domestics, etc?
    - level of participation
    - ease and comfort of experience
    - level of effort required to make the most of the learning
    - perceived practicability

- Level 2: Learning: This is the measurement of the increase in knowledge and intellectual capability from before to after the learning experience and concerns the following:
    - did the trainees learn what intended to be taught?
    - did the trainee experience what was intended for them to experience?
    - what is the extent of advancement or change in the trainees after the training, in the direction or area that was intended?
- Level 3: Behavior: This is the extent to which the trainees applied the learning and changed their behavior, and this can be immediately and several months after the training, depending on the situation and concerns the following:
    - did the trainees put their learning into effect when back on the job?
    - were the relevant skills and knowledge used?
    - was there noticeable and measurable change in the activity and performance of the trainees when back in their roles?
    - was the change in behavior and new level of knowledge sustained?
    - would the trainee be able to transfer their learning to another person?
    - is the trainee aware of their change in behavior, knowledge, skill level?
- Level 4: Results: This is the effect on the business or environment resulting from the improved performance of the trainee. Measures would typically be business or organizational key performance indicators, such as: volumes, values, percentages, timescales, return on investment, and other quantifiable aspects of organizational performance.

7.1.1. Criteria

The definition of the evaluation should be defined initially. The proposed criteria are the following:

- Students' satisfaction about the e-learning system. Specifically, it concerns the degree of satisfaction in terms of the adaptation and effectiveness provided by the e-learning platform. Hence, the students' perspective towards the educational environment plays an important role.

- Students' performance. It concerns the performance of learners on the knowledge domain. Especially, it seeks to investigate the extent to which the learners gain knowledge on the taught concepts of the English and French languages.
- The changes that were caused on the individual state of the students. In other words, we want to assess the effect of the e-learning program on the behavior and thoughts of students about foreign language learning and distance learning.
- The results of the e-learning program to students' progress. It concerns the effects of the e-learning program to students' progress on their further studies.
- The validity of learning style detection, being done automatically by POLYGLOT for each student.
- The validity of recommendation for win-win collaboration between students seeking to cooperate with peers in a beneficial way for both parties.

7.1.2. Method

The method used for this evaluation coincides with the Kirkpatrick's model. Particularly, the assess of satisfaction coincides with the Kirkpatrick's evaluation of reaction level, the measurement of students' performance is similar to the Kirkpatrick's evaluation level of learning and the students' individual state/behavior and progress can be matched with the Kirkpatrick's evaluation levels of behavior and results, accordingly. Thus, the method of evaluation can be described as follows:

I. Assessing the learners' satisfaction about the e-learning environment. The level of satisfaction also involves the learner's satisfaction of the motivational messages that POLYGLOT delivered to them. For gathering this kind of information a questionnaire (Questionnaire A, section 7.3) was used. The questions were close-ended based on Likert scale with five responses ranging from the low grade "Not at all" (1) to the high grade "Very much" (5). The questions were divided into two sections based on the type of information we were interested in. The questions of the first section were related to the effectiveness of the tutoring program. The second section was aimed at evaluating the adaptivity of the system.

II. Measuring the students' performance by conducting an experiment with an experimental group (the group of students which used the POLYGLOT environment) and a control group (the group of students which used a similar educational environment from which the student model was absent).

III. Assessing the changes on the students' state/behavior about language learning and e-learning. For gathering this kind of information a questionnaire (Questionnaire B, section 7.3) was used. The questions were close-ended based on Likert scale with five responses ranging from the low grade "Not at all" (1) to the high grade "Very much" (5). The questions were divided into three sections based on the type of information we were interested in. The questions of the first section were related to the students' perception about language learning. The second section was aimed at evaluating the students' state towards e-learning. The third section included questions related to students' motivation to be involved in e-learning programs.

IV. Assessing the effects of the e-learning program on the students' progress concerning their further studies. For assessing this criterion a questionnaire (Questionnaire C, section 7.3) was used, which included five close-ended questions based on Likert scale with five responses ranging from the low grade "Not at all" (1) to the high grade "Very much" (5).

V. Assessing the validity of the detection of the learning style of the students being done in an automatic way at the first interaction of the student with POLYGLOT. More specifically, all the population taking part at the experiment (80 students) was asked to answer the Felder Silverman questionnaire in order to detect their learning style in a traditional way. After that, the results of the traditional learning style detection were compared to the results of the automatic learning style detection.

VI. Assessing the validity of recommendation for win-win collaboration, which support students' learning experience by proposing the proper classmate for cooperation. To this direction, based on the student models, POLYGLOT decides who is the proper student to propose to another student to work together so that the collaboration is advantageous and beneficial to both students involved. Hence, the only method to assess the validity of win-win collaboration is to ask the learners' opinion about the collaboration and if it indeed helps them. Thus, a questionnaire (Questionnaire D, section 7.3) with close-ended questions based on Likert scale with five responses ranging from "Not at all" (1) to "Very much" (5), was used.

7.1.3. Population

In total, the number of students that used POLYGLOT was 80. Apart from that, 20 users holding a degree in Informatics also used POLYGLOT. More specifically, POLYGLOT was used by a group of 40 students (group A) of a private school of foreign languages in Athens. After their participation in the training program, the learners completed the questionnaires A and D that are displayed in section 7.3. After 6 months, the learners were asked to answer the questionnaires B and C (evaluation of behavior and the evaluation of results levels of the Kirkpatrick's model) that are displayed in section 7.3. The answers of the above four questionnaires helped to assess students' satisfaction, the changes on students' state/behavior, the results on students' progress on their further studies and the validity of adaptation decision making.

Moreover, students' performance was measured and was compared with the performance of another group of 40 students (group B) of the same private school, which used a similar educational system from which all the mechanisms for adaptation and assistance were absent. Both systems had the same knowledge domain, which holds concepts in the English and French languages, but the second system delivers the concepts of the learning material in sequence without taking into account the students; learning style, error diagnosis, motivational messages recommendation for collaboration.

Learners of both groups had different ages, varying from 10 to 35, and backgrounds. Some of the students were primary or secondary school students, others were university students or people that already work. Furthermore, some of the students have computer skills. The number of students, which belong to either each age category or background category, is the same for both groups (Table 28). The reason for this is the fact that the homogeneity of the experiment's samples simplifies the experiment's performing. The learners of both groups used the corresponding systems without attending any courses on language learning, over a period of six months.

Table 41. Distribution of students' ages and backgrounds

Ages	**10-14**	**15-18**	**19-25**	**26-30**	**31-35**
	28.36%	32.68%	14.24%	16.42%	8.30%
Background	**Primary/Secondary School students**		**University students**		**Working people**
	61.04%		16.21%		22.75%

Table 12. Distribution of students' knowledge of other languages

Language	**English**	**French**	**English & French**
Group A	34.24%	27.12%	38.64%
Group B	35.95%	26.86%	37.19%

7.2. Results

7.2.1. Satisfaction

As mentioned above, students' satisfaction coincides with the level 1 of the Kirkpatrick's model and as such it is very important for the evaluation of every learning environment. Based on the results of the questionnaires, the students' satisfaction about the adaptivity and effectiveness of POLYGLOT is high. Specifically, the students are very satisfied with the educational environment with the social characteristics and its contribution to the learning process. The results of the questionnaire are depicted in Figure 45. This information is easy to collect, but does not tell enough about the learning success.

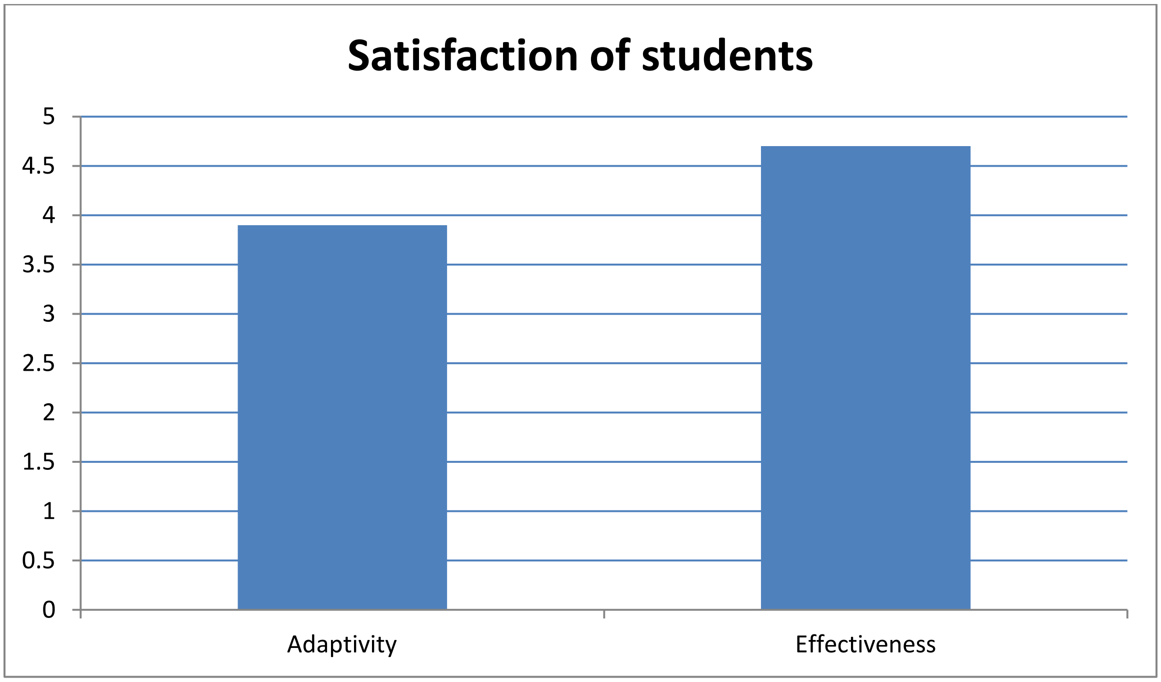

Figure 45. Students' satisfaction

7.2.2. Performance

This is the evaluation given before, during, and after learning. The purpose of evaluating performance is to measure the degree to which learners have obtained knowledge based on their participation in the learning event. The evaluation conducted before learning determines the learners starting point. Each learner will have a different level of background knowledge prior to learning course material, so understanding where everyone stands to begin with allows for a more accurate measure. Evaluation during the learning event allows learners to self-evaluate, and measure their own progress. It also gives facilitators a sense of how well learners are doing in relation to the learning objectives. The evaluation at the end of the learning event is also referred to as a summative evaluation, and it is done individually. According to Hamtini (2008), LaMotte (2015) and Galloway (2005), the most appropriate method of evaluation is to conduct pre-tests and post-tests. For this reason, Student's t-Tests were chosen to conduct this evaluation.

In the evaluation study, 80 students from different classrooms participated. As mentioned above, the students were all from a private school of foreign languages. The school, that was chosen, is located in Athens, the capital city of the country. Hence, it can be seen as a representative sample, since it adequately replicates the larger statistical population in terms of students' characteristics. School teachers also provided very valuable help in the whole evaluation study since they also participated both in the use of the ITS from the students and also provided assistance to their students while they interacted with the educational platform. The first group evaluated POLYGLOT, while the second group evaluated an ITS offering the same learning material and tests but without the same user interface all the modules of POLYGLOT. This division was very crucial in order to compare the performance of students using POLYGLOT in comparison with a simple e-learning platform. As a result, both groups had given a brief presentation on how to use the educational platform. Consequently, each group had the appropriate knowledge and enough time (6 moths) to spend interacting with POLYGLOT. After the completion of their interaction (group A with POLYGLOT and group B with simple e-learning platform), all students were given questionnaires to complete with guidance from the evaluators and also their teachers.

The evaluation study was conducted with the use of self-supplemented scale questionnaires incorporating closed questions for the students. For this research, the Questionnaire C is used.

It was observed that students became familiar easily and very quickly with the educational software, its features and its functionalities. Their interest was undiminished during the whole 6-month period of their interaction with the educational application.

Finally, Table 13, Table 14, Table 15, Table 16 and Table 17 illustrate the statistical significance of the questions 1-5 respectively (Questionnaire C, section 7.3). Assuming the null hypothesis, the probability of this result is 0. As such, for the null hypothesis "There is no difference between the two groups of students", the t-Test rejects the hypothesis for all the questions. The absolute value of the calculated t exceeds the critical value, so the means are significantly different. Hence, it is concluded that the tutoring system has a statistically significant effect on performance.

Table 13. Statistical significance in a student's t-Test for question 1

t-Test: Two-Sample Assuming Equal Variances		
	Variable 1	*Variable 2*
Mean	2.9	4
Variance	1.476923077	0.666666667
Observations	40	40
Pooled Variance	1.07179487179487	
Hypothesized Mean Difference	0	
Degrees of freedom	78	
t	-4.751730987	
P(T<=t) one-tail	4.52	
t Critical one-tail	1.664624645	
P(T<=t) two-tail	9.03057	
t Critical two-tail	1.990847036	

Table 14. Statistical significance in a student's t-Test for question 2

t-Test: Two-Sample Assuming Equal Variances		
	Variable 1	*Variable 2*
Mean	2.85	4.275
Variance	1.515384615	0.51217949
Observations	40	40
Pooled Variance	1.01378205128205	
Hypothesized Mean Difference	0	
Degrees of freedom	78	
t	-6.32932743	
P(T<=t) one-tail	7.20749	
t Critical one-tail	1.664624645	
P(T<=t) two-tail	1.4415	
t Critical two-tail	1.990847036	

Table 15. Statistical significance in a student's t-Test for question 3

t-Test: Two-Sample Assuming Equal Variances		
	Variable 1	*Variable 2*
Mean	2.8	4.25
Variance	1.497436	0.602564
Observations	40	40
Pooled Variance	1.05	
Hypothesized Mean Difference	0	
Degrees of freedom	78	
t	-6.32832	
P(T<=t) one-tail	7.24	
t Critical one-tail	1.664625	
P(T<=t) two-tail	1.45	
t Critical two-tail	1.990847	

Table 16. Statistical significance in a student's t-Test for question 4

t-Test: Two-Sample Assuming Equal Variances		
	Variable 1	*Variable 2*
Mean	2.325	4.325
Variance	1.250641	0.430128
Observations	40	40
Pooled Variance	0.840384615384615	
Hypothesized Mean Difference	0	
Degrees of freedom	78	
t	-9.75677	
P(T<=t) one-tail	1.85	
t Critical one-tail	1.664625	

P(T<=t) two-tail	3.71	
t Critical two-tail	1.990847	

Table 17. Statistical significance in a student's t-Test for question 5

t-Test: Two-Sample Assuming Equal Variances		
	Variable 1	*Variable 2*
Mean	2.375	4.425
Variance	1.112179	0.353205
Observations	40	40
Pooled Variance	0.732692307692307	
Hypothesized Mean Difference	0	
Degrees of freedom	78	
t	-10.7105	
P(T<=t) one-tail	2.77	
t Critical one-tail	1.664625	
P(T<=t) two-tail	5.54	
t Critical two-tail	1.990847	

It was expected that younger students with an inherent tend towards new technology would welcome e-learning learning with social characteristics adapted to their needs, supporting their learning. The findings of this preliminary study are rewarding the authors' attempts towards moving education to the fast growing field of intelligent tutoring systems incorporating social features and adaptivity. Analyzing the results of the evaluation study there is considerable evidence that this new technology is quite welcome from young learners and could be incorporated in schools supporting the educational process. The above tables illustrate that the performance of students using POLYGLOT was exceptionally high and as such POLYGLOT serves as a great tool for learning.

7.2.3. Individual state of learners

The individual state of the learners along with their behavior has significantly changed in a more positive level. The interaction with POLYGLOT notably ameliorated the students' perspective and opinion towards the language learning and e-learning. The results showed that the students are very keen on using an e-learning platform for learning foreign languages. This fact is attested by the teachers of the private school of foreign languages who assured that the students were very interested in using POLYGLOT for learning the taught concepts. In order to enhance the accuracy of the results, students were divided in two distinct categories. The first category includes students who are prone to foreign language learning, while the second category includes students with no foreign language knowledge. It should be clarified that the proneness to foreign language learning means that the students are very keen on learning foreign languages or they are novice, intermediate or expert in one or more foreign languages. The reason why students were categorized as mentioned is because of the fact that the changes in the state of students who are prone to foreign language learning may be less important. Furthermore, it should be noted that POLYGLOT takes into consideration the previous level of knowledge in the use of computers. The students having been involved in the experiment had a high level of knowledge in the use of computers. As such, they do not meet any obstacle in using POLYGLOT and they focus on the instruction issues. The questionnaire B that was answered by the learners and the mean of students' answers are displayed later in this section. The results of the questionnaire are depicted in Figures 46 and 47.

The results show that the students' state towards foreign language learning (specifically English and French languages) and e-learning, who are not prone to foreign language learning or who had no previous knowledge on foreign languages, was improved by 81.1% and 78.3% respectively. While their willingness to be engaged in e-learning programs, was increased by 76.2%. Similarly, the state of the learners, who are prone to language learning and namely who have been involved in the learning of at least one foreign language, towards foreign language learning and e-learning was improved by 86.8% and 88.2% respectively. Also, their motivation to be involved in e-learning programs was increased by 74.4%.

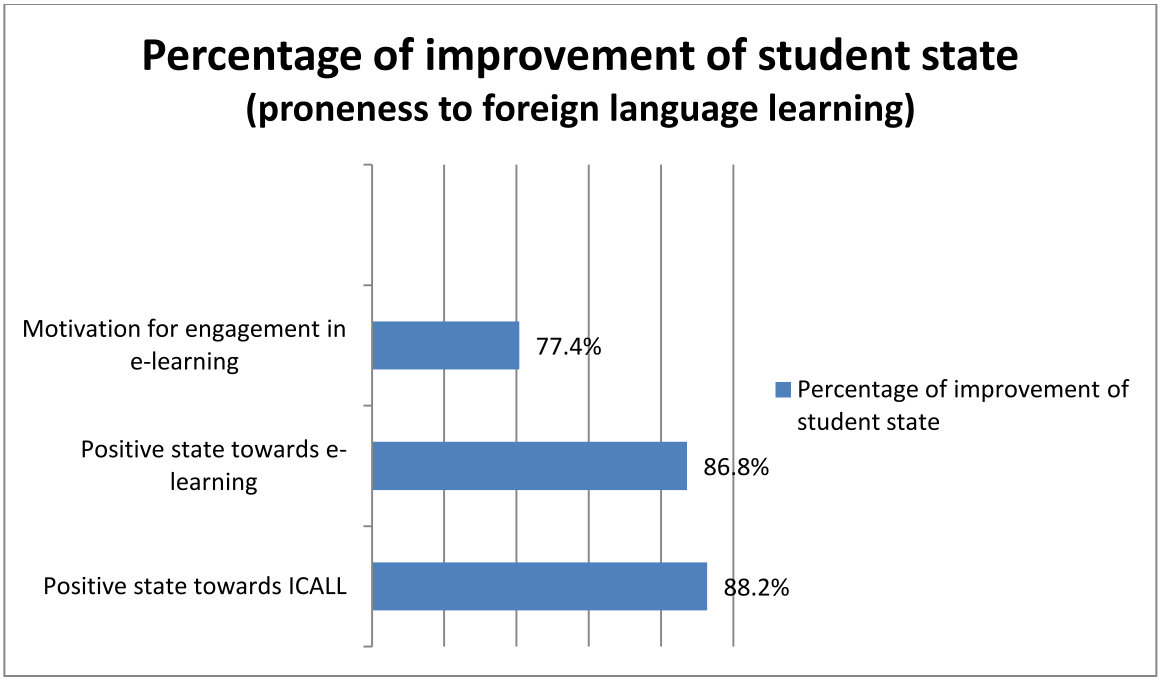

Figure 46. Changes on individual state of students with no previous knowledge on foreign languages (no proneness to language learning)

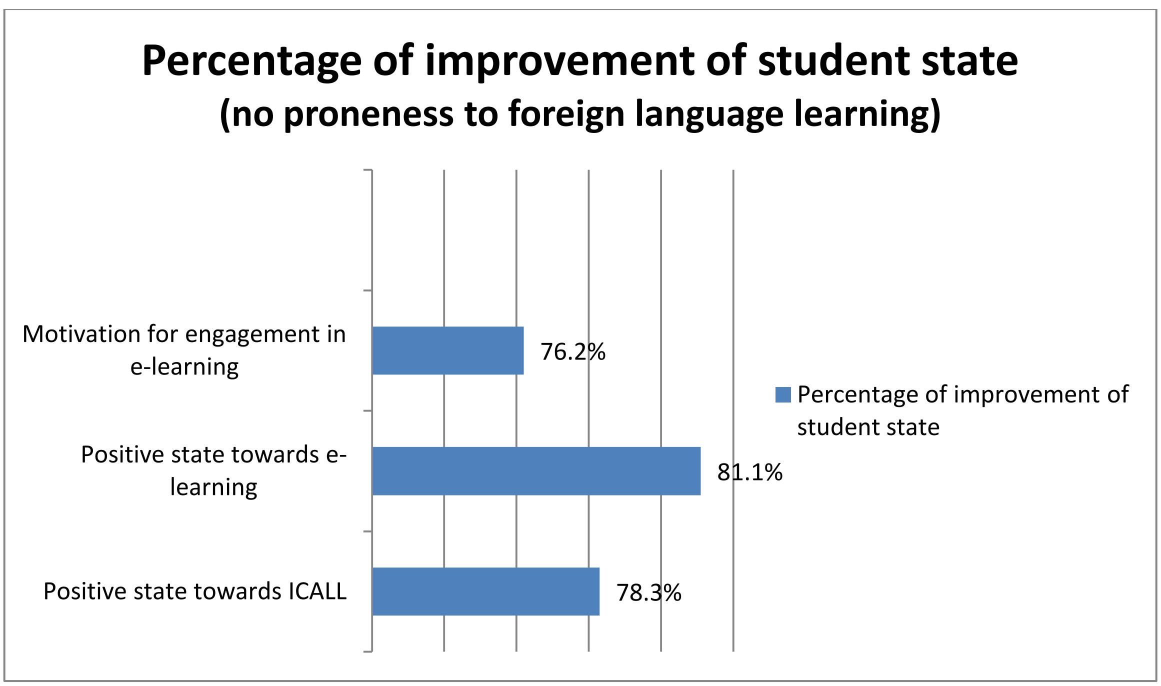

Figure 47. Changes on individual state of students with previous knowledge on foreign languages (proneness to language learning)

7.2.4. Results concerning students' progress

The results of the e-learning program to the learners' progress on their further studies are satisfactory. The results of the questionnaire reveal that the e-learning program helped the users. The questionnaire C that was answered by the learners is displayed later in this section, while the results are depicted in Figure 48. The teachers of the students in the private school of foreign languages along with the grades of the tests (on the concepts being taught in POLYGLOT) which were delivered to students after the period of using POLYGLOT can confirm the aforementioned results.

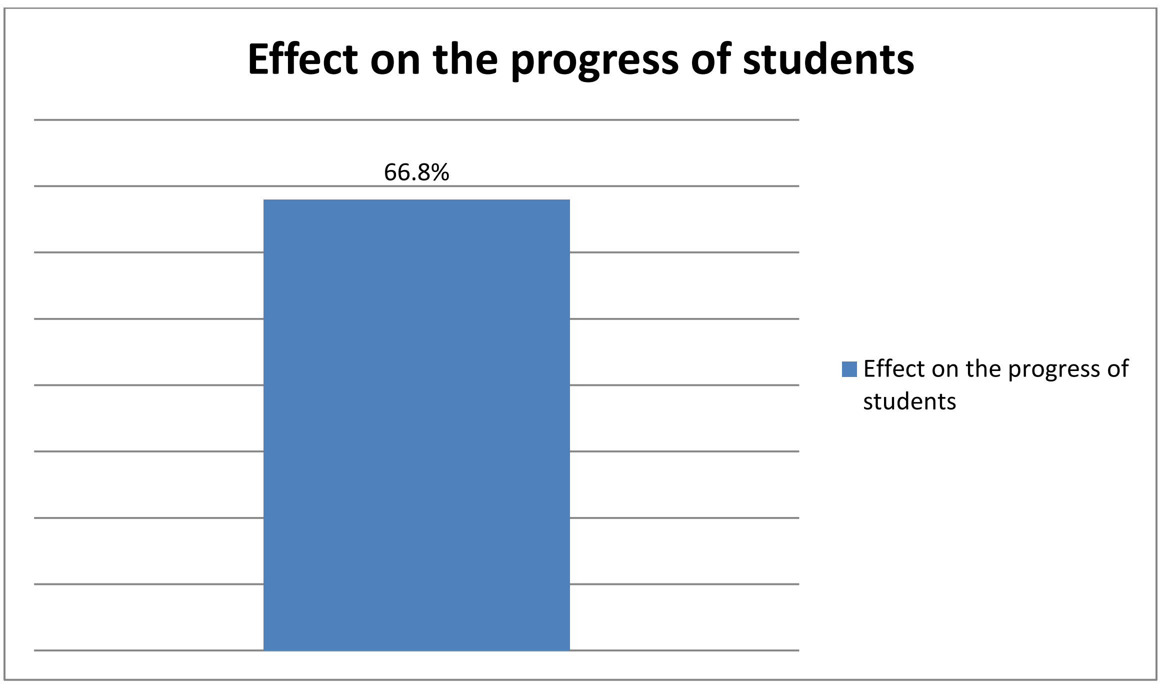

Figure 48. Results on learners' progress

7.2.5. Validity of the detection of the students' learning style

The detection of the students' learning style seems to be very satisfactorily valid. According to the results, POLYGLOT's automatic detection coincides with the traditional discovery (discovery based on the Felder Silverman questionnaire) of the learning style, giving the impressively high percentage of 95%. More specifically, after their interaction with POLYGLOT, students were asked to fill in the Felder-Silverman questionnaire in order to check if the automatic detection of their learning style coincides with the results of the questionnaire. After the students' interaction with POLYGLOT, they were also asked to answer if they are satisfied with the learning style which POLYGLOT detected for them; the percentage of students' satisfaction was again 95%. The high percentage of the validity of the automatic detection of the learning style was almost expected. Following, the reason for this expectation is clarified. As mentioned above, the automatic detection is conducted using the k-NN, which is a supervised machine learning algorithm. A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples. The optimal scenario will allow for the algorithm to correctly determine the class labels for unseen instances. Hence, this requires the learning algorithm to generalize from the training data to unseen situations in a "reasonable" way. To this direction, the algorithm was rendered able to learn to predict a certain target output. To achieve this, k-NN was given 100 training examples that demonstrate the intended relation of input and output values. Then it was supposed to approximate the correct output, even for examples that have not been shown during training. With several additional assumptions, this problem was solved exactly since unseen situations might have an arbitrary output value.

7.2.6. Validity of win-win collaboration

The results of the validity of the recommendation for win-win collaboration were positive (Questionnaire D, section 7.3). According to the results, 85% of the students liked the experience by stating that they had a fruitful collaboration with the right classmate. Furthermore, 90% of the students took assistance from this process by collaborating with a classmate who has complementary knowledge level or conducts different type of mistakes. The above percentages are sufficiently satisfactory to be able to lead to the conclusion that the recommendation for win-win collaboration is proper and supports the tutoring process.

7.3. Questionnaires

Following, the questionnaires, which have been used for the evaluation, are presented.

Questionnaire A

	Questions
Effectiveness	Does the educational software meet your expectations?
	Does the educational software help you understanding the rationale of learning foreign languages?
	Do you think that this educational software is useful as an educational “tool”?
	Do you think that the use of this educational software is a waste of time?
	After the end of the educational process, do you feel that you have assimilated all the subjects that you are taught?
Adaptivity	Does the program correspond to your knowledge level each time?
	Does the program correspond to your educational needs level each time?
	How time do you spend on issues that you already known?
	Does the test adapt to your educational needs?
	Does the learning style which POLYGLOT picked for you match to your needs?
	Do the motivational messages assist you on language learning?

Questionnaire B

	Questions
State on foreign language learning	Does the educational software affect positively your perception about foreign language learning?
	Does the educational software draw your interest on foreign language learning?
	Does the educational software motivate you to be involved in foreign language learning?
State on e-learning	Does the educational software help you to understand the subject of computers in education?
	Does the educational software affect positively your perception about distance learning?
Engagement in e-learning	Does the educational software motivate you to deal with distance education?
	Does the educational software motivate you to join other e-learning programs?

Questionnaire C

Questions
Does the educational software help you understanding better concepts on foreign language learning?
Does the educational software help you to learn other foreign languages?
Does the educational software help you in your studies?
Does the educational software help you understanding other lessons related to language learning?

Does the educational software help you in the elaboration of tasks and activities considering your studies?

Questionnaire D

Questions
Do you think that the person that POLYGLOT recommended to you for collaboration was the right one in terms of helping each other?
Is the collaboration with your classmate (proposed by POLYGLOT) fruitful?
Do you believe that you take and receive assistance from the proposed classmates having complementary knowledge level or type of misconceptions?

Chapter 8:

Conclusions & Contribution to the science

7.1. Conclusions and Discussion

The objective of this research was to create a novel social e-learning system which provides adaptive and personalized instruction to students. The developed system incorporates social characteristics and particularly posting on a wall, tagging a classmate, instant, declaring the affective state, liking/disliking of the exercises and instant and asynchronous text messaging. As such, the learning process takes place in an already familiar interface given that nowadays people spend a lot of their spare time in social networking sites, such as Facebook, and are very aware of this technology. Furthermore, POLYGLOT employs machine learning techniques, namely the k-nearest neighbors algorithm, in order to automatically define the learning style of the student based on the Felder-Silverman Learning Style Model. As such, the user does not need to answer a great deal of the questions proposed by the aforementioned model. Thereby, POLYGLOT can infer about the way with which the student prefers to process information (active and reflective learners) and the student progress towards understanding (sequential and global learners).The learning style of the student adapts the program on the student based on his/her preferences and needs. Therefore, the system allows each individual learner to complete the e-learning course at a friendlier interface that takes into consideration the individuality of the learners in terms of the way and pace of learning. In this way, the system helps learners to save time and effort during the learning process.

Moreover, POLYGLOT supports win-win collaboration. More specifically, the algorithmic techniques that have been used serve as a recommendation tool to students and assist them concerning the right classmate to choose for collaboration. The system incorporates two different approaches for collaboration. The first one is the win-win collaboration based on the already learnt language concepts. The second approach concerns the types of misconception that the user made. For example, if a student is good at concept A but has poor knowledge on concept B, the system proposes him/her a collaboration with another learner who is complementary to the concepts. Also, under the same rationale, if a student is prone to conduct misconceptions of category A but s/he does not conduct misconception of category B, the system proposes him/her collaboration with a student who conducts misconception of category B but not of category A. As such, based on two significant characteristic, namely the gained knowledge on taught concepts and the type of students' misconceptions, the system recommends collaboration between classmates and they will both learn from each other. To this direction, the system provides advising to learners to collaborate with peers in such a way that both of them can reap the benefits of collaboration and learn while collaborating.

Moreover, POLYGLOT employs an error diagnosis module in order to successfully recognize the categories of errors that students make. The types of misconceptions that are diagnosed by the system are the accidental slips, pronoun mistakes, spelling mistakes, verb tense mistakes, language transfer interference. For this reason, two algorithmic approaches are incorporated. The first technique is the Approximate string matching which finds string similarities by matching a student's given "exact" wrong answer with the systems correct stored answer. This technique is responsible for finding strings that match a pattern approximately. The problem of approximate string matching is typically divided into two sub-problems: finding approximate substring matches inside a given string and finding dictionary strings that match the pattern approximately. If string matching occurs in a high percentage, POLYGLOT decides whether the mistake lies among the categories of accidental slips, pronoun mistakes, spelling mistakes or verb mistakes. Correspondingly, using the second technique of string meaning similarity, POLYGLOT also tries to find meaning similarities between the given and the correct answer by translating these two answers to the system's available supported languages, namely the English and French languages. As such, the type of Language Transfer Inference mistake can be detected and diagnosed. Towards this direction, POLYGLOT can perform misconception detection and diagnosis so that POLYGLOT holds this information and assists the student in the tutoring process.

Also, one main innovation of the implemented system is the provision of personalized motivational messages to students in case of frustration. The system creates and displays messages to motivate the learners according to the reasons why the student is frustrated. The prime reason for frustration is goal failure. The possible reasons for goal failure are identified from the students' goal while they interact with the ITS. Upon the first interaction of the student with POLYGLOT, s/he can state his/her affective state. This adheres to the same rationale of posting one's emotion in social networking services, such as Facebook. Based on the information of the student's affective state, POLYGLOT delivers motivational messages to the student in support of his/her educational effort. When the student, tries the first test, POLYGLOT receives new information, namely the grade of the student and the time s/he needed to complete the test. Based on this new information, the algorithmic approaches of POLYGLOT may change the affective state of the student and then s/he is presented different motivational messages which adhere to the new affective state. Hence, the student is further assisted and motivated since these messages can indeed support his/her effort. It should be noted that the motivational messages are held in a library and selected every time based on the corresponding affective state.

The presented novel approach of knowledge domain representation and student modeling has been fully implemented in a web-based educational application, which teaches two foreign languages, namely the English and French languages. POLYGLOT is also accompanied with an authoring tool. POLYGLOT's authoring tool allows a non-programmer, usually an instructional designer or technologist, to easily create software with programming features. The programming features are built in but hidden behind buttons and other tools, so the author does not need to know how to program. It provide lots of graphics, interaction, and other tools for educational software needs. The three main components of the authoring system are the content management the type of assessment. The content management allows the user to structure the instructional content and media. The type of assessment refers to the ability to test learning outcomes within the system, usually in the form of tests, discussions, assignments, and other activities which can be evaluated. Finally, it incorporates students' reports and statistics so that the instructor can have a clear understanding of the educational process.

Learning styles are theories that try to separate students by their different and optimum methods of learning. The goal of a learning style model is to find a structure to explain why students have different preferences for learning, and why teaching something one way can be best for one student, while teaching something another way can be best for another student. Individualized instruction is achieved by the use of learning style models because they identify the differentiation and multimodality in the tutoring process. In order to identify the learning styles, it is required by the students to answer a great deal of questions. However, this study initiates the user using a few personal questions about him/her and a machine learning technique to automatic classify them to the appropriate learning style.

Collaborative learning is a situation in which two or more people learn or attempt to learn something together. Unlike individual learning, people engaged in collaborative learning capitalize on one another's resources and skills (asking one another for information, evaluating one another's ideas, monitoring one another's work, etc.). More specifically, collaborative learning is based on the model that knowledge can be created within a population where members actively interact by sharing experiences and take on asymmetry roles. Hence, this study exploits the social networking features, such as digital wall, instant and asynchronous text messaging, in order to provide a collaborative environment and recommend collaborations between students towards promoting mutual learning.

Error diagnosis can identify incorrect learning behaviors, misconceptions the learner may have, and skill sets that need to be developed. It can also be used to determine learners' level of knowledge in between eLearning lessons or modules. Using an error diagnosis mechanism, this study identifies the category of the error that the user made and adapts the learning process by offering personalized advice. Summarizing, POLYGLOT incorporates the following:

- the Stephen Krashen's Theory of Second Language Acquisition
- the Felder-Silverman learning style model
- a supervised machine learning algorithm (k-nearest neighbors algorithm) which takes as input several students' features, including their age, gender, educational level, computer knowledge level number of languages spoken and grade on preliminary test, in order to detect their learning style
- Approximate String matching for diagnosing types of students' errors
- String meaning similarity for diagnosing errors due to language transfer interference
- the Linear Regression model to automatically detect students' frustration
- the Attribution Theory to deliver appropriate motivational messages to students.

The implemented novel educational system that teaches the English and French languages has been evaluated. In particular, the Kirkpatrick's evaluation model was used and POLYGLOT was evaluated based on its four layers. Particularly, the four levels of Kirkpatrick's evaluation model essentially measure:

- the reaction of student: what they thought and felt about the training
- the learning: the resulting increase in knowledge or capability
- the behavior: extent of behavior and capability improvement and implementation/application
- the results: the effects on the business or environment resulting from the trainee's performance

POLYGLOT's application was based on close-ended questionnaires and on experimental research. The questionnaire survey was performed in two stages. In particular, two questionnaires were answered immediately after the end of the training program, while the other two questionnaires were answered six months later. The six months waiting time for the follow-up evaluation could have as a result the responses to have affected by students' personal factors. It is known that there is no objective way to deal with it. However, the large amount of students (80) of the experimental group, their answers in the questionnaires of the first stage and the objective experimental research enhance the evaluation results.

The system's evaluation revealed that the automatic detection of the learning style along with the automatic frustration recognition and the delivery of motivational messages contribute, significantly, to the personalization of the learning process to each individual learner. The results of the evaluation demonstrated learning improvements in students and adaptation success to their needs. They revealed that the incorporated error diagnosis mechanism assists the students in the educational process and improves significantly the student's performance. Furthermore, the majority of the learners were very satisfied with the educational program. They obtained a more positive state and behavior towards foreign language learning and distance learning.

7.2. Contribution to Science

Following, the contribution to science in the related scientific fields is presented.

7.2.1. Contribution to Intelligent Tutoring Systems

One important novelty concerning the field of Intelligent Tutoring Systems lies in the fact that social media characteristics are incorporated in the user interface of the learning environment. Social media characteristics, such as posting on a wall, tagging a classmate, instant and asynchronous text messaging, declaring affective state and liking of the exercises, have been included in the Intelligent Tutoring Systems. Furthermore, it uses such features so that the student model is further enriched and the educational process is student-centered. Such features include the following:

- the automatic detection of the learning style based on the Felder-Silverman model,
- the automatic detection of the students' frustration using the Linear Regression model and the respond on this using motivational messages based on the Attribution Theory,
- the recommendation for win-win collaboration and
- the hybrid model for error diagnosis mechanism employing the Approximate String Matching and the String Meaning Similarity algorithms.

Finally, one new aera in e-learning has been accentuated in this research. When e-learning incorporates social networking characteristics along with intelligence in the instructional process, there is the birth of a new area in e-learning which is called Social Networking-based Learning (SN E- Learning). SN E- Learning combines a Social Media User Interface with the intelligence of ITSs and as being in its infancy, there is a fertile ground research on this new area.

7.2.2. Contribution to Computer-Supported Collaborative learning

One important novel module of POLYGLOT regarding the collaboration between students is the win-win collaboration module. The contribution of this module, employing algorithmic techniques, assists students to find the right classmate for collaboration. Win-win collaboration module serves as a recommendation tool which promotes collaboration between students in a way that both of them can benefit from this process. The module supports two different approaches for collaboration. The first one is the win-win collaboration based on the already learnt language concepts. The second approach concerns the types of misconception that the user made. For example, if a student is good at concept A but has poor knowledge on concept B, the system proposes him/her a collaboration with another learner who is complementary to the concepts. Also, under the same rationale, if a student is prone to conduct misconceptions of category A but s/he does not conduct misconception of category B, the system proposes him/her collaboration with a student who conducts misconception of category B but not of category A. As such, based on two significant characteristics, namely the gained knowledge on taught concepts and the type of students' misconceptions, the system recommends collaboration between classmates and they will both learn from each other. To this direction, the system provides advising to learners to collaborate with peers in such a way that both of them can reap the benefits of collaboration and learn while collaborating. The module constitutes an ideal way for collaboration tailored to students' needs.

7.2.3. Contribution to Student Modeling

One of the targets of this research was the automatic detection of the learning style of the student based on the Felder-Silverman model. The target of this research was to offer a more personalized environment to students so that they can learn at their pace, as stipulated by their learning style. The system's evaluation revealed that it contributes significantly to the adaptation of the learning process and to the learning pace of each individual learner. In this way, the presented novel approach helps the learners to save time and effort during the learning process, since the learning style detection is automatic, and to experience a more personalized tutoring process. As such, the learning material is delivered to each individual learner according to his/her learning style, taking into account his/her learning needs and different learning pace.

Furthermore, the hybrid error diagnosis module reveals to the students the type of their misconception in an automatic way and supports them in understanding the gap in the knowledge of the taught concepts. Particularly, the error diagnosis module combined two different algorithmic techniques (approximate string matching and string meaning similarity) into a hybrid approach and supports the user in case of possible confusion with features of the previously-known foreign language. In this way, the system allows each learner to understand the reason of his/her mistake; as such, the student learning can become more effective.

7.2.4. Contribution to Computer-Assisted Language Learning

Computer-assisted language learning systems teach foreign languages to learners, providing adaptivity. Mainly, these systems adapt the learning process dynamically to the student's knowledge level and needs. However, they do not provide automatic inference about the learner's learning style as POLYGLOT does. Consequently, the gain of the presented approach is that it allows each learner to complete the e-training course in a way that the system adapts dynamically to each individual learner's pedagogical needs. Furthermore, POLYGLOT delivers motivational messages to students based on the Attribution Theory in order to support them in their effort and prevent them for quitting the learning. Moreover, POLYGLOT constructs its learning strategy using the Krashen's Theory of Second Language Acquisition which contributes to the field of Computer-Assisted Language Learning in terms of the way of instruction, means of collaboration, time constraints in learning, holding students' records, logical gradation of learning concepts and response on negative affective state (frustration) in the form of motivational messages.

7.2.5. Contribution to Affective Computing

The contribution of this research on Affective computing is the automatic detection of the emotional state of frustration based on students' interaction with the social media user interface and the provision of appropriate response to those emotions in the form of motivational messages. The automatic detection of frustration takes place with the use of the Linear Regression Model which also finds the reason of frustration of the student.

7.3. Future Work

This Ph.D. thesis presents a social web-based application, incorporating automatic detection of students' learning style using the k-NN machine learning algorithm, two algorithmic approaches for effective error diagnosis, frustration detection based on the linear regression model and motivational messages based on the Attribution Theory. Given that the evaluation results are very encouraging, future work includes the incorporation of other knowledge domains in the system. Furthermore, future plans include the employment of other machine learning techniques, such as Support Vector Machines or C4.5 algorithm, and ensembles of classifiers being based on a variety of classification methodologies and achieving different rate of correctly classified individuals.

Another interesting field of further research is the creation of a model that will adapt the learning content to the students based on their affective states and the experimental investigation on whether this model can indeed promote the educational process. In order to create this model, the first step will be the utilization of the linear regression model, presented in this dissertation. The next step will be the forming of a dynamic Bayesian network for each of the affective states using associated features. The influence of the one affective state on the other can be modeled as a transition matrix of affective states. Using the transition matrix and features associated with the affective states can lead to the employment of the Hidden Markov Model (HMM) for cognitive affective states. In HMM, the affective state which is expressed at the specific time t is dependent on the affective state at time t-1. Hence, the adaptation and the personalization to students will be enhanced.

Finally, the development of a hybrid system which will include a web camera, microphone, eye tracking system, pressure-sensitive keyboard and equipment in order to capture the student's emotions and further ameliorate the students’ learning experience.

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Appendix

Papers being published during the research in the context of my Ph.D.:

In international conferences:

1. Virvou, M., Troussas, C. (2011): "CAMELL: Towards a ubiquitous multilingual e-learning system" in CSEDU 2011 - Proceedings of the 3rd International Conference on Computer Supported Education, Volume 2, Pages 509-513.
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