ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ
ΤΜΗΜΑ ΠΛΗΡΟΦΟΡΙΚΗΣ

Μοντελοποίηση χρηστών και προσαρμοστικότητα σε συνεργατικά περιβάλλοντα μάθησης για αντικειμενοστρεφείς μεθοδολογίες ανάπτυξης λογισμικού

Καλλιόπη Τουρτόγλου

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Αφιερωμένο στον πατέρα μου, Κυριάκο Τουρτόγλου

PHD THESIS

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Kalliopi Tourtoglou

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ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

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ΔΙΑΤΡΙΒΗ

για την απόκτηση Διδακτορικού

Διπλώματος του Τμήματος Πληροφορικής

Καλλιόπης Κ. Τουρτόγλου

ΜΟΝΤΕΛΟΠΟΙΗΣΗ ΧΡΗΣΤΩΝ ΚΑΙ ΠΡΟΣΑΡΜΟΣΤΙΚΟΤΗΤΑ ΣΕ ΣΥΝΕΡΓΑΤΙΚΑ ΠΕΡΙΒΑΛΛΟΝΤΑ ΜΑΘΗΣΗΣ ΓΙΑ ΑΝΤΙΚΕΙΜΕΝΟΣΤΡΕΦΕΙΣ ΜΕΘΟΔΟΛΟΓΙΕΣ ΑΝΑΠΤΥΞΗΣ ΛΟΓΙΣΜΙΚΟΥ

Τριμελής Συμβουλευτική Επιτροπή :

Επιβλέπουσα :
Μαρία Βίρβου
Καθηγήτρια
Πανεπιστημίου Πειραιώς

Μέλη :
Νικόλαος Αλεξανδρής
Καθηγητής
Πανεπιστημίου Πειραιώς

Θεμιστοκλής Παναγιωτόπουλος
Καθηγητής
Πανεπιστημίου Πειραιώς

Επταμελής Εξεταστική Επιτροπή :

Νικόλαος Αλεξανδρής
Καθηγητής
Πανεπιστημίου Πειραιώς

Μαρία Βίρβου
Καθηγήτρια
Πανεπιστημίου Πειραιώς

Θεμιστοκλής Παναγιωτόπουλος
Καθηγητής
Πανεπιστημίου Πειραιώς

Εμμανουήλ Γιακουμάκης
Αναπληρωτής Καθηγητής
Οικονομικού Πανεπιστημίου Αθηνών

Νικόλαος Μαλεύρης
Αναπληρωτής Καθηγητής
Οικονομικού Πανεπιστημίου Αθηνών

Κωνσταντίνος Μεταξιώτης
Επίκουρος Καθηγητής
Πανεπιστημίου Πειραιώς

Αθανασία Αλωνιστιώτη
Λέκτορας Εθνικού & Καποδιστριακού
Πανεπιστημίου Αθηνών

Περίληψη

Βασικός σκοπός της παρούσας διατριβής είναι η ανάπτυξη και παρουσίαση μιας καινοτόμου προσέγγισης σχετικά με την παροχή ευφυούς βοήθειας σε ένα λογισμικό συνεργατικής μάθησης (Computer Supported Collaborative Learning - CSCL system), που ονομάζεται AUTO-COLLEAGUE (AUTOmated COLLaborativE leArninG Uml Environment). Πρόκειται για ένα περιβάλλον εκπαίδευσης χρηστών στη UML (Unified Modelling Language), αλλά είναι έτσι σχεδιασμένο, ώστε να μπορεί να χρησιμοποιηθεί και για άλλα γνωστικά αντικείμενα, όπως γλώσσες προγραμματισμού. Είναι κατάλληλο για χρήση τόσο σε εκπαιδευτικά ιδρύματα, όσο και σε εταιρείες παραγωγής λογισμικού. Το AUTO-COLLEAGUE παρακολουθεί κάθε ενέργεια καθώς και κάθε πιθανή ένδειξη επίδοσης των εκπαιδευομένων προκειμένου να παράγει και, ακολούθως, να προσφέρει χρήσιμες συμβουλές στους εκπαιδευόμενους, αλλά και στον εκπαιδευτή, ο ρόλος του οποίου συχνά παραμελείται από παρόμοια περιβάλλοντα.

Η συνεισφορά του συστήματος που παρουσιάζεται σε αυτή τη διατριβή αφορά τα επιστημονικά πεδία ανάπτυξης λογισμικού συνεργατικής μάθησης (CSCL systems) και των εργαλείων αυτόματου σχηματισμού ομάδων συνεργασίας (group formation tools). Συγκεκριμένα, οι καινοτόμες προσεγγίσεις που υλοποιήθηκαν στο AUTO-COLLEAGUE είναι:

- Η χρήση χαρακτηριστικών της προσωπικότητας των εκπαιδευομένων και ειδικά ο αυτόματος τρόπος που αυτά εκτιμώνται από το σύστημα,
- Η συνεκτίμηση της συναισθηματικής αλληλεπίδρασης μεταξύ των εκπαιδευομένων στην αυτοματοποιημένη διαδικασία σχηματισμού προτεινόμενων ομάδων συνεργασίας και
- Η χρήση της θεωρίας συγκυριακής ηγεσίας των Hersey και Blanchard στη διαδικασία εξατομικευμένης προσαρμογής των παρεχόμενων συμβουλών προς τους εκπαιδευόμενους.

Η παρεχόμενη βοήθεια στους εκπαιδευόμενους συνίσταται (α) στα προτεινόμενα θέματα της UML προς μελέτη, (β) στους πιο κατάλληλους για συνεργασία συναδέλφους και (γ) σε ενθαρρυντικά μηνύματα που θα μπορούσαν να αυξήσουν την αποδοτικότητά τους. Η παρεχόμενη βοήθεια στον εκπαιδευτή αφορά (α) στατιστικές

αναφορές και διαγράμματα σχετικά με την πρόοδο των εκπαιδευομένων και (β) ένα εργαλείο αυτόματου σχηματισμού ομάδων που προτείνει τη βέλτιστη οργάνωση των εκπαιδευομένων σε ομάδες συνεργασίας. Όλοι οι προαναφερόμενοι τύποι βοήθειας παράγονται από ένα ενσωματωμένο σύστημα συστάσεων (recommender system) που βασίζεται στις προσεγγίσεις του φιλτραρίσματος με βάση το περιεχόμενο (content-based filtering) και του συνεργατικού φιλτραρίσματος (collaborative filtering).

Για την παραγωγή ευφυών συστάσεων/συμβουλών, το σύστημα δημιουργεί και ενημερώνει εξατομικευμένα μοντέλα μαθητών (student models) για κάθε εκπαιδευόμενο. Τα μοντέλα αυτά περιγράφουν τον εκπαιδευόμενο και είναι υλοποιημένα βάσει μιας υβριδικής προσέγγισης μοντελοποίησης μαθητών που συνδυάζει το μοντέλο διατάραξης γνώσης (perturbation/buggy models) και τη μέθοδο των στερεοτύπων (stereotype-based models). Το μοντέλο μαθητή περιέχει δεδομένα σχετιζόμενα, αλλά και μη σχετιζόμενα με το γνωστικό αντικείμενο.

Τα σχετιζόμενα με το γνωστικό αντικείμενο δεδομένα αφορούν το επίπεδο γνώσης και εμπειρίας σχετικά με αυτό. Το γνωστικό αντικείμενο, δηλαδή όλη η γνώση που επιθυμούμε να διδαχθεί, είναι καταγεγραμμένη στη βάση δεδομένων του συστήματος δομημένη σε έννοιες, κάθε μία από τις οποίες φέρει ένα βαθμό γνώσης. Τα μη σχετιζόμενα με το γνωστικό αντικείμενο δεδομένα αφορούν (α) τη γενική συναισθηματική κατάσταση του εκπαιδευομένου (θετική ή αρνητική) και (β) ένα σύνολο συγκεκριμένων χαρακτηριστικών περιγραφής της προσωπικότητας που επηρεάζουν τη διαδικασία μάθησης και συνεργασίας των εκπαιδευομένων.

Η γενική συναισθηματική κατάσταση των εκπαιδευομένων εκτιμάται αυτόματα από το σύστημα χρησιμοποιώντας τη γνωστική θεωρία των συναισθημάτων OCC. Αυτή η θεωρία, που είναι η πιο δημοφιλής στην υλοποίηση συστημάτων συναισθηματικής νοημοσύνης, προτείνει ένα υπολογιστικό μοντέλο αναγνώρισης και μοντελοποίησης των συναισθημάτων. Αυτή, λοιπόν, η γενική συναισθηματική κατάσταση των εκπαιδευομένων χρησιμοποιείται ως κριτήριο στο εργαλείο αυτόματου σχηματισμού ομάδων συνεργασίας, καθώς και στην εμφάνιση των ενθαρρυντικών μηνυμάτων προς τους εκπαιδευόμενους.

Τα χαρακτηριστικά που περιγράφουν την προσωπικότητα των εκπαιδευομένων είναι δομημένα σε οκτώ στερεότυπα: ο έχων αυτοπεποίθηση, ο εργατικός, ο συμμετοχικός, ο πρόθυμος να βοηθήσει, ο σκεπτικός, ο βιαστικός/επιπόλαιος, ο έχων έλλειψη αυτοσυγκέντρωσης και ο ικανός. Το σύστημα κατατάσσει τους εκπαιδευόμενους σε αυτά τα στερεότυπα αξιολογώντας συγκεκριμένα χαρακτηριστικά, που είναι συναφή με τον τρόπο χρήσης του περιβάλλοντος, αλλά και με την πρόοδό τους στο γνωστικό αντικείμενο. Ο τρόπος που το σύστημα συσχετίζει τις τιμές αυτών των χαρακτηριστικών με κάθε στερεότυπο είναι προϊόν εμπειρικής μελέτης που διεξήχθη μεταξύ έμπειρων εκπαιδευτών.

Όπως προαναφέρθηκε, μία από τις σημαντικότερες συνεισφορές της έρευνας που παρουσιάζεται σε αυτήν τη διατριβή σχετίζεται με τα χαρακτηριστικά της προσωπικότητας των εκπαιδευομένων που εκτιμώνται από το σύστημα, καθώς και με τα κριτήρια που χρησιμοποιούνται στο εργαλείο αυτόματου σχηματισμού ομάδων. Τα περισσότερα από τα υπάρχοντα συστήματα συνεργατικής μάθησης βασίζονται στις γνώσεις και στις ικανότητες των εκπαιδευομένων για την παραγωγή ευφυών και προσαρμοστικών συμβουλών. Κάποια άλλα χρησιμοποιούν τους εξατομικευμένους τύπους μάθησης (learning styles) ή/και τους εργασιακούς χαρακτήρες (team roles) των εκπαιδευομένων. Η συντριπτική τους πλειοψηφία δεν υπολογίζει αυτοματοποιημένα τις τιμές αυτών για κάθε εκπαιδευόμενο, μα χρησιμοποιεί επιστημονικά εργαλεία απευθείας εισαγωγής δεδομένων από το χρήστη, όπως ερωτηματολόγια. Αντίθετα, το σύστημα που υλοποιήθηκε στα πλαίσια αυτής της έρευνας εκτιμά τα χαρακτηριστικά της προσωπικότητας των εκπαιδευομένων αυτοματοποιημένα.

Παρά τη σπουδαιότητα της αποδοτικής οργάνωσης των ομάδων που εργάζονται συνεργατικά σε διαδικασίες εκπαίδευσης, δεν υπάρχουν αρκετά εργαλεία αυτόματου σχηματισμού ομάδων. Πράγματι, υπάρχουν στη διεθνή βιβλιογραφία κάποιες πολύ ενδιαφέρουσες μέθοδοι σχηματισμού ομάδων, αλλά στις περισσότερες από αυτές προτείνονται ομάδες σχηματισμένες με όσο το δυνατόν μεγαλύτερη ετερογένεια ή ομογένεια σχετικά με τις γνώσεις, τους τύπος μάθησης ή τους εργασιακούς χαρακτήρες των εκπαιδευομένων. Αντίθετα, το εργαλείο σχηματισμού ομάδων που παρουσιάζεται στην παρούσα έρευνα είναι βασισμένο στους επιθυμητούς και μη επιθυμητούς (από τον εκπαιδευτή) συνδυασμούς των χαρακτηριστικών της προσωπικότητας των εκπαιδευομένων, καθώς και στη συναισθηματική αλληλεπίδραση μεταξύ αυτών κατά τη διάρκεια της συνεργασίας τους. Μία άλλη καινοτομία του εν λόγω εργαλείου είναι ότι το εργαλείο σχηματισμού ομάδων έχει υλοποιηθεί με τον αλγόριθμο προσομοιωμένης ανόπτησης (Simulated Annealing algorithm), ο οποίος δεν έχει χρησιμοποιηθεί ούτε σε επίλυση παρόμοιων προβλημάτων ούτε σε παρόμοια εκπαιδευτικά περιβάλλοντα. Πρόκειται για ένα γενετικό αλγόριθμο που χρησιμοποιείται για την επίλυση προβλημάτων βελτιστοποίησης. Αποφεύγει τα τοπικά βέλτιστα χρησιμοποιώντας μια μεταβλητή ελέγχου, που ονομάζεται θερμοκρασία.

Μία άλλη συνεισφορά της έρευνας αυτής σχετίζεται με τη χρήση της θεωρίας συγκυριακής ηγεσίας των Hersey και Blanchard προκειμένου το σύστημα να προσαρμόζει ανάλογα τόσο το περιβάλλον, όσο και τη βοήθεια προς τους εκπαιδευόμενους. Η ίδια θεωρία μάλιστα χρησιμοποιείται και για να προτείνει στον εκπαιδευτή το πιο αποδοτικό στυλ ηγεσίας για κάθε εκπαιδευόμενο και για κάθε ανατιθέμενη εργασία. Η θεωρία συγκυριακής ηγεσίας των Hersey και Blanchard βασίζεται στο ότι οι επιτυχημένοι ηγέτες θα πρέπει να προσαρμόζουν τη συμπεριφορά τους ανάλογα με την ωριμότητα των καθοδηγούμενών τους σε επίπεδο ανατιθέμενης εργασίας. Προς το παρόν, δεν έχει αναπτυχθεί άλλο εκπαιδευτικό περιβάλλον που να εφαρμόζει αυτήν ή κάποια άλλη θεωρία ηγεσίας.

Η αποτελεσματικότητα της επίδρασης της παρεχόμενης από το σύστημα βοήθειας στη μάθηση των εκπαιδευομένων έχει αποδειχθεί από τα θετικά συμπεράσματα δύο πειραμάτων αξιολόγησης που διεξήχθησαν σε πραγματικό περιβάλλον με πραγματικούς χρήστες.

Ένα εκτενές μέρος αυτής της διατριβής είναι αφιερωμένο στην περιγραφή της σημασίας των συνεργατικών εργαλείων μάθησης, καθώς και στην ανάλυση του υπόβαθρού τους στη βιβλιογραφία των επιστημών της Ψυχολογίας και της Εκπαίδευσης.

Abstract

The aim of this thesis is to introduce a new approach to intelligent and affective recommendations offered by a Computer Supported Collaborative Learning (CSCL) system, called AUTO-COLLEAGUE (AUTOmated COLLaborativE leArninG Uml Environment). It is an environment for training users in UML, but it can also be used for other popular domains, such as programming languages. It may be used both in educational institutes and software houses. AUTO-COLLEAGUE traces every action and performance indication in order to provide useful recommendations to the trainees, as well as the trainer who is often neglected in similar environments.

The contributions of the system presented in this thesis concern CSCL systems and group formation tools. In specific, the novel approaches implemented in AUTO-COLLEAGUE are:

- The personality-related characteristics included in the student models and, especially, the way they are automatically traced and evaluated,
- The affectivity implemented to recommend optimum groups of trainees and
- The use of a leadership theory, and specifically the Hersey and Blanchard Situational Leadership Theory, for adapting intelligent recommendations in a learning environment.

The recommendations to the trainees concern (a) the next UML topics they should study, (b) the appropriate colleagues with whom they should collaborate and (c) supportive/encouraging messages that would increase their performance. The recommendations to the trainer include (a) historical/statistical reports and charts of showing the progress of the trainees and (b) a group formation tool that proposes optimum organization of the trainees into groups. The recommender system is built using both the content-based and the collaborative filtering methods.

The intelligence of the recommendations is based on the individual student models of the trainees. The system uses a hybrid student modelling technique, combining perturbation (buggy) and stereotype-based student models to describe the trainees. The student model contains both domain dependent and domain independent data. The domain dependent data represent the level of expertise referring to the domain

knowledge description. It is structured in topics, each of which bears a degree of knowledge. The domain independent data refer to (a) the overall emotional state (positive/negative) of the trainee and (b) a set of personality characteristics that affect the trainee's learning and collaboration processes.

The overall emotional state of the trainee is inferred using the OCC theory. OCC is a cognitive theory of emotions that suggests a computational model for emotion recognition and modelling. It is the most popular theory of emotions adapted in affective systems. The emotional state of trainee is used as a criterion for the group formation recommendations and the supportive messages offered to the trainee.

The personality characteristics are structured in eight stereotypes: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. In order for the system to update the student model, it monitors specific attributes that are relevant to the included stereotypes and concern the trainee's use of the environment and performance on the domain knowledge. The way the system manipulates the values of these attributes to make inferences is instructed by the results of an empirical study conducted amongst experienced trainers.

The contributions of this thesis are associated mainly to the kinds of personality characteristics evaluated and the criteria of the group formation algorithm. Most of the CSCL systems are based on the abilities and knowledge of the trainees to provide intelligent and adaptive advice. Others use learning styles and team roles, but the vast majority does not automatically traces their values observing the student. Instead, they use scientific instruments, such as questionnaires. None of these systems use personality characteristics similar to ours.

In addition, considering experimental studies on group formation tools, limited work is done despite the recognized importance of effective group formation in collaborative learning tasks. Indeed, there are interesting approaches of group formation, but most of them attempt to create heterogeneous or homogeneous groups considering the knowledge, learning styles or team roles. On the contrary, the group formation algorithm proposed in this thesis is based on desired and undesired combinations of personality attributes and the emotional influence between the trainees during the collaborative learning activities. Furthermore, the group formation tool is implemented using the Simulated Annealing algorithm, which has never been used in similar processes and environments. The Simulated Annealing algorithm is a genetic algorithm that serves as a general optimization technique for solving combinatorial optimization problems. It uses a control parameter (called temperature) to avoid getting trapped in poor local optima.

Another contribution of our study lies in the use of the Hersey and Blanchard Situational Leadership Theory for adapting the environment and recommendations to the trainee and for proposing to the trainee the most appropriate leadership style to follow per trainee and per learning task. We were inspired by educational studies that emphasized on the importance of the teacher to take a leadership role in classroom. The Hersey and Blanchard Leadership Theory is based on the principle that successful leaders should be flexible enough to adapt their leadership style according to the maturity of the followers for each assigned task. No other learning system has yet used a leadership theory.

The effectiveness of the provided recommendations has been demonstrated by the positive results of two evaluation experiments conducted in real time with real trainees.

An extended part of this thesis has been dedicated to describing the importance of intelligent Computer Supported Collaborative Learning systems and analyzing the origins of collaborative learning in the psychology and educational literature.

ΕΥΧΑΡΙΣΤΙΕΣ

Θα ήθελα να ξεκινήσω τονίζοντας ότι ίσως το πιο σημαντικό στοιχείο που χρειάζεται ένας υποψήφιος διδάκτορας είναι η σωστή καθοδήγηση και υποστήριξη από έναν ικανό και άξιο επιβλέποντα. Έτσι, θα ήθελα να εκφράσω το θαυμασμό και την ευγνωμοσύνη μου στην Καθηγήτρια Μαρία Βίρβου, η οποία καθοδήγησε την έρευνα αυτή στο σύνολό της, με τις δημιουργικές και έμπειρες συμβουλές της. Είναι αναμφίβολο πως χωρίς την υποστήριξή της σε όλα τα επίπεδα, δε θα είχα καταφέρει ποτέ να φέρω σε πέρας αυτό το εγχείρημα.

Θα ήθελα επίσης να ευχαριστήσω και τα άλλα δύο μέλη της συμβουλευτικής επιτροπής, τους κ. Νικόλαο Αλεξανδρή, Καθηγητή στο Πανεπιστήμιο Πειραιά, και κ. Θεμιστοκλή Παναγιωτόπουλο, Καθηγητή στο Πανεπιστήμιο Πειραιά, για τη στήριξη και τις εποικοδομητικές συμβουλές τους, καθώς και τα υπόλοιπα μέλη της επταμελούς εξεταστικής επιτροπής, τους κ. Εμμανουήλ Γιακουμάκη, Αναπληρωτή Καθηγητή στο Οικονομικό Πανεπιστήμιο Αθηνών, κ. Νικόλαο Μαλεύρη, Αναπληρωτή Καθηγητή στο Οικονομικό Πανεπιστήμιο Αθηνών, κ. Κωνσταντίνο Μεταξιώτη, Επίκουρο Καθηγητή στο Πανεπιστήμιο Πειραιά και κα. Αθανασία Αλωνιστιώτη, Λέκτορα στο Εθνικό & Καποδιστριακό Πανεπιστήμιο Αθηνών, για το χρόνο που αφιέρωσαν, αλλά και την προθυμία τους να συμμετάσχουν στην εξέταση της διατριβής μου. Η συμμετοχή όλων των καθηγητών στην επταμελή επιτροπή του διδακτορικού μου με τιμά ιδιαίτερα.

Θα ήθελα να ευχαριστήσω το σύζυγό μου, Νεκτάριο, για την υποστήριξη, την ενθάρρυνσή του, αλλά και τις πολύτιμες συμβουλές και ιδέες του σχετικά με τεχνικά θέματα. Θα ήθελα να ζητήσω συγγνώμη από τα δύο υπέροχα παιδιά μου, Νεφέλη και Κώστα, που με στερήθηκαν κάποιες φορές εξαιτίας του φόρτου εργασίας μου. Παρόλα αυτά, θα πρέπει να σημειώσω πως αποτέλεσαν έμπνευση στην προσπάθεια μου αυτή, όπως ευελπιστώ η προσπάθειά μου αυτή να αποτελέσει έμπνευση για αυτά. μελλοντικά.

Επίσης, θα ήθελα να ευχαριστήσω τη μητέρα μου και ιδιαίτερα τον αγαπημένο μου πατέρα, Κυριάκο, που με στηρίζει από τότε που μπορώ να θυμηθώ τον εαυτό μου.

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INTRODUCTION AND OVERVIEW

1.1. Background and Motivation

1.1.1. Learning Theories and their Influences on Software Learning Environments

A variety of approaches and theories about learning have been presented and adopted by psychologists during the last century. They differentiate mainly on their view of *how* learning is achieved. The three relevant schools of psychology influence the main approaches of teaching: the behaviorist, cognitivism and socio-cultural approaches.

The leading exponents of behaviorism are Watson (1924; 1928), Thorndike (1932), Pavlov (1906), Bloomfield and Skinner (1954). Based on scientific founding that associated animals' learning with repetition and rewards, behaviorists related stimuli and reinforcement with responses during human learning. The behaviorist learning theories view learning as the result of observable changes in the behaviour. Therefore, behaviorists study the external reactions of humans during learning ignoring internal cognitive processes, as they are not considered to lead to any safe prediction about human learning. In specific, behaviorists believe that learning is achieved through repetitions and rewards (positive reinforcement). Thus, tactics such as active learning and immediate feedback are promoted. Moreover, any domain of knowledge, no matter how complicated it is, can be analyzed into simpler domains in order to make them easier to learn. These principles of behaviorism formed the inspiration and theoretical base of Instructional Design (Gagné et al., 2005), which is a practice of structuring and preparing learning processes. Instructional Design imposes five stages: analyze (identification of learners' state and learning goals), design, develop, implement and evaluate. Due to its discrete and computable stages, this model appeared to be applicable in computer-based learning environments and, especially, in Intelligent Tutoring Systems. Nevertheless, the principles of reinforcement, active learning and immediate feedback have influenced the vast majority of computer-based learning systems.

Contrary to behaviorist, cognitive learning theories regard learning as an internal brain process of manipulating and storing knowledge viewing the learner as an information processor (input-process-output). The originator of cognitivism was Tolman (1932) that developed the Cognitive Learning Theory, whose main principle was that learning is purposive and goal-directed. Thus, cognitivism does not regard humans are pre-programmed animals that react to stimuli, as behaviorism suggests. Humans use logic, rational thinking in order to actively learn. Changes in behaviour only indicate the current state of the learning process, rather than cause learning as argued by behaviorists.

In line with cognitivism, the constructivist approach of Piaget (Piaget, 1952; Piaget & Inhelder, 1971; Piaget, 1980) suggests that humans construct knowledge from their experiences. Therefore, learning is an individualized and subjective process as new information is linked to prior knowledge. Learning is achieved when the learner is active (not a passive receiver of information). The learning environment should be interactive and enriched with various external stimuli to activate and support learning. Influenced by constructivism, Bruner (Bruner et al., 1956; Bruner, 1966) presented Discovery Learning Theory, according to which learners discover and acquaint new knowledge by interacting with the environment. Such interactions are experiments, dealing with questions, problems or controversies and examining objects. The teacher should motivate the learners, facilitate and guide their discovery tasks.

Cognitive and especially constructivist theories provide the essential theoretical foundations for the computer-based learning systems that seek to enhance their environment with interactivity and tools for active-learning, motivation and intelligent guidance through adaptivity. The importance of employing the constructivist approach in learning environments is highlighted in literature (Jonassen et al., 1999; Perkins, 1991). In practice, computer-based learning systems that empower learners to construct knowledge from their experiences have already been developed, such as Logo environment (Papert, 1980).

The socio-cultural theory can be considered as complementary of the cognitivism. As its name suggests, the socio-cultural theory views psychological development as greatly affected by social interactions. The leader of this paradigm is considered to be Vygotsky (1978), who suggested that cognitive development is the product of social learning: "Every function in the child's cultural development appears twice: first, on the social level, and later, on the individual level; first, between people (interpsychological) and then inside the child (intrapsychological)". Under this perspective, the socio-cultural learning theories proposed since then contemplate learning as a social process rather than individual (as the Piagetian approach considered it). Such theories/frameworks are the activity theory (Leont'ev, 1978; Nardi, 1996; Kaptelinin et al., 1995), the situated learning theory (Lave, 1988; Lave & Wenger, 1990; Brown et al., 1989) and the distributed cognition meta theory (Hutchins, 1995). The socio-cultural learning theories support collaborative and cooperative learning and provide principles that have important implications for the construction of Computer-Supported Collaborative Learning (CSCL) systems. At the same time, CSCL systems needed this theoretical framework, as every form of technology needs relevant theoretical support to establish new practices (Stahl et al., 2006). Recent research on the role of collaboration in learning has tried to find deeper theoretical frameworks that could better guide the developing of technology-aided learning environments (Lehtinen et al., 1999).

1.1.2. Computer-Supported Collaborative Learning (CSCL) Systems

CSCL systems are learning software environments that allow distant users to collaborate with each other in groups having a common goal. CSCL systems should not be confused with e-learning environments. The facilities provided by e-learning environments are based on the sharing of educational/training resources (such as presentations, notes, books, assignments) over the Internet or a local network. On the contrary, CSCL systems focus mainly on the social interactions and collaboration between learners. Their aim and challenge (imposed by the socio-cultural learning theories) is to promote and direct collaboration processes according to the group learning goals considering the individualized nature of every learner. Materializing such functionalities still remains a challenge for CSCL (Stahl et al., 2006).

CSCL systems followed not only the evolutions of educational psychology, but also the rapid development of information technology implementing new approaches in monitoring and mentoring the individual characteristics of the learners and the learning process. The ancestors of CSCL systems are the Intelligent Tutoring and Intelligent Learning systems, which were based on the behaviorist school of thought and learning. The aim of these systems was to simulate the human tutor providing individualized help and guidance to the student on the domain knowledge. They were intelligently adaptive according to the learner's needs and traits (at the beginning mainly to the learner's cognitive level).

Like their ancestors, CSCL systems also need to adapt their environment and facilities according to the learners and groups of learners. This is achieved by building individual student models that describe learners' characteristics relatively to the system's context. In general, such characteristics can be associated either to the knowledge level and skills of the learners or their psychological and generic nature (e.g. learning style, personality, age, gender, interests, preferences). The task of building a student model is extremely difficult and laborious, due to huge search spaces involved (Mitrovic et al., 2001). There is a great variety proposed in literature of student modelling (the process of building students models) techniques. The most interesting and frequently used are overlay model, the perturbation (or buggy) model, stereotypes, the constraint-based model, fuzzy logic/fuzzy sets and Bayesian networks. The current trend in student modelling suggests combinative use of student modelling techniques attempting to blend their strengths and weaknesses.

The system described in this thesis is a CSCL system that uses a hybrid student modelling technique. It combines the buggy model for describing the knowledge and stereotypes for describing personality characteristics and emotional influences of the trainees. A buggy student model describes both misconceptions and missing conceptions assembling in this way the knowledge of the student. Stereotype-based user modelling simulates the way people make assumptions on others, based on relevant information about them. The personality related stereotypes used in the system are: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. Most of the learning systems base their inferences on the performance and the collaborative attitudes (e.g. participation). There are other systems that consider domain independent data, such as learning styles, but not similar to the personality attributes used in our system. There are studies proving that embedding human personality characteristics into the computer interface would enhance the users' performance, as well as the outcomes of the human-computer interaction (Richter & Salvendy, 1995; Murray & Bevan, 1985; Rothrock et al., 2002). Furthermore, most of these related systems do not evaluate automatically these domain independent data. Instead, they use relative questionnaires and psychometric instruments (Carver et al., 1999; Shang, Shi & Chen, 2001; Bajraktarevic, Hall & Fullick, 2003; Wolf, 2003; Papanikolaou et al., 2003; Brown & Brailsford, 2004) or explicitly receive them as input (de Bra & Calvi, 1998; Stash et al., 2006; Grigoriadou et al., 2001). On the contrary, in AUTO-COLLEAGUE the personality characteristics are inferred automatically during the collaborative learning activities. The use of such psychometric instruments needs caution, as in some cases reliability can be low (Lawrence & Martin, 2001) and learning styles are likely to change over time (Kolb, 1984; Gonyeau et al., 2006).

1.1.3. Affective Computing

As neurological and psychology scientists presented new findings on emotion recognition and proofs that related emotions to cognition, a new branch appeared in the Artificial Intelligence field: Affective Computing (Picard, 1997), which entangles with the users' emotions. In specific, affective computing deals with the automatic recognition of users' emotions and how emotions can be used to produce affectivity and empathy. The notion of affective computing triggered the interest of researchers on intelligent learning and CSCL systems. As educational psychologists had already associated emotions with the learning process, emotions were integrated in learning systems. Emotions bear valuable information that can potentially improve the efficiency of computer software. As described in the literature (Damasio, 1994), (Izard, 1984), emotions lead to rational behaviours and, therefore, can provide important information for making inferences about a user reactions. Consequently, these inferences can be used further for decision making based on emotions. In addition, the emotion theories (Frijda, 1986; Lazarus, 1991) and computational models of emotions (Ortony, Clore & Collins, 1988) that were developed constituted an accommodation of integrating emotions in computer software.

Emotion recognition has already been applied in learning environments for animated pedagogical agents (Gratch & Marsella, 2001; Jaques & Vicari, 2007; Lester et al., 1999; Craig et al., 2004; Jaques et al., 2004; Elliott et al., 1999; Nkambou, 2006) and affective system responses, support and adaptation (Katsionis & Virvou, 2005; Moridis & Economides, 2008b; Poel et al., 2004; Leontidis et al., 2009; Conati & Zhou, 2004). However, as emphasized in (Dillenbourg et al., 2009): "affective and motivational aspects that influence collaborative learning have been neglected by experimental CSCL researchers".

A contribution of this thesis is based on affectivity. The presented system includes an emotion recognition agent that infers the overall emotional state of the trainees adapting the OCC Theory of emotions (Ortony, Clore & Collins, 1988). This theory is a de facto in emotion recognition systems in a variety of fields (Karunaratne & Yan, 2001; Liu & Pan, 2005; Paiva et al., 2004; Dias & Paiva, 2005; Bartneck, 2002; Ochs, 2005; Allbeck & Badler, 2002; Van Dyke Parunak et al., 2001; van Breemen & Bartneck, 2003; Streit et al., 2004; Zong et al., 2000) and, recently, in intelligent learning environments (Moridis & Economides, 2008b; Jaques & Vicari, 2007; Katsionis & Virvou, 2004; Conati & Zhou, 2004; Chalfoun et al., 2006; Jaques et al., 2004; Elliott et al., 1999; Chaffar & Frasson, 2006).

1.1.4. Automatic Group Formation

CSCL systems facilitate collaborative learning enabling students to work collaboratively into groups. An important but often neglected aspect in Computer-Supported Collaborative Learning is the formation of learning groups (Mühlenbrock, 2005). There are various proposed methods of groups' formation based mainly on creating homogeneous or heterogeneous groups based on knowledge (Johnson & Johnson, 1985; Mugny & Doise, 1978), team roles (Belbin, 1993), learning styles (Kolb, 1984; Honey & Mumford, 1986) and personality (Myers & McCaulley, 1985). Other researchers support homogeneous and others heterogeneous grouping. Nevertheless, most of them agree that heterogeneous grouping is more beneficial for the low-ability students opposed to homogeneous grouping that seems to benefit the high-ability students.

There are many studies that highlight the importance of group formation in collaborative learning tools (Daradoumis et al., 2002; Inaba et al., 2000). However, there are few experimental studies that provide automatic group formation. Most of them are stand-alone group formation tools (Christodoulopoulos & Papanikolaou, 2007; Graf & Bekele, 2006; Cavanaugh et al., 2004; Wang et al., 2007; Gogoulou et al., 2007a; Martin & Paredes, 2004; Ounnas et al., 2009; Khandaker & Soh, 2010; Paredes et al., 2009; Kyprianidou et al., 2009) and few of them are integrated tools in CSCL systems (Soh et al., 2006; Liu et al., 2008; Ikeda et al., 1997; de Faria et al., 2006; Kreijns et al., 2002). The majority of the existing group formation tools do not evaluate in real-time the criteria values (student characteristics) of their group formation algorithm. They receive it as input by the instructor of the systems or evaluate them based on scientific instruments, such as psychometric tests (Christodoulopoulos & Papanikolaou, 2007; Graf & Bekele, 2006; Cavanaugh et al., 2004; Wang et al., 2007; Gogoulou et al., 2007a; Martin & Paredes, 2004; Ounnas et al., 2009; Paredes et al., 2009; Kyprianidou et al., 2009). In almost all of these systems, the group formation method is homogeneous and/or heterogeneous according to a variety of characteristics, such as knowledge, skills, performance, learning styles and social skills. The existing group formation tools use a wide range of searching algorithms and techniques for grouping, such as the Fuzzy C-Means algorithm, Ant Colony Optimization, hill-climbing, semantic web technologies, randomized and genetics algorithms.

The system described in this thesis includes recommendations on optimum group formation. The implemented grouping method is differentiated from other related group formation tools in (a) the criteria taken into consideration, (b) the grouping method and (c) the grouping algorithm. The considered criteria are related to:

- The desired and undesired combinations of personality-related stereotypes in the same group,
- The desired group structure concerning the levels of expertise and
- The observed by the system emotional affect between the trainees.

The desired/undesired combinations of stereotypes are the pairs of personality-related stereotypes that their coexistence in the same groups would have a positive/negative influence on the performance of the individual trainees and of the groups. The default combinations are the outcome of an empirical study. The desired group structure concerns the number and kinds of levels of expertise (basics, junior, senior and expert) that should constitute each group. The emotional affect between the trainees is related to the observed emotional state during the collaboration of a trainee with the members of the same group. AUTO-COLLEAGUE includes an emotion recognition agent that infers the overall emotional state of the trainees adapting the OCC Theory of emotions (Ortony, Clore & Collins, 1988). The criteria values for each trainee are evaluated automatically. The grouping algorithm used is the Simulated Annealing algorithm (Kirkpatrick et al., 1983), which has not been used in similar situations. It is a genetic algorithm that serves as a general optimization technique for solving combinatorial optimization problems. Simulated Annealing is motivated by the desire to avoid getting trapped in poor local optima, and hence, occasionally allows "uphill moves" to solutions of higher cost, doing this under the guidance of a control parameter called the temperature (Johnson et al., 1989).

1.1.5. Recommender Systems

Nowadays, the era of computer and internet technology evolution, it seems as if people are bombarded with a huge load of information, news, software and alternatives in choosing products and services. Recommender systems appeared aiming at solving this everyday information overload problem. Recommender systems are defined as systems that can offer adaptive and intelligent advice to users on what information to receive. Recommender systems have become fundamental applications in electronic commerce and information access, providing suggestions that effectively prune large information spaces so that users are directed toward those items that best meet their needs and preferences (Burke, 2002). Recommender systems have become an important research area since the appearance of the first papers on collaborative filtering in the mid-1990s (Adomavicius & Tuzhilin, 2005).

In the literature, there are two methods of building recommender systems often described as: the Content-based Prediction and the Collaborative/Social Filtering. The Content-based Recommendation Systems export their user recommendation evaluating the preferences and characteristics of the user in association with the description of the system's information. According to the Collaborative/Social Filtering approach, the system recommends the information, that users with similar preferences and characteristics used in the past. Over the last years, the hybrid technique of combining these two methods has been preferred and efficiently applied in a great extent.

Recommender systems are a de facto in e-commerce environments (Prasad, 2005), tourist information (Sánchez-Anguix et al., 2010; Ricci & Werthner, 2002), books (Liao et al., 2010), movies (Jung et al., 2004; Nguyen et al., 2007), TV programs (Blanco-Fernandez et al., 2004; Velusamy et al., 2008; Blanco et al., 2005) music

(Nakahara & Morita, 2009; Lampropoulou et al., 2009; Kim et al., 2009), restaurants (Park et al., 2008) and news (Billsus & Pazzani, 2000). Many of the largest commerce Web sites are already using recommender systems to help their customers find products to purchase (Schafer et al., 1999).

Quite recently, recommender systems have also been developed for recommending learning objects (Lu, 2004; Zaíane, 2002; Wan et al., 2008; Linton et al., 2000; Chen et al., 2005; Tang & McCalla, 2005; Khribi et al., 2008; Furugori et al., 2002; Hummel et al., 2007; Hsu, 2008). Most of them focus on recommendations on learning objects or paths and rarely on adequate colleagues to collaborate with.

On the other hand, the recommendations offered by AUTO-COLLEAGUE concern learning objects and colleagues for collaboration. The recommendations are extracted using both the content-based and the collaborative filtering methods. The recommendations are content-based since the system evaluates the trainees' upgrades/downgrades of the level of expertise, the errors, the actions, the preferences in collaboration and the help topics already studied. In addition, the recommendations are collaborative as the agent consults the successful recommendations offered to other trainees with similar state or problems. A recommendation is considered as successful if the receiver trainee had overcome his/her problems in UML after following the steps described by it.

1.1.6. Teacher Leadership

A usually neglected aspect in education is teacher leadership. As Wilmore (2007) notices: "Most of the time when we think of school leaders we think of superintendents, principals, or other people in positions of authority". In the same study, she is wondering, "If teachers do not lead and guide students in their classrooms and in the cocurricular and extracurricular activities they sponsor, who does?" Teacher leadership is considered essential, however it is often neglected and somehow meets impediments (Gabriel, 2005; Barth, 2001; Wilmore, 2007; York-Barr & Duke, 2004; Suranna & Moss, 1999). The effort to create a cadre of leaders within the teaching ranks is rhetorically supported by nearly everybody and actually supported by very few (Tyson, 1993). The process of student learning benefits from an automatic definition of leadership style, as fairness amongst all students can be ensured. In the absence of fairness, attempts at instruction will not yield any significant amount of student learning (Walbesser, 2002).

Taking into consideration these risen needs in education, we decided to provide support to the trainers focusing on their leadership roles in the virtual classroom. One of the main fields of interest in the organizational and managerial literature is leadership. There are many definitions for the leadership depending on the research field. In (Achua & Lussier, 2009) leadership is defined as "the influencing process of leaders and followers to achieve organizational objectives through change". During the past decades a variety of leadership theories have been proposed, studied and applied in effort of organizing leadership. These theories involve different views of the leader, the follower instances and the variables that affect them. A common classification of leadership theories are: Great Man Theory, Trait Theory (Stogdill, 1974), Behavioral Theories (Blake & Mouton, 1964; Merton, 1957), Participative Leadership (Lewin et al., 1939; Likert, 1967), Situational Theories (Hersey & Blanchard, 1999; Hersey et al., 2007; Vroom & Yetton, 1973; House & Mitchell, 1974), Contingency Theories (Fiedler, 1964; Fiedler, 1963; Fiedler & Garcia, 1987), Transactional Leadership (Dansereau et al., 1975) and Transformational Leadership (Bass, 1985; Burns, 1978; Bass & Avolio, 1994).

In our system, we decided to use the Hersey-Blanchard Situational Leadership Theory (Hersey et al., 2007), because it has gained general acceptance and can be incorporated as a computational model due to its simple nature (Vasu et al., 1998; Baker, 2009). Additionally, there are studies that suggest the adaptation of this theory in education (Hersey et al., 1982; Donahoo & Hunter, 2007; Weber & Karman, 1991).

According to the Hersey-Blanchard Situational Leadership Theory, leaders should continually adjust their leadership styles depending on the maturity or readiness of the followers. Maturity is a variable defined by the ability and the willingness of the followers. Ability is related to the knowledge, skills and experience of a follower to complete a given task. Willingness concerns the degree of readiness, motivation and self-confidence of a follower to accomplish a given task. Another crucial element of the theory is that the maturity is dependent on each task given to the follower, rather than a global variable. Hersey and Blanchard have defined four different levels of maturity and four leadership styles (one for each maturity level).

In the approach described in this thesis, we attribute the role of the followers to the trainees and the role of the leader to both the trainer and the system itself as it serves pedagogical functions while interacting with the trainees. The appearance and frequency of the recommendation messages are adapted to the trainees according to their maturity levels and following the principles imposed by the respective leadership style. Additionally, the system suggests to the trainer the estimated appropriate leadership style to follow per trainee and per task according to the calculated trainee's maturity.

We should notice that no other learning environment have ever used any leadership theory to adapt advice or suggest to the trainer the most effective leadership style.

1.2. Overview of the System (AUTO-COLLEAGUE)

1.2.1. General Description

The system developed in the framework of this thesis is a Computer Supported Collaborative Learning (CSCL) environment, called AUTO-COLLEAGUE (AUTOmated COLLaborativE leArninG Uml Environment). The purpose of this system is to propose an integrated collaborative learning tool to support both trainers and trainees. The domain knowledge of the system concerns the Unified Modelling Language (UML) and, specifically, UML class diagrams and activity diagrams. It seems that UML is a suitable domain to use as a test bed in a CSCL system, as it is suitable for discussion due to its open-ended nature (Baghaei et al., 2007).

The Unified Modelling Language (UML) is an object-oriented visual modelling language that is used to specify, visualize, construct, and document the artifacts of a software system (Rumbaugh et al., 1999). The use of UML has grown enormously in many organizations that develop software during the last decade. UML is, also, very popular amongst education institutes, that use it as a tool for software engineering training. Being widely used in industry by now, proficiency in UML is certainly a valuable asset for every computer science student (Engels et al., 2006). However, there are studies that highlight the difficulties in learning UML (Basheri, 2010; Simons et al., 1999; Siau et al., 2006). Furthermore, UML is a domain that students need to practice, rather than attend theoretical courses in order to actually learn it (Baghaei, 2007). The professional CASE tools usually used in laboratories to teach UML seem to be unfriendly and too complicated for educational purposes (Siau et al., 2006). Therefore, a CSCL environment based on social constructivist principles intended for training would be a powerful tool for UML trainers. AUTO-COLLEAGUE is suitable for educational institutes that teach UML, as well as for organizations that use UML for modeling business analysis.

In AUTO-COLLEAGUE two kinds of users are supported: the trainer and the trainees. The trainees may study the help topics on UML and at the same time practice on drawing UML diagrams (figure 1.1). They can also solve tests/exercises authored and assigned by the trainer (figure 1.2). The tests are given in a multiple-choice format, as UML is not a well-defined process and there is no single best solution for a problem (Baghaei et al., 2007). During these activities, the trainees, who are organized into groups, can collaborate with their colleagues through a chat system.

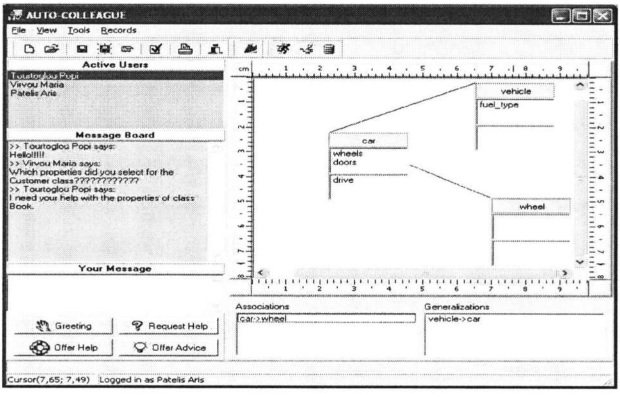


Figure 1.1. Main Form

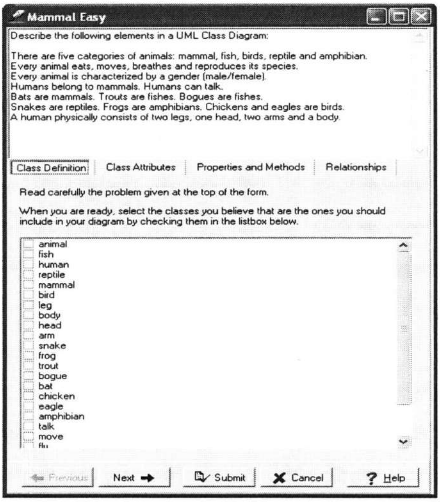


Figure 1.2. Tests/Exercises Form

The core of the system is to promote the collaborative learning processes offering intelligent recommendations to both the trainees and the trainer. The recommendations to the trainees concern (a) the next UML topics they should study, (b) the appropriate colleagues with whom they should collaborate and (c) supportive/encouraging messages that would increase their performance. The recommendations to the trainer include (a) historical/statistical reports and charts of showing the progress of the trainees and (b) a group formation tool that proposes optimum organization of the trainees into groups. The recommender system is built using both the content-based and the collaborative filtering methods.

The intelligence of the system relies on the individual student models built automatically combining buggy and stereotype-based student models. The trainees' characteristics included in the student models are related to (a) their level of expertise on UML, (b) specific personality attributes that influence their learning and collaboration performance and (c) their overall emotional states that indicate their inter-influences during collaboration. The personality characteristics used and are structured in eight stereotypes: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. They are inferred automatically tracing and evaluating the actions and performance of the trainees. These personality characteristics are used for adapting the recommendations. The emotional states, which are automatically predicted using the OCC cognitive theory of emotions, are used as criteria for the group formation tool and the recommendations to the trainees about the most appropriate colleague to collaborate with.

A major contribution of this thesis is related to the use of a managerial leadership theory to adapt the appearance and content of the recommendation messages to the trainees and to suggest to the trainer the most suitable leadership style s/he should follow for each trainee per assigned task. This theory is the Hersey and Blanchard Situational Leadership Theory (Hersey et al., 2007). Our motivation to use such a theory was findings in the literature indicating:

- The necessity of the teacher to undertake leadership roles (Gabriel, 2005; Barth, 2001; Wilmore, 2007; York-Barr & Duke, 2004; Suranna & Moss, 1999),
- The general acceptance of this theory (Vasu et al., 1998; Baker, 2009) and
- Various studies that advocated the use of this theory in educational settings (Hersey et al., 1982; Donahoo & Hunter, 2007; Weber & Karman, 1991).

The main principle of the Hersey-Blanchard Situational Leadership Theory is that leaders (the trainer and the system in our case) should continually adjust their leadership styles depending on the ability and the willingness of the followers (trainees in our case). The ability and the willingness are variables dependent on the tasks to be accomplished. Hersey and Blanchard have defined four different leadership styles suggesting the most appropriate attitude of the leader towards the followers for increasing individual and group improvement.

1.2.2. Evaluation Experiments

In effort of checking the performance of AUTO-COLLEAGUE and make decisions on further improvements and extensions, we conducted two evaluation experiments with real users.

The first experiment was conducted in the University of Piraeus among 80 postgraduate students. The aim of this experiment was to evaluate the educational effectiveness of our system after applying the automatic group formation versus a random group formation. The results were:

- 30% of the trainees presented no difference,
- 65% of the trainees presented progress and
- 4% of the trainees presented reduction in their level of expertise comparing the two days of the experiment.

Furthermore, as far as number of errors is concerned:

- 1.25% of the trainees presented no difference
- 90% presented reduction and
- 8.75% presented increase in the number of errors.

The second experiment was conducted in a high school among 70 students of the software engineering class of the last grade. The aim of the evaluation was to have evidence on the successfulness of our choice to choose the Hersey and Blanchard Situational Leadership Theory, the way of calculating the maturity of the trainees and the adaptation of the intelligent recommendations provided by the system. To evaluate the effect of the use of our system's adaptation of the Hersey and Blanchard Situational Leadership Theory versus a traditional class, we calculated the average increase rate of the ability and willingness (the variables that form the maturity). The resulted difference between the first (use of AUTO-COLLEAGUE) and the second (traditional laboratory course) stage of the experiment was:

- 29% increase in ability and
- 16% increase in willingness.

These evaluation experiments are discussed further in chapter 11.

1.3. Contributions of this Thesis

The contributions of the system presented in this thesis concern CSCL systems and group formation tools. In specific, the novel approaches implemented are:

- The personality-related characteristics included in the student models and, especially, the way they are automatically traced and evaluated,
- The affectivity implemented to recommend optimum groups of trainees and
- The use of a leadership theory, and specifically the Hersey and Blanchard Situational Leadership Theory, for adapting intelligent recommendations in a learning environment.

A novelty presented in this thesis concerning Intelligent Computer Supported Collaborative Learning environments is the personality-related characteristics it automatically traces and the way perceived emotions are used to infer optimum groups of learners. There is no other CSCL system to have used emotional affect and/or similar to ours personality characteristics that are automatically traced. Another important contribution of this thesis to Intelligent Computer Supported Collaborative Learning environments is based on the fact that no other learning environment has ever used any leadership theory to adapt intelligent recommendations or suggest to the trainer the most effective leadership style.

The contributions of our research in Group Formation Tools are found in:

- The criteria of matching the trainees,
- The way of calculating these criteria and
- The algorithm used.

The group formation tool presented in this thesis uses a novel approach in the considered criteria, which are related to (a) the desired and undesired combinations of personality-related stereotypes in the same group, (b) the desired group structure concerning the levels of expertise and (c) the observed by the system emotional affect between the trainees. The majority of the existing group formation tools do not evaluate in real-time their criteria values (student characteristics) of their group formation algorithm. On the contrary, in our system, all criteria values are evaluated automatically. In AUTO-COLLEAGUE, the grouping algorithm, used for the first time in related systems, is the Simulated Annealing algorithm, which seems adequate for such a large search space as when using various characteristics to form groups.

1.4. Dissertation Outline

This thesis is organized as follows: In **Chapter 2**, we review the literature regarding a great variety of fields that are in the scope of our research. These fields are UML and CASE Tools, Computer Supported Collaborative Learning Systems, student modelling for adaptive learning environments, affective learning systems, group formation tools, recommender tools in learning systems and teacher leadership. The aim of this chapter is to introduce the reader to the theoretical principles, the origins and the evolution of these fields. We also review in detail existing related systems for each field aiming at indicating the current state and challenges for researchers to meet.

In **Chapter 3**, we introduce our system, presenting the user interface, explaining the architecture, describing the offered recommendations and the results of the conducted evaluation experiments. The purpose of this chapter is to impart to the reader the main concepts and functionality of AUTO-COLLEAGUE emphasizing at the points that novel approaches have been used.

In **Chapter 4**, we make an overview of the student models used in the system. In specific, we describe the structure of the student models, how they are used and built. A more detailed description of the three different aspects that constitute our student models is given in the next respective chapters.

In **Chapter 5**, we analyze the part of the student model that concerns the personality-related characteristics used. After presenting the theoretical background taken into consideration for choosing personality stereotypes, we describe how they are assessed, built and used in the system. We also explain the stereotype-based method of user modelling. In addition, there is a description of the user interface for defining the personality-related stereotypes by the trainer if s/he wishes to change the default ones.

In **Chapter 6**, we explain the part of the student model that describes the knowledge of the trainees on UML. We present how the buggy and expert models are represented, built and used. A study on the buggy and overlay student modelling techniques are also included in this chapter.

In **Chapter 7**, we explain the OCC Theory of Emotions and the way we have adapted it in our emotion perception subsystem in order to predict the overall emotional state of the trainees. Finally, we describe how we have used the inferred emotional states in our system.

In **Chapter 8**, we emphasize on the importance of teacher leadership and describe existing leadership theories and, especially, the Hersey and Blanchard Situational Leadership Theory. We specify the way we have adapted this theory and the way that the suggested leadership styles are adapted by our recommender system.

In **Chapter 9**, we describe the intelligent recommendations offered to the trainees of the system. In specific, the kinds of recommendations, how they are generated and how they are adapted based on the Hersey and Blanchard Situational Leadership Theory. We also cite an example of recommendations.

In **Chapter 10**, the intelligent recommendations provided to the trainer of the system are described. We emphasize on the group formation tool and, more specifically, the grouping criteria, a related empirical study conducted and the grouping algorithm.

In **Chapter 11**, we present the two experiments conducted for evaluating our system regarding the effectiveness of the group formation (first experiment) and the use of the Hersey and Blanchard Situational Leadership Theory (second experiment).

Finally, in **Chapter 12**, we summarize the contributions of this thesis to Intelligent Computer Supported Collaborative Learning Environments and group formation tools.

2

REVIEW OF THE LITERATURE

2.1. UML and CASE Tools

The Unified Modelling Language (UML) is an object-oriented visual modelling language that is used to specify, visualize, construct, and document the artifacts of a software system (Rumbaugh et al., 1999). UML is a collection of best engineering practices to model large and complex software systems (Bansal et al., 2010). UML includes a variety of diagrams in order to satisfy different needs of modelling, such as class diagram, use case diagram, activity diagram and many others. The use of UML has grown enormously in many organizations that develop software during the last two decades. Along with the evolution of UML, there have been developed powerful and integrated professional Computer Aided Software Engineering (CASE) tools that assist in creating and maintaining a requirements management database for documenting and controlling requirements (Schwalbe, 2000). CASE tools usually include UML modelling support for creating, maintaining, transforming, importing and exporting UML models. Such tools are Rational Rose (Quatrani, 2002), MagicDraw, PowerDesigner, ArgoUML, Poseidon for UML, Visual Paradigm for

UML and StarUML. As these tools are designed for professional use, they seem to be quite complicated for training people in UML.

UML is, also, very popular amongst educational institutes, that use it as a tool for software engineering training. Being widely used in industry by now, proficiency in UML is certainly a valuable asset for every computer science student (Engels et al., 2006). However, there are studies that highlight the difficulties in learning UML (Basheri, 2010; Simons et al., 1999; Siau et al., 2006). Furthermore, UML is a domain that students need to practice, rather than attend theoretical courses in order to actually learn it (Baghaei, 2007). The professional CASE tools usually used in laboratories to teach UML seem to be unfriendly and too complicated for educational purposes (Siau et al., 2006). Therefore, a CSCL environment based on social constructivist principles intended for training would be a powerful tool for UML trainers. There are few CSCL systems that are designed for training people in UML (Chen et al., 2006; Baghaei & Mitrovic, 2006; Kuriyama et al., 2004; Jondahl & Mørch, 2002). The advice offered in all of these systems concerns the domain knowledge and encouragement on participating in the collaboration processes after evaluating their performance and participation.

2.2. Computer Supported Collaborative Learning Systems

2.2.1. Theoretical Background of Computer Supported Collaborative Learning Systems

It was in the late 1970's when Vygotsky (Vygotsky, 1978) brought to the surface the advantages of collaborative learning through setting the foundations of the social constructivism theory, according to which learners construct their knowledge collaboratively in social settings. The social constructivism was influenced by the constructivism theory developed by Piaget (Piaget, 1952; Piaget & Inhelder, 1971; Piaget, 1980) who claimed that learners construct knowledge out of their experiences. There are other similar to the constructivism theories also influenced by Piaget's constructivism (Papert, 1980; Dewey, 1938; Lave & Wenger, 1998), all based on the principles that:

- Learners learn by experimentation/active learning and not instruction and
- Learners build new knowledge upon existing knowledge.

Collaborative learning is based on the fact that learning is and should be regarded as a social activity. As Gokhale stated in a classic and one of the most frequently cited study (Gokhale, 1995):

The term "collaborative learning" refers to an instruction method in which students at various performance levels work together in small groups toward a common goal. The students are responsible for one another's learning as well as their own. Thus, the success of one student helps other students to be successful.

According to many research studies, collaborative learning can be more effective than individual learning (Forman & Cazden, 1985), (Roschelle, 1992), (Bruner, 1985), (Brookfield, 1986), (Bruffee, 1994), (Slavin, 1991), (Stahl & VanSickle, 1992), (Cohen et al., 2004), (Duffy & Jonassen, 1992), (Bereiter, 2002; Scardamalia & Bereiter, 1996). The benefits of collaborative learning are based on the social and emotional interaction between the learners. The main benefits stated in the literature are related to the fact that collaborative learning:

- Forces learners to deal with their emotional and psychological state (Johnson & Johnson, 1978), (Smith & MacGregor, 1992),
- Affects positively their motivation (Slavin, 1977),
- Increases their social interaction, communication and leadership skills (Johnson, Johnson & Holubec 1993; Bryant, 1978; Gerlach, 1994; Smith & MacGregor, 1992; Kirschner, 2001; Dillenbourg et al., 1995; Johnson & Johnson, 1989; Mesh et al., 1986)
- Promotes active learning (Meyers & Jones, 1993; Smith. & MacGregor, 1992; Kirschner, 2001),

- Enhances critical thinking promoting democratic discussion and decision-making techniques (Miyake, 1986; Gokhale, 1995; Totten et al., 1991),
- Increases their self-confidence and self-assessment (Slavin, 1990; Kirschner, 2001),
- Develops their sense of responsibility and autonomy (Totten et al., 1991; Benson, 1996; Kirschner, 2001),
- Stimulates their interest providing a more safe, friendly and social environment (Slavin, 1990),
- Increases pleasure and satisfaction comparing to non-participative activities (Fry & Coe, 1980),
- Prepares learners for their incorporation to the society, as it simulates the real world (Linden et al., 2002; Bruffee, 1994)
- Creates broad-minded and adaptable learners providing interaction with diverse types of people (Whatley & Bell, 2003; Smith & MacGregor, 1992)
- Facilitates planning and problem solving (Blaye et al., 1990; Blaye et al., 1991; Uribe et al., 2003),
- The teacher is usually more a facilitator than a "sage on the stage" (Kirschner, 2001).

2.2.2 Existing Computer Supported Collaborative Learning Systems

During the early 1970's, as computer technology was thriving and great interest in new educational methods was intense, a new branch of computer software for assisting and supporting learning appeared: the Intelligent Tutoring Systems. Such systems simulate the human tutor providing help and guidance to the student on the domain knowledge. Since then, and especially in the 1990's, the Intelligent Tutoring Systems were evolved to Intelligent and Adaptive Learning Systems (also known as ILE's). The evolution of this kind of software lies in the flexibility of offering different type of help (concerning both appearance and content) depending on the student's background of experience, knowledge and preferences. In this way, ILE's adapt their interaction with the student and intelligently apply pedagogical tactics appropriately to the student's characteristics.

As Brusilovsky, an important pioneer of these systems, and Peylo have described in (Brusilovsky & Peylo, 2003), there are three main technologies of Intelligent Tutoring Systems: the curriculum sequencing, the intelligent solution analysis and the problem solving support. The curriculum sequencing concerns recommendations to the students about the appropriate learning objects to study and their order. The intelligent solution analysis involves the system's analyzing a submitted solution concluding to exactly what was correct and incorrect, rather than simply stating if the solution was correct or incorrect. The advantages of this technology consist in the fact that the system can extract detailed information about the student's knowledge and, thus, advise him/her more accurately. The problem solving support technology aims at providing help and support to the student during the problem solving process and not after student's demand or solution submission. In this way, the system acquires more pedagogical features and less examinational.

The main modules comprising ILE's are the expert module, the student model, the tutor/pedagogical module and the communication module. The expert module contains knowledge of the system's subject area to teach. The system uses the expert module to define the student's degree of knowledge. The student model describes the attributes of the student, concerning not only his/her knowledge, but also other characteristics that influence learning, such as age, sex, preferences, learning style and personality. There is a variety of student modelling techniques described in literature proposing different ways of tracing and representing the students' characteristics. Some of the most popular methods are: overlay model, differential model, perturbation (or buggy) model, stereotype-based theory, fuzzy-logic and Bayesian Belief Networks. The tutor/pedagogical module comprises all the possible pedagogical approaches towards the student according to his/her student model. These pedagogical approaches are related to the content, the appearance and the frequency and timing of the provided by the system help. The communication module is responsible for regulating the interaction among the three aforementioned modules and the student.

As both education and psychology sciences advocated collaborative learning, a new kind of learning software appeared in the 1990's to gain and retain until today the attention of many researchers and put into practice the benefits of collaborative learning: the Computer-Supported Collaborative Learning (CSCL) systems. There are studies to support the use of computers for facilitating collaborative learning, e.g. (Koschmann et al., 2002) and (Lehtinen et al., 1999). Computer-supported collaborative learning (CSCL) is an emerging branch of the learning sciences concerned with studying how people can learn together with the help of computers (Stahl et al., 2006). When the computer is brought into the field as a mediating influence in collaborative activities, many more options and possibilities are opened up (Oliver et al., 1997). The approaches used in developing CSCL tools and models, as well as the CSCL research from the last few years, provide us with novel ideas and empirically proofed information base, which can be used in developing powerful learning environments for different educational purposes (Lehtinen, 2003).

CSCL systems are learning software environments that allow distant users to collaborate with each other in groups having a common goal. CSCL systems consider all levels and kinds of education, such as primary schools, graduate studies, professional training and informal education (e.g. museums). CSCL systems incorporate communication tools for mediating the collaboration and interaction between the learners. These tools may present and share information in both asynchronous (learners collaborate at different times) and synchronous (learners must be on-line to collaborate with each other) ways in any multimedia format, such as text, audio and video. The communication in these tools is supported by chat systems, message boards, forums, file sharing, shared workspaces etc.

Their aim is to support and enhance collaborative learning accommodating knowledge sharing through collaborative and cooperative problem solving. CSCL systems can be viewed as the evolution of the aforementioned Intelligent Learning Environments (ILEs). At first, the aim of the researchers was to provide tutoring guidance to the learners in an individual-learning environment. Then, as collaborative learning was gaining more supporters and the networking technologies were advancing, CSCL systems were introduced to provide an integrated environment for collaborative learning. The learning sciences as a whole have shifted from a narrow focus on individual learning to an incorporation of both individual and group learning, and the evolution of CSCL has paralleled this movement (Stahl et al., 2006).

CSCL systems should not be regarded as software that only offers cooperative tools (chat, shared workspace etc). The challenge of these systems is to also add intelligence in order to:

- Enable learners to have a common goal,
- Foster social interaction
- Encourage them to collaborate with each other and
- Apply pedagogical approaches to motivate them and facilitate their learning based on learning theories.

Aiming at these goals, CSCL systems evolved to Intelligent CSCL (I-CSCL) systems. Contrary to CSCL systems, I-CSCL systems are not limited to supporting collaborative learning in a computer-aided environment. They, also, apply pedagogical tactics and intelligent recommendations to assist effectively the students and be enriched with theoretical frameworks. Kreijns (Kreijns et al., 2002) has noted about I-CSCL systems:

"I-CSCL environments can be used for supporting or automating some guidelines, strategies, and recommendations suggested by educational researchers thereby freeing educators and instructors from some coaching responsibilities. I-CSCL environments promise to be more cost-effective since there are less educators and instructors needed or their involvement in the education process is reduced. [...]. However, research on I-CSCL environments is just beginning, particularly for research on environments incorporating support software for initiating, sustaining, and promoting social interaction in the social-psychological dimension."

The advantages of CSCL systems can be viewed as an extension of the aforementioned advantages of collaborative learning applied in learners from different geographical locations. Additionally, as CSCL systems are computer mediated, they also bear other benefits implicated by computer employment. There are many studies reporting that assigning computer based learning activities has positive effects on the learners' social development and high-order thinking (Hoyles et al., 1994; Light, 1993; Light et al., 1994; Kulik et al., 1985; Watson et al., 1993; Crook, 1994; Howe et al., 1996). More specifically, the use of CSCL systems in education supports social interactions between learners, allowing them to share experiences, knowledge and skills and learn from each other. Moreover, CSCL systems have a positive impact on the development of social skills, such as conversational and communicational. CSCL systems also enhance critical thinking (Gokhale, 1995), which is considered as a very crucial skill that facilitates the learner to have a better understanding of the curriculum (Kreijns et al., 2003). The learner also benefits from the use of CSCL systems as they help them to consider learning as a social habit (Gillet et al., 2006).

The benefits of CSCL systems and collaborative learning between distant users are not only educational but financial and social as well. For instance, CSCL systems are beneficial for educational institutes that can save money from not equipping computer laboratories. There are, also, many open universities whose students do not attend courses on occasional bases. In this case, a CSCL system would be useful, as it would enhance the students' learning. Furthermore, CSCL systems are socially beneficial as they can bring together people from all over the world and allow them to share their knowledge and experience at a very low cost.

As not only educational institutes need to educate people, CSCL systems can be used in almost any kind of organization. Many organisations have recognised the importance of integrating learning within their work structures and procedures so as to promote collaborative learning at work (Mwanza, 2001). Industry deregulation, decreasing numbers of middle managers, and expanding geographical distances between organizational entities have challenged organizations to employ new and more innovative structural concepts in order to remain competitive (Morrison et al., 1992). Changes in support technology, economic factors and globalisation of the software process are resulting in the geographical separation of personnel (Layzell et al., 2000). Therefore, a major influencing factor of the effectiveness of the projects and groups is the effectiveness of the communication and co-operation between employees. The use of a CSCL system for training employees would also save organizations money and time. The rapid advance of networking technology has enabled universities and corporate training programs to reach out and educate students who, because of schedule or location constraints, would not otherwise be able to take advantage of many educational opportunities (Soller et al., 1999).

According to Kumar (Kumar, 1996), collaborative learning research can be viewed from seven different dimensions:

- *Control of collaborative interactions*: It refers to whether the system is active or passive. A system is active when it plays an active role in the collaboration by analyzing and controlling the collaboration processes. A system is passive when it is limited to offering a collaborative environment without intervening.
- *Tasks of collaborative learning*: Kumar identifies three kinds of tasks assigned to learners in CSCL systems: collaborative concept-learning tasks, collaborative problem-solving tasks and collaborative designing tasks.
- *Theories of learning in collaboration*: Referring to Dillenbourgh (Dillenbourgh et al., 1995), Kumar identifies three learning theories used in CSCL systems: socio-constructivist theory, socio-cultural theory and shared cognition theory.
- *Design of collaborative learning context*: The collaborative learning design concerns a variety of issues related to the supported by the system number of collaborating peers, the kind of peers (real or simulated), the existence of an active tutor, the facilitation of automatic grouping of peers etc.
- *Roles of the peers*: Each peer can be assigned with a specific role in the system concerning the kind of participation s/he will have during the collaboration. Kumar identifies six roles: decomposing, defining, critiquing, convincing, reviewing and referencing.
- *Domains of collaboration*: The domains refer to the curriculum to be imparted.
- *Teaching/Tutoring methodologies that inherently support collaboration*: Kumar mentions six such distinctive methodologies: practice, Socratic learning, learning by teaching, situated learning, negotiated learning and discovery learning.

There are hundreds of CSCL systems developed during the last two decades for a variety of domains. Their approaches vary mainly in the content (collaboration/participation/knowledge domain) and the direction (human tutor/learners) of the offered automatic advice. Other CSCL systems (Martinez Carreras et al., 2005; Bravo et al., 2002; Lukosch et al., 2006; Tamura & Furukawa, 2007; Casamayor et al., 2009; Cerri et al., 2006; Rick & Gudzial, 2006; Graves & Klawe, 1997; Baker & Lund, 1997) do not offer advice, but still provide an environment for facilitating and promoting collaborative learning. In table 2.1 a summarized overview of the CSCL systems that offer advice is described.

Table 2.1. Overview of Existing CSCL Systems.

CSCL SYSTEM	DOMAIN KNOWLEDGE	ADVICE	MONITORED CHARACTERISTICS
Constantino-González & Suthers, 2000	Entity-relationship diagrams	Encourages students to share and discuss solution components that conflict with components of the group solution	Performance and participation
Rosatelli & Self, 2004	Case study system	Intervenes with advice when the student appears to need support on the domain or have a low degree of participation or exceed the time limits	Performance, participation and time of completing tasks
Ayala & Yano, 1998	Second language learning	Motivate and help on domain	Capabilities, commitments, intentions and group-based knowledge frontier
Chen et al., 2006	UML modelling	Provides help on the domain-knowledge and advice to regulate participation and collaboration	Performance and participation
Baghaei & Mitrovic, 2006	UML class diagrams	Encourages student participation in problem-solving	Participation/collaborative skills
Gogoulou et al., 2007b	Abstract	Recommends learning activities and provides personalized informative and tutoring feedback	Knowledge level, learning goals, learner's behaviour during his/her interaction with the environment
Vizcaíno et al., 2000	Programming (develops good programming habits)	Adapts level of difficulty and type of exercises, promotes individual learning by awarding with points or asking	Motivation to learn, participation, abilities, preferred

		specific students	types of exercises, mistakes at group level
Kuriyama et al., 2004	UML	Advice on participation and domain	Participation and knowledge
Constantino-González & Suthers, 2007	Entity-relationship diagrams	Encourages participation and negotiation between different solutions	Participation, knowledge, comparisons between students' individual and group solutions
Barros & Verdejo, 2000	General purpose domains (learning activities)	Help students reflect on the collaboration process and improve their collaboration skills	Type of contribution in collaboration (proposal, contraproposal, question, comments, clarification, agreement)
Kojiri et al., 2006	Mathematical exercises	Offers hints for deriving answers and promotes individual students in the group activity by pointing out differences between group's opinions and student's opinion privately	Submitted solutions
Or-Bach & Van Joolingen, 2004	Science class for junior-high	Interventions to integrate communication and content issues	Learners' activities related to the subject matter tasks and the communication
Sheremetov & Arenas, 2002	Multi-book (personalized electronic book)	Advice on personalized study plan and collaboration	Performance and participation
Khandaker & Soh, 2009	Abstract	Group formation	Knowledge, motivation, emotion and social relationship with other students (only the representation structure)
Aiken et al., 2005	Java	Provides to the students an assessment of their knowledge and their collaborative skills	Knowledge and interaction of students
Teixeira et al., 2002	Engineering and Mathematics	Help on domain knowledge and cooperation	Activities, knowledge and cooperation
Jondahl & Mørch, 2002	UML	Help on technical and domain knowledge and collaboration	Knowledge and collaboration
Khandaker et al., 2006	Programming (java)	Team formation	The peers that the student interacted, number and type of messages sent and capabilities

Linton et al., 2003	Add-on tool for CSCL systems	Encourage further discussion on a topic when the learners are about to go on to another topic and the current topic is incomplete or incorrect	Participation and contribution to the topic (learners' conversation and problem-solving actions)
Chen, 2006	Abstract	Advice to the teacher on the subject domain and the collaboration process	Knowledge and collaboration activities
Huang et al., 2009	Database courses	Encouragement messages and advice on domain	Knowledge and collaboration activities
Razek et al., 2002	Data Structures	Adapts the presentation of the subject matter aiming at improving the students' performance and self-confidence	Knowledge, learning style and behaviour during collaboration
Kreijns et al., 2002	Abstract	Encourages social interaction	Abilities

Researchers have been exploring different approaches to analyse and support the collaborative learning interaction. However, the concept of supporting peer-to-peer interaction in Computer-Supported Collaborative Learning (CSCL) systems is still in its infancy, and more studies are needed that test the utility of these techniques (Baghaei & Mitrovic, 2005).

2.3. Student Modelling for Adaptive Learning Environments

2.3.1. User/Student Modelling

Kobsa (Kobsa, 2001) references Allen, Cohen, Perrault (Perrault, Allen & Cohen, 1978; Cohen, & Perrault, 1979; Allen, 1979) and Rich (Rich, 1979a; Rich, 1979b) as the scholars that introduced user modelling as a technique of describing user information in adaptive software systems. As Brusilovsky (Brusilovsky & Millán, 2007) has described:

"The user model is a representation of information about an individual user that is essential for an adaptive system to provide the adaptation effect, i.e., to behave differently for different users. [...] To create and maintain an up-to-date user model,

an adaptive system collects data for the user model from various sources that may include implicitly observing user interaction and explicitly requesting direct input from the user. This process is known as user modeling. User modeling and adaptation are two sides of the same coin."

The kinds of user information represented in the user model are related to the type of the adaptive system. Characteristic examples of such information are demographic data (e.g. sex, nationality, age, religion), educational level (e.g. MBA, PhD), preferences (e.g. on the user interface), interests (e.g. in sports, music, movies), personality characteristics and emotional state/mood. The user model may include those user characteristics that will leverage it to be adapted in the most accurate, integrated and versatile way.

Since its presentation, user modelling has been applied in many fields of software to make them user adaptive. Kobsa (Kobsa, 1993) mentions the most prominent fields: Human-Computer Interaction, Intelligent Interfaces, Adaptive Interfaces, Cognitive Engineering, Intelligent Information Retrieval, Intelligent Tutoring, Active and Passive Help Systems, Guidance Systems, Hypertext Systems and Expert Systems.

It is commonplace that user models are necessary for any kind of adaptive system. User modeling provides the basis for a system to meet the particular needs and preferences of the individual user (Kay, 2000b). Also, according to Rich (Rich, 1983):

"It has long been recognized that in order to build a good system in which a person and a machine cooperate to perform a task it is important to take into account some significant characteristics of people. These characteristics are used to build some kind of a "user model"."

Student modelling is a special type of user modelling which is relevant to the adaptability of intelligent tutoring systems (Elsom-Cook, 1993). As intelligent learning systems adapt their environment and recommendations according to the learner(s), they need to incorporate a mechanism of describing the individual student characteristics. This is achieved via student modelling that is an extension of user modelling adapted in intelligent learning systems. Student modelling is the process of creating a student model (Self, 1994). In a classic study (Holt et al., 1994) the student model is defined as "a representation of the computer systems' beliefs about the learner and is, therefore, an abstract representation of the learner in the system". Student modelling is a dynamic process, as the traced student characteristics are likely to be continually changed and the system must adapt to them. Student modelling necessarily occurs mainly at run-time, when the student uses the system, since it is mainly through the evidence provided by the student's inputs to the system that the student model is created (Self, 1994).

2.3.2. User Characteristics Described in Student Models

Martins (Martins et al., 2008) referencing to Benyon (Benyon, 1993) and Kobsa (Kobsa, 2001) identifies two different types of data included in a student model:

- Domain Independent Data: characteristics referred to psychological (cognitive and affective aspects of the student) and generic information (such as interests and background) about the student.
- Domain Dependent Data: characteristics related to the learning goals and the student's knowledge on the domain.

Choosing which characteristics are necessary and appropriate for a system depends mainly on the environment features to be adapted. The most typical student characteristics used in intelligent and adaptive learning environments found in literature are: personal and demographic data, knowledge, personality, learning style and goals.

Personal and demographic data are related to the information such as name, age, sex, nationality, language, race, academic degrees and previous experience/knowledge on the domain or on relative domains. All these data bear significant information about the students that may influence their performance.

Knowledge, which refers to the user's knowledge on the domain, is a very crucial characteristic for the adaptivity of the system. All learning environments include this characteristic, whose identification is a very complicated task. User's knowledge of the subject represented in the hyperspace appears to be the most important feature of the user for existing adaptive hypermedia systems (Brusilovsky, 1996a). For a system to recognize the user's knowledge, it is necessary to maintain the domain knowledge structured in domain concepts that describe it in detail. The domain concepts are usually linked to each other indicating their associations. This representation of the domain knowledge is known as the expert/domain model/module. The most popular student modelling techniques are based on an expert model. These expert-based modelling methods can use either overlay models or buggy models to represent the student's knowledge.

Personality refers to personality traits that can influence the user's behaviour through the learning process, such as introvert/extrovert. Usually, the systems that include personality characteristics use psychological instruments (tests and questionnaires), such as the Myers-Briggs Type Indicator (Myers & McCaulley, 1985), rather than tracing them during run-time. Few studies have been conducted on adding personality traits in student models. While adaptive hypermedia researchers have begun exploring the use of individual traits for adaptation in several areas, it cannot be described as a success story at present (Brusilovsky, 2001).

The term "learning styles" refers to the concept that individuals differ in regard to what mode of instruction or study is most effective for them (Pashler et al., 2009). There have been proposed several models and instruments for defining students' learning styles, e.g. (Kolb, 1984; Honey & Mumford, 1986; Entwistle & Ramsden, 1983; Felder & Silverman, 1988; Dunn & Dunn, 1978). There are few learning systems that take into consideration for their adaptation the learning styles of the students. These systems detect the student's learning style using either:

- A scientific instrument at the registration of the user (Carver et al., 1999; Shang, Shi & Chen, 2001; Bajraktarevic, Hall & Fullick, 2003; Wolf, 2003; Papanikolaou et al., 2003; Brown & Brailsford, 2004) or
- Automated techniques of tracking specific user data for inferring the user's learning style (Stern et al., 1997) or

- A scientific instrument/questionnaire at the registration of the students for initializing their learning styles and automated techniques for updating them, e.g. (Peña et al., 2002; Carro et al., 2001; Grigoriadou et al., 2001) or
- A simple question to the students about their learning styles, e.g. (de Bra & Calvi, 1998; Stash et al., 2006; Grigoriadou et al., 2001).

Goals are related to the objectives of the student during the learning process or the use of the system in general. Such goals can be associated to learning achievements (the degree of knowledge of the domain, the performance on exercises/tests) or social achievements (the social development, in case the system includes communication/collaboration tools with others).

2.3.3. Techniques of Building Student Models

Kay (Kay, 2000b) describes two methods for acquiring information about the user: the *elicitation of user modelling information* and the *modelling based upon observing the user*. This classification is similar respectively to the *explicit* and *implicit* categorization of user models described in (Rich, 1989). Implementing the first method means that the users are asked to fill in questionnaires providing in this way information about their state of knowledge and their preferences. The second method is automated and much more complex. Following this method, the system traces the user actions and their consequences in order to infer the tracked user characteristics described in the user model. The invisibility of such monitoring processes has the advantage of placing no load on the user (Kay, 2000b). A user model can be built using both methods. There are several student-modelling techniques, such as the overlay model, the perturbation (or buggy) model, stereotypes, the constraint-based model, fuzzy logic/fuzzy sets and Bayesian networks.

The overlay and the buggy model are used for modelling the student's knowledge. During the recent years, researchers tend to combine user-modelling techniques to achieve the maximum accuracy of their user models, e.g. stereotype and fuzzy sets: (Piyawat & Norcio, 2001), (Jeremic et al., 2009), stereotype and overlay: (Jeremic et al., 2004), (Koutsojannis et al., 2001), (Lee & Baba, 2005), (Virvou & Moundridou, 2000), (Virvou & Tsiriga, 2001a) and (Virvou & Tsiriga, 2001b), overlay and Bayesian networks (Nguyen & Do, 2009).

The fuzzy logic and Bayesian networks belong to uncertainty-based user modelling (Brusilovsky & Millán, 2007).

Overlay Model

The principle of the overlay modelling method is that the student's knowledge is a subset of the expert model. The expert model contains the full domain knowledge structured in concepts/topics. This approach assumes that all differences between the learner's behaviour and that of the expert model can be explained as the learner's lack of skill (Holt et al., 1994). At implementation level, the overlay student model has the same structure with the expert model bearing a degree for each concept. This degree can be of boolean type (true/false), qualitative type (e.g. good/average/poor) or any quantitative type indicating probability of the existence of knowledge (e.g. a real number in [0, 1]).

Overlay student models have been part of the earliest teaching systems (Kay, 1997). Overlay models are powerful and flexible, they can independently measure user knowledge of different topics (Brusilovsky, 1996a). There is a great amount of adaptive systems to have used the overlay modelling technique, such as (Zhou & Evens, 1999), (Brusilovsky & Cooper, 2002), (Brusilovsky et al., 1996b), (Virvou & Tsiriga, 2001a), (Virvou & Tsiriga, 2001b), (Brusilovsky & Pesin, 1994), (El-Khouly & El-Seoud, 2006), (Lu et al., 2005), (Ogata et al., 2005) and (Piyawat & Norcio, 2001). However, overlay models appear to be old-fashioned and their exclusive use tends to be abandoned, e.g. (VanLehn, 1988). In another study (Bierman et al., 1992) it is stated that the overlay models "are acknowledged to be essentially incorrect because they assume the knowledge of the student to be a subset of the expert's knowledge".

Perturbation/Buggy Model

Despite their efficacy, overlay models can be deficient as they only represent the correct knowledge and miss possible misconceptions of the student on the domain. This deficiency of the overlay model was the motivation for the perturbation modelling technique. A buggy student model describes not only the correct knowledge and the missing knowledge (like overlay model), but also the faulty knowledge a student may have on the domain. To achieve this, additionally to the expert model, it maintains a bug library where the possible misconceptions (bugs) are predefined. Assembling the library is the biggest hurdle in the bug library approach (VanLehn, 1988). The goal of a system with a bug model is not just to declare that a specific element of domain knowledge is incomplete or missing, but to identify, if possible, specific buggy knowledge that can be used to provide a higher quality adaptation (Brusilovsky & Millán, 2007).

Perturbation modelling is a common technique for adaptive environments, such as (Brown & Burton, 1978; Brown & Van Lehn, 1980; Faraco et al., 2004; Labidi & Sergio, 2000; Sleeman & Smith, 1981; Soloway & Johnson, 1984; Sleeman, 1987; Hoppe, 1994; Murray, 2003; Teixeira et al., 2002). Student models are less frequently implemented exclusively with perturbation (buggy) models in recent studies, as they eventually do not seem to increase the effectiveness of teaching (Bierman et al., 1992) and they need highly descriptive bug libraries (VanLehn, 1988; Lin, 2007).

Stereotypes

Stereotype based user modelling was introduced by Rich (Rich, 1979a), (Rich, 1979b) presenting GRUNDY, an intelligent system that recommended books to users after inferring their preferences based on their individual characteristics. This method simulates the way people make assumptions on others, based on relevant information about them. A major technique people use to build models of other people very quickly is the evocation of stereotypes, or clusters of characteristics (Rich, 1979b). A stereotype represents a collection of attributes that often co-occur in people (Rich, 1989). The general notion of stereotypes is well described by Kay (Kay, 2000b):

"Essentially, the stereotype mimics intuitive human reasoning from a small amount of information about a person to a large number default assumptions about them. As more information becomes available about individual assumptions, these are revised. Meanwhile the overall initial classification of the user and most of the default assumptions continue to hold unless we acquire information to indicate that the initial classification of the user was incorrect."

The operation of stereotypes is also well defined in (Kobsa, 1995):

"Stereotypes contain typical characteristics of user groups in the application domain of the system. Often they also contain so called activation conditions which represent key characteristics that allow one to identify an individual as belonging to the respective user group. Stereotypes become applied to the current user if they are "manually" assigned, or if their activation conditions match available information about the user (automatic classification). As a consequence, all characteristics in the corresponding stereotypes are attributed to the user. Stereotypical assumptions about a user can be supplemented, or even overridden, if additional information pertaining to this individual user is available. The resulting collection of assumptions forms the individual user model, which should be taken into account when adapting the system to the user."

To implement stereotypes it is necessary to define the facets and the triggers. Facets are the users' characteristics that the system observes in order to classify them in the appropriate stereotypes. In other words, facets are the user traits that describe the stereotypes. A trigger is a set of rules/conditions. If these conditions are satisfied/dissatisfied for a user, then the corresponding stereotype will be activated/deactivated. These conditions examine the values of the facets used in the system.

The main benefit of stereotypes is that the system can infer much information about the user using the already possessed user data. The concept of stereotyping is simple, yet powerful (Johansson, 2002). Stereotypes have been used during the past decades in a variety of software, such as:

- Generalised user modeling tools (Vergara, 1994; Paiva & Self, 1994; Brajnik & Tasso, 1994; Kay, 1995; Finin, 1989; Piyawat & Norcio, 2001),
- Intelligent learning and tutoring environments (Jeremic et al., 2009; Hatzilygeroudis & Prentzas, 2004; Eklund & Brusilovski, 1999; Kabassi et al., 2006; Wei et al., 2005; Virvou & Moundridou, 2001; Surjono & Maltby, 2003; Koutsojannis et al., 2001; Hatzilygeroudis & Prentzas, 2004; Lee & Baba, 2005; Virvou & Moundridou, 2000; Virvou & Tsiriga, 2001a; Virvou & Tsiriga, 2001b).
- Recommender systems (Rich, 1979a; Ardissono et al., 2004; Shapira et al., 1997; Kurapati & Gutta 2002; Krulwich, 1997; Chin 1989; Fink et al., 1997; Gena, 2001).

However, arguments have been expressed about the successfulness of a system that uses only the stereotype modelling method. For example, Kay (Kay, 1994) argues that stereotypes should be used only initially, while the system waits to collect something better, e.g. (Hatzilygeroudis & Prentzas, 2004; Virvou & Moundridou, 2000; Virvou & Tsiriga, 2001b). She, also, stresses out that overusing of stereotypes should be avoided. Self (Self, 1994) concludes that stereotypes are useful for initializing the user models, but, for student modelling, stereotypes are not of much use beyond the initialisation stage because they do not permit the necessary fine-grained analysis.

Constraint-based Student Modelling

Constraint-based student modelling, a relatively new technique, was proposed by Ohlsson (Ohlsson, 1994) aiming at reducing the computations required for student modelling to pattern matching. Its main principle is to describe the domain and student's knowledge by "a set of constraints on problem states" (Ohlsson, 1994). Ohlsson focuses on the possible faulty knowledge of the student, rather than on the correct/expert knowledge on the domain. As Mitrovic (Mitrovic et al., 2001) explains about the implementation of constraints in constraint-based student modelling:

"Because the space of false knowledge is vast, much more so than the space of correct knowledge, Ohlsson suggest the use of an abstraction mechanism realized in the form of state constraints. A state constraint is an ordered pair (Cr, Cs), where Cr is the relevance condition and Cs is the satisfaction condition. Cr is used to identify the equivalence class, or the class of problem states in which Cr is relevant. Cs identifies the class of relevant states in which Cs is satisfied. Each constraint specifies the property of the domain that is shared by all correct paths. In other words, if Cr is satisfied in a problem state, in order for that problem state to be a correct one, it must also satisfy Cs. Conditions may be any kinds of logical formulas, hence may be constructed from various tests on the problem state in question."

As stated in (Ohlsson, 1994), the main advantages of the constraint-based technique are that (a) it does not require a runnable expert model, (b) it does not demand high computational power due to the low complexity of the inference algorithm used, (c) it does not require extensive empirical research of student errors and (d) it is neutral with respect to pedagogy. However, there are recent studies that explain disadvantageous points of constraint-based student modelling. In (Galvez et al., 2009), the authors argue that "most student models of CBM-based tutors handle simple long-term models or based on heuristics to quantitatively estimate the knowledge measured". In (Kodaganallur et al., 2005), it is claimed that: "the constraint-based paradigm is feasible only for domains in which the solution itself is rich in information".

Intelligent learning environments have recently started to implement constraint-based student models. Such studies are: (Kodaganallur et al., 2004), (Thomson & Mitrovic, 2009), (Galvez et al., 2009), (Baghaei et al., 2007) and (Mitrovic et al., 2001).

Fuzzy Logic

Fuzzy logic is based on fuzzy sets. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristic) function, which assigns to each object a grade of membership ranging between zero and one (Zadeh, 1965).

Apparently, the use of fuzzy logic seems adequate for modelling the student's knowledge, as the task of defining it is complex and, thus, involves uncertainty. It is difficult for a system to presume in a binary value (true/false) that a student knows or does not know a concept of knowledge. The main advantages of using fuzzy sets are in the systems where we process an inexact user input in a verbal form, or use inference or manipulate knowledge which can be naturally described and explained in the form of imprecise concepts, operators, and rules (Kavcic, 2004).

The use of fuzzy logic/fuzzy sets in adaptive learning environments is not so frequent as the use of other modelling methods. As Brusilovsky notes in (Brusilovsky & Millán, 2007), there are few studies that report the use of approximate reasoning techniques. However, there are such systems that have integrated fuzzy logic, such as (Kavcic, 2004), (Kosba, 2004), (Capuano, 2000) and (Di Lascio et al., 1999).

Bayesian Belief Networks

A Bayesian Belief Network (BBN) (Pearl, 1988) is a directed acyclic graph that represents variables and the relations between them. Bayesian Belief Networks have been effectively used in many areas, especially in modelling domain and student knowledge. BNs are a probabilistic model inspired by causality and provide a graphical model in which each node represents a variable and each link represents a causal influence relationship (Brusilovsky & Millán, 2007). As explained in (Akiba & Tanaka, 1992), the Bayesian networks are used to represent the user's knowledge, draw inferences from that, and provide fine-grained solutions to problems.

These networks provide a compact and natural representation, effective inference, and efficient learning (Friedman, 1997). Bayesian Belief Networks provide a principled, mathematically sound, and logically rational mechanism to represent student models (Zapata-Rivera & Greer, 2001). Belief networks provide an important way to represent and reason about uncertainty – significant factors for modelling students (Reye, 2004). Brusilovsky (Brusilovsky & Millán, 2007) states that "a powerful feature of BNs is that they allow for diagnosis (inferences about possible causes of an event) and prediction (future state/evolution of variables given evidence)". One of the main problems found when using Bayesian networks is the intense knowledge engineering effort of specifying prior and conditional probabilities (Villano, 1992). Bayesian student models for intelligent learning environments have been implemented for the last two decades (Nguyen & Do, 2009), (Zapata-Rivera & Greer, 2001), (Conati et al., 2002), (Reye, 2004), (Collins et al., 1996), (Gitomer et al., 1995), (Martin & VanLehn, 1995), (Mislevy, 1995), (Petrushin & Sinitsa, 1993), (Akiba & Tanaka, 1992), (Mayo, 2001).

2.4. Affective Learning Systems

2.4.1. Affective Computing – Overview

Affective computing is a relatively new branch of Artificial Intelligence that emerged during the late 1990's by a study of Picard (Picard, 1997). In this study, she defined affective computing as "computing that relates to, arises from, or infuences emotions". There is a variety of neurological (Cytowic, 1993; Cytowic, 1996; Damasio, 1994; Le Doux, 1998) and psychological (Izard, 1993; Izard, 1984; Leidelmeijer, 1991; Bechara, Damasio, Tranel, & Damasio, 1997; Goleman, 1995; Tomkins, 1984; Tomkins, 1963; Tomkins, 1962; Ekman, 1984) studies that support the realization of affective computing, expressing the great impact of emotions on human cognition and behaviour and relate emotions with rational behaviour (Greenspan, 1999).

Picard (Picard, 1997) explained why we need computers to be affective, concluding that computer affectivity would (a) enhance assistance towards the users and (b) facilitate computer decision-making. In other words, affective computing is related to adding emotional intelligence (Salovey & Mayer, 1990), (Goleman, 1995) to computers, recognizing user emotions to increase their performance and respond to the users accordingly. The ability to detect and understand affective states and other social signals of someone with whom we are communicating is the core of social and emotional intelligence (Pantic et al., 2005). Furthermore, adding affectivity characteristics to computers would probably bring them closer to a more human nature. Although computers perform as well as or better than people in selected domains, they have not yet risen to human levels of mentoring (Moridis & Economides, 2008a).

However, the use of affectivity in computer systems should be made with prudence, as it involves risks (Burleson & Picard, 2004), (Alder, 2007), (Moridis & Economides, 2008a). These risks are related to the accuracy of the emotion recognition and the ways the system reacts according to the recognized emotions.

Despite these studies on advocating affective computing, it seems that affective feedback in Human-Computer Interaction systems is not frequent. Indeed, the development of such affective systems that recognize emotions and provide response tailored to the needs generated by them is in its infancy, e.g. (Picard & Klein, 2002), (Moridis & Economides, 2008a), (Picard et al., 2004), (Mavrikis et al., 2003). With regard to learning, there have been very few approaches for the purpose of affect recognition (Moridis & Economides, 2009).

Affective computing is adequate for use in all the sub-fields of Human-Computer Interaction, such as robotics (Nourbakhsh et al., 1999; Velasquez, 1998; Malfaz & Salichs, 2004; Breazeal, 2001), interactive computer games (Katsionis & Virvou, 2004; Rani et al., 2005; Paiva et al., 2002) and, essentially, in intelligent learning environments (Jaques & Vicari, 2007; Katsionis & Virvou, 2004; Conati & Zhou, 2004; Chalfoun et al., 2006; Jaques et al., 2004).

For a system to be affective, it should primarily be able to recognize the user's emotions. This process is known as emotion recognition. The foundation of affective computing will be the ability to recognize emotions, to infer an emotional state from observation of emotional expressions and through reasoning about an emotion-generating situation (Vesterinen, 2001).

2.4.2. Emotion Recognition

Emotions

Yet, there is no consensus on a definition of emotion or at least the defining features of emotions causing a major problem in the field of emotions (English & English, 1958; Fantino, 1973; Young, 1973; Mandler, 1979; Chaplin & Krawiec, 1979; Scherer, 2005). Over 100 different and conflicting definitions of emotions have been proposed in literature. Apparently, this is so due to the fact that the scholars conclude to their definitions viewing different aspects of the emotions. Without consensual conceptualization and operationalization of exactly what phenomenon is to be studied, progress in theory and research is difficult to achieve and fruitless debates are likely to proliferate (Scherer, 2005). Ostensibly competing theories are often not incompatible; they simply address different phenomena, or different aspects of the same phenomenon (Averill, 1980).

There few studies related to classifying the proposed emotion definitions based on the emotional phenomena they examine, e.g. (Fantino, 1973; Plutchik, 1980; Kleinginna & Kleinginna, 1981). For example, in (Kleinginna & Kleinginna, 1981), the categories of the emotion definitions are affective (emphasizing feelings of arousal and/or hedonic value), cognitive (emphasizing appraisal and/or labeling processes), external stimuli (emphasizing external emotion-generating stimuli), physiological (emphasizing internal physical mechanisms of emotion), emotional/expressive behavior (emphasizing externally observable emotional responses), disruptive (emphasizing disorganizing or dysfunctional effects of emotion), adaptive (emphasizing organizing or functional effects of emotion), multiaspect (emphasizing several interrelated components of emotion), restrictive (distinguishing emotion from other psychological processes), motivational (emphasizing the relationship between emotion and motivation) and skeptical (questioning the usefulness of the concept of emotion). In the same study (Kleinginna & Kleinginna, 1981), the authors proposed the following definition for emotion:

"Emotion is a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems, which can (a) give rise to affective experiences such as feelings of arousal, pleasure/displeasure; (b) generate cognitive processes such as emotionally relevant perceptual effects, appraisals, labeling processes; (c) activate widespread physiological adjustments to the arousing conditions; and (d) lead to behavior that is often, but not always, expressive, goal-directed, and adaptive."

We should stress at this point that affect is a different concept from emotion, although they are often used as synonyms. In (A.P. Association, 1984) affect is defined as "a pattern of observable behaviors that is the expression of a subjectively experienced feeling state or emotion". Tasman (Tasman et al., 1997) defined affect as "the way one modulates and conveys one's feeling state from moment to moment".

Theories of Emotions

There are many theories of emotions proposed by psychologists and behaviorists. According to Lazarus (Lazarus, 2000), the aims of these theories are to offer propositions about:

- The generation of emotions in general terms,
- The classification of emotions,
- The elicitation and the result (impact on subsequent actions and reactions) of each emotion.

Theories of emotions are classified in two basic categories: cognitive and non-cognitive/somatic.

Cognitive theories regard the association between emotions and cognitive states as essential (Prinz, 2002). They are concerned with the emotion experience and with the phenomenology of emotion (Zajonc & Markus, 1988). Some cognitive theories of emotions are described in (Frijda, 1986; Lazarus, 1991; Mandler, 1975; Schachter & Singer, 1962; Cannon, 1927; Ortony, Clore & Collins, 1988).

Especially, the OCC theory of emotions (Ortony, Clore & Collins, 1988) was designed with the purpose of offering a computational model of emotions for use in affective computer systems. According to the OCC Theory of Emotions, emotions (negative or positive) are considered to be reactions to stimulus evoked by certain objects of the environment at a certain moment. These objects can be *events*, *people* (quoted as agents) or *objects*. The type of the aroused emotion is determined by three major factors: the *situations* that are responsible for the emotion, the *person* who experiences the emotion and the *cognitive appraisal* of the situation by the person. The cognitive appraisal depends on the *standards*, the *goals* and the *attitudes* of the person experiencing the emotion.

According to Zajonc (Zajonc & Markus, 1988), cognitive theories can be further categorized to appraisal (e.g. (Arnold, 1960; Lazarus, 1966)) and discrepancy cognitive theories based on the quality of the elicitor. A central tenet of appraisal theory is the claim that emotions are elicited and differentiated on the basis of a person's subjective evaluation or appraisal of the personal significance of a situation, object, or event on a number of dimensions or criteria (Scherer, 1999). In discrepancy theories, emotions are regarded as the product of certain discrepancies or incongruities between external events and internal representations or schemas (Zajonc & Markus, 1988).

Non-cognitive theories consider the motor system and the expressive movements as the main factors in the emotion generation, but without excluding the cognitive factor which plays a more prominent role (Zajonc & Markus, 1988). These theories "attempt mainly to describe the expression of emotion and to explicate the perception of emotional expressions" (Zajonc & Markus, 1988). They attempt to identify the most common bodily expressions of emotions aiming at providing emotion recognition methods (Zajonc & Markus, 1988). Some non-cognitive theories of emotions are described in (James, 1884; Lange, 1887; Tomkins, 1962; Ekman & Friesen, 1975; Izard, 1977; Leventhal, 1980).

Methods of Emotion Recognition

The emotion recognition can be potentially achieved through observing affect neurological/physiological/biological (non-cognitive approach) indicators and/or emotion-generating situations (cognitive approach) (Moridis & Economides, 2008a; Vesterinen, 2001).

The first method (non-cognitive) is based on scientific findings that relate emotion expression with:

- Speech/Vocal Expression (Banse & Sherer, 1996; Oudeyer, 2003; Murray & Arnott, 1993; McNair et al., 1981; Cowie, 2003; Dellaert et al., 1996; Lee & Narayanan, 2005),
- Facial expressions (Stathopoulou, 2009; Yang et al., 2002; Hjelmas & Low, 2001; Zhao et al., 2003; Ekman & Friesen, 1978; Russell & Bullock, 1985),
- Eye Tracking (Duchowski, 2002; Ji, 2005),
- Gestures, body language and motion (Marcel, 2002; Turk, 2001; Pavlovic et al., 1997; Aggarwal, J.K. & Cai, 1999; Hu et al., 2004; Wang & Singh, 2003; Feldman et al., 2005; Mota & Picard, 2003).
- Physiological data, such as blood pressure, temperature (James, 1884; Ekman et al., 1983), respiration rate, electromyographic activity of muscles (Picard, 1988), skin temperature, galvanic skin response, heart rate (Ark et al., 1999).

The experiments of this method make use of basic input devices (keyboard, mouse) or sensor technology (such as cameras, haptic sensors, pressure sensors on chairs, microphones). So, emotion recognition using sensors involves risks related to failure leading to misleading results (Kapoor & Picard, 2005). Moreover, there have been controversies concerning the sufficiency of physiological measures for accurate emotion recognition (Cannon, 1927; Schachter, 1964; Schachter & Singer, 1962).

The second method of emotion recognition (cognitive) makes predictions about the potentially aroused emotions based on emotion-generating situations, such as goals, standards, attitudes and perception of events and objects. Taking the perspective of empirical psychology and cognitive science, we start with the assumption that emotions arise as a result of the way in which the situations that initiate them are construed by the experiencer (Ortony, Clore & Collins, 1988). The implementation of the second method is based on adapting emotion theories for (a) classifying emotions and (b) designing the processes of making inferences about the possibility of emotions to arouse. The cognitive method of emotion recognition provides a more friendly and safe environment than the non-cognitive method, as users do not have to wear or use special equipment (Moridis & Economides, 2008a).

Recently, there has been a great interest from researchers to develop affective systems using the cognitive approach for emotion recognition. Most of them adapt the OCC cognitive theory of emotions (Ortony, Clore & Collins, 1988) in a variety of fields, such as in creating animated virtual agents/characters (Karunaratne & Yan, 2001; Liu & Pan, 2005; Paiva et al., 2004; Dias & Paiva, 2005; Bartneck, 2002; Ochs, 2005; Allbeck & Badler, 2002) in virtual environments, for simulating combat scenarios (Van Dyke Parunak et al., 2001), for automatically gathering music (van Breemen & Bartneck, 2003), in multi-modal dialog systems and presentations (Streit et al., 2004; Zong et al., 2000) and intelligent learning environments (Moridis & Economides, 2008b; Jaques & Vicari, 2007; Katsionis & Virvou, 2004; Conati & Zhou, 2004; Chalfoun et al., 2006; Jaques et al., 2004; Elliott et al., 1999; Chaffar & Frasson, 2006).

There are other approaches that instead of adapting a specific emotion theory, they have used a blend of theories using common characteristics and proposing computational models of emotions (Kort et al., 2001; Craig et al., 2004; D'Mello et al., 2007; Neal Reilly, 1996; Elliott, 1992; Pereira et al., 2006). There is, also, a recent trend in creating hybrid emotion recognition systems using both cognitive and non-cognitive methods (Kapoor & Picard, 2005; Avradinis et al., 2004).

2.4.3. Affective Computing in Intelligent Learning Systems

It appears that emotions can be powerful in encouraging and inhibiting effective learning and approaches to study, but educational research and models of learning have shed little light on the interrelationships between emotions and learning (Ingleton, 2000). Indeed, there are studies that prove the impact of emotions on education and motivation for learning (Vygotsky, 1994; Bickmore & Picard, 2004; Simon, 1967; Norman, 1981; Norman, 2002; Craig et al., 2004; Bower, 1992;

Schwarz & Bless, 1991; Mowrer, 1960; Postle, 1993; Sylwester, 1994; Jensen, 2005; Graham & Weiner, 1996; Zimmerman, 2000; Best, 2003; Isen, 2003), as well as the positive effect of affectivity. Other studies relate emotions with memory (Bower, 1981), decision-making and cognition (de Souza, 1987; Bower, 1983; Damasio, 1994; Goleman, 1995), attention (Lang et al., 1990). There are, also, studies that associate specific emotions with the learning process, such as pride and shame (Ingleton, 1995), uncertainty, hope and fear (Salzberger-Wittenberg et al., 1983), confidence, anxiety and fear (Barbalet, 1998), self-conscious emotions and pride (Kitayama et al., 1995; Scheff, 1997). In general terms, researchers agree that positive emotions (e.g. joy, pride, satisfaction, confidence) have positive impact on learning and negative emotions (e.g. distress, shame, anxiety, anger) may impair the learning process. As Muijs and Reynolds (Muijs & Reynolds, 2001) state:

"Emotions can both help and hinder learning. On the positive side, emotions help us to recall information from the long-term memory, through allowing any information received through the sensory buffer to be perceived as positive or as a threat. Research suggests that the brain learns best when confronted with a balance between high challenge and low threat. The brain needs some challenge to activate emotions and learning. If there is no stress the brain becomes too relaxed and cannot actively engage in learning. Too much stress is also negative, however, as it will lead to anxiety and a 'flight' response, which are inimical to learning."

The literature, also, highlights the importance of the teacher embracing emotions and being affective (Day, 1998; Hargreaves, 2000; Sutton & Wheatley, 2003; Daloz, 1986; Postle, 1993; Coles, 1998; Brand et al., 2007; Efklides & Petkakim, 2005). In the same way, intelligent learning environments should add affectivity in order to (a) enhance the student-adapted support and (b) facilitate the human trainer with a useful toolkit for assessing the students' emotions.

In view of the aforementioned literature, researchers have shown a great interest in adding affectivity in intelligent learning systems. The recognized students' emotions have been used mainly for animated pedagogical agents (Gratch & Marsella, 2001;

Jaques & Vicari, 2007; Lester et al., 1999; Craig et al., 2004; Jaques et al., 2004; Elliott et al., 1999; Nkambou, 2006) and affective system responses, support and adaptation (Katsionis & Virvou, 2005; Moridis & Economides, 2008b; Poel et al., 2004; Leontidis et al., 2009; Conati & Zhou, 2004).

Pedagogical agents are lifelike virtual characters that intelligently assist students and provide visual feedback aiming at supporting them empathetically and creating a more interesting and stimulus virtual learning environment. The emotions enhance believability of educational agents and increase the bandwidth of communication between educational agents and the student (Choua et al., 2003).

Concerning CSCL and affective computing, Dillenbourg notices that: "affective and motivational aspects that influence collaborative learning have been neglected by experimental CSCL researchers" (Dillenbourg et al., 2009). In fact, only the educational game described in (Conati & Zhou, 2004) could be considered as a CSCL environment, as it provides pair-peer working. However, the affective responses of the system towards the players-students are not related to the collaboration process.

Moridis (Moridis & Economides, 2008a), reviewing the literature, identifies two different emotional instructional strategies, depending on whether the support based on the recognized student's emotions is *domain dependant* or *domain independent*. The aim of domain dependant instructional strategies is to assist the students advising them on the domain knowledge taking into consideration their emotional state (cognitive and emotional ways). Domain independent strategies concern supporting students emotionally (emotional way) attempting to increase positive emotions and decrease negative emotions.

Domain independent emotional instructional strategies are found in (Jaques et al., 2004; Leontidis et al., 2009; Astleitner, 2000; Jia et al., 2009). Some domain dependent emotional instructional strategies are described in (Poel et al., 2004; Katsionis & Virvou, 2005; Moridis & Economides, 2008b; Craig et al., 2004; Poel et al., 2004; Elliott et al., 1999).

In table 2.2, an overview of existing affective learning systems is cited. Regarding this review, it may be concluded that:

- The vast majority of these systems implements affect recognition using the OCC theory.
- Not all of them have integrated affective tactics based on the recognized students' emotions.
- Only two of them include an affective animated agent to promote empathy and learning.
- Only one of these systems both non-cognitive and cognitive emotion recognition methods.
- None of these systems is CSCL.
- None of these systems has used the recognized emotions for suggesting optimum group formation of students.

Table 2.2. Overview of Existing Affective Learning Systems.

AFFECTIVE LEARNING SYSTEM	EMOTION THEORY/MODEL	AFFECTIVE TACTICS	ANIMATED AGENT
Jaques & Vicari, 2007	OCC	Increase the student's self-ability, increase the student's effort and offer help	X
Katsionis & Virvou, 2005	OCC	Assistance	X
Jia et al., 2009	Discrete-dimensions Duality Emotion (DDE) model	Foster positive emotions and help to avoid or to cope with negative emotions	X
Jaques et al., 2004	OCC	Motivating the student to learn and promoting a positive mood	√
Poel et al., 2004	OCC	Feedback, motivation, explanation, steering, adaptivity of dialogue	X
Leontidis et al., 2009	OCC	Motivating the student to learn and promoting a positive mood	X
Conati & Zhou, 2004	OCC	Not implemented	X
Chaffar & Frasson, 2006	OCC	Not implemented	X
Chalfoun et al., 2006	OCC	Not implemented	X
Nkambou, 2006	facial expression analysis and OCC	Content planning, learning/tutoring strategies and tutoring dialogues	√

2.5. Group Formation Tools

The formation of learning groups is an issue discussed in a great extent in the literature. There are various proposed methods of groups' formation based mainly on creating homogeneous or heterogeneous groups based on:

- Knowledge levels (Johnson & Johnson, 1985; Mugny & Doise, 1978),
- Team roles (Belbin, 1993),
- Learning styles (Kolb, 1984; Honey & Mumford, 1986; Entwistle & Ramsden, 1983; Felder & Silverman, 1988; Dunn & Dunn, 1978),
- Gender and Race (Yeoh & Mohamad Nor, 2009; Aronson & Patnoe, 1997; Miller & Harrington, 1990; Cohen, 1994) and
- Personality types (Myers & McCaulley, 1985).

There is plenty ongoing research on whether groups are more beneficial when they are heterogeneously or homogeneously formed. Others advocate heterogeneous (Kagan, 1992; Slavin, 1990; Azmitia, 1988; Tudge, 1989; Webb, 1980) and others homogeneous (Ames & Murray, 1981; Glachan & Light, 1982; Hooper et al., 1989) group formation. Most of them agree that heterogeneous grouping seems to be beneficial though risky for the performance of high-ability students, as they may end up spending much time in helping low-ability students (Abrami et al., 1995). On the other hand, homogeneous grouping appears to benefit high-ability students, but often low-ability students will have less possibility for progress.

CSCL systems facilitate collaborative learning enabling students to work collaboratively into groups. An important but often neglected aspect in Computer-Supported Collaborative Learning is the formation of learning groups (Mühlenbrock, 2005). There are many studies that highlight the importance of group formation in collaborative learning tools. As emphasized in (Daradoumis et al., 2002): "An important issue to consider is group formation: the factors that influence and promote the creation of a group and the processes that take place and govern and condition the group construction". Inaba et al. (Inaba et al., 2000) emphasize that: "how to form an effective group for the collaborative learning is critical to ensure education benefit to the members".

There have been experiments presented in literature that provide group formation tools (Christodoulopoulos & Papanikolaou, 2007; Graf & Bekele, 2006; Cavanaugh et al., 2004; de Faria et al., 2006; Wang et al., 2007; Gogoulou et al., 2007a; Ounnas et al., 2009; Martin & Paredes, 2004; Khandaker & Soh, 2010; Paredes et al., 2009; Ikeda et al., 1997; Liu et al., 2008; Kyprianidou et al., 2009; Kreijns et al., 2002; Soh et al., 2006). In Table 2.3 a summarized overview of the existing group formation tools is cited. These approaches of automatic group formation use a variety of students' characteristics, search algorithms and method (heterogeneous/homogeneous groups).

For example, in (Christodoulopoulos & Papanikolaou, 2007) a web-based group formation tool that supports the instructor to automatically create both homogeneous and heterogeneous groups is presented. The group formation process is based on the knowledge level and the learning styles of the students. The algorithms used are the Fuzzy C-Means algorithm (fuzzy version of the k-means algorithm) for the homogeneity and a random sorting algorithm for the heterogeneity. This group formation tool can be used as a stand-alone web-based application, or as a module of an e-learning environment for matching peers and, thus, there is no process of automatically evaluating the knowledge level and the learning styles.

In (Graf & Bekele, 2006), the authors propose a mathematical approach to form heterogeneous groups based on personality traits and the performance of students. The personality traits are group work attitude, interest for the subject, achievement motivation, self-confidence and shyness. The performance of students is related to the level of performance in the subject and fluency in the language of instruction. The algorithm used for this group formation approach is the Ant Colony Optimization algorithm. As the described approach is mathematical, it is beyond the scope of the study to present the method of tracing the personality traits and the performance of the students.

Cavanaugh (Cavanaugh et al., 2004) describes a web-based system to assign students to teams using instructor-defined criteria. The students through questionnaires submit the criteria values (every question mirrors a criterion). The instructor defines the team sizes and assigns a weight to each question indicating the importance of considering the criterion. The algorithm used is based on the hill-climbing algorithm. As this tool is based on questions-answers, there is no automatic inference mechanism of student characteristics.

In (de Faria et al., 2006), the authors present an approach for constructing groups for collaborative learning of computer programming. The group formation is based on criteria related to the students' level of knowledge and programming styles (length of identifiers, size and number of modules and numbers of indented, commented and blank lines). The criteria values are automatically assessed as the students work in the environment. The tool was designed for both heterogeneous and homogeneous group formation. The algorithm is not explained.

DIANA (Wang et al., 2007) is also a group formation system based on heterogeneous grouping using genetic algorithms. The kinds of criteria are loaded in the system by the teacher and may concern any psychological variables adequate for the course (up to 7 variables). The values of these psychological variables are assigned to the students after answering to related psychological questionnaires.

OmadoGenesis (Gogoulou et al., 2007a) is tool for instructors to automatically form random, homogeneous, heterogeneous or mixed groups based on learners' characteristics. The instructor defines the types of learner characteristics and their values for each student. OmadoGenesis uses Genetic and k-means based algorithms.

Martin and Paredes (Martin & Paredes, 2004) describe a group formation tool used in a CSCL system called TANGOW (Carro et al., 2003). The purpose of this tool is to create groups based on the students' Felder learning styles (Felder & Silverman, 1988), which are defined through the ILS (Index of Learning Styles) questionnaire. The teacher defines the groups' structure considering the students' learning styles (homogeneous/heterogeneous) or any other knowledge characteristic (previous knowledge, scores in exercises). The algorithm is not explained.

In (Ounnas et al., 2009), the authors present a group formation tool based on Semantic Web technologies and disjunctive logic programming that performs a forward checking algorithm. The group formation takes into consideration the interests, the learning style, the gender and the Belbin team role of the students. These data are extracted from users' direct input (interests, friends and gender) and completing questionnaires (learning style and Belbin team role). The formed groups can be either heterogeneous or homogeneous according to the instructor's preferences. The authors, also, describe how they have created an ontology called Semantic Learner Profile, an extension of the Friend Of A Friend ontology that describes people for building communities and social groupings.

ClassroomWiki (Khandaker & Soh, 2010) is a Web-based collaborative Wiki writing tool that includes a tool for creating random or heterogeneous student groups based on their performance (knowledge and skills), which are assessed automatically. This group formation tool uses the MHCF (Multiagent Human Coalition Formation framework) algorithm described in (Khandaker & Soh, 2007).

I-MINDS (Soh et al., 2006) is a CSCL system that includes group formation support based on the Jigsaw model (Aronson & Patnoe, 1997) using the VALCAM (Vickrey Auction-Based Learning-Enabled Coalition and Adaptation for Multiagent Systems) algorithm (Khandaker, 2005). The student characteristics used and automatically evaluated by the system include the number of messages sent among group members, types of messages, self-reported teamwork capabilities, peer-based evaluations as a team member and evaluation of each team.

In (Liu et al., 2008) a collaborative learning tool that incorporates group formation processes is presented. The formed groups are heterogeneously structured based on the students' learning styles of Felder and Silverman model (Felder & Silverman, 1988) using a randomized algorithm. The learning styles are initially acquired through the ILS questionnaire. Then, they are fine-tuned through monitoring collaborative interactions between learners.

Paredes et al. (Paredes et al., 2009) propose TOGETHER, a tool for forming heterogeneous groups using a heuristic algorithm that uses Euclidean Distance to calculate the degree of similarity between the students concerning their learning style. The teacher may choose the final group formation among the optimum ones calculated by the tool. The learning styles of the students are extracted though the Index of Learning Styles (ILS) questionnaire that is a tool for the Felder and Silverman model of learning styles.

Opportunistic Group Formation (Ikeda et al., 1997) is a model for forming learning groups dynamically based on learning goals. This tool monitors the learners to detect if a learner has to shift from individual learning mode to collaborative learning mode. Then, it forms learning groups assigning to their members learning and social roles consistent with the goal of the whole group.

PEGASUS (Kyprianidou et al., 2009) is a web-based system that suggests homogeneous or heterogeneous workgroups, supporting also teacher-students negotiations of the final group synthesis. It is based on the learning styles of the learners to form both heterogeneous and homogeneous groups. The learning styles are measured through psychometric tests.

An intelligent CSCL environment that acts as social contextual facilitators to initiate and sustains learner's social interactions is described in (Kreijns et al., 2002). It also includes a heterogeneous group composition tool that takes into consideration the gender, age and abilities of students.

Table 2.3. Overview of Existing Group Formation Tools.

GROUP FORMATION TOOL	ALGORITHM	CRITERIA	AUTOMATIC RECOGNITI ON OF CRITERIA VALUES	TYPE OF GROUPS	CSCL
Christodoulopo ulos & Papanikolaou, 2007	Fuzzy C-Means algorithm	Knowledge level and the learning styles	X	Homogeneous and heterogeneous	X
Graf & Bekele, 2006	Ant Colony Optimization	Personality traits and the performance	X	Heterogeneou s	X
Cavanaugh et al., 2004	Hill-climbing	Abstract (defined by the instructor)	X	Defined by the instructor	X
de Faria et al., 2006	Undefined	Level of knowledge and programming styles	√	Homogeneous and heterogeneous	X Uses a CSCL system
Wang et al., 2007	Genetic	Abstract (defined by the teacher)	X	Heterogeneou s	X
Gogoulou et al., 2007a	k-means based	Abstract (defined by the teacher)	X	Homogeneous , heterogeneous or mixed groups	X
Martin & Paredes, 2004	Undefined	Learning styles and knowledge	X	Homogeneous and heterogeneous	X Uses a CSCL

					system
Ounnas et al., 2009	Semantic Web technologies and disjunctive logic programming	Interests, learning style, gender and Belbin team role	X	Homogeneous and heterogeneous	X
Khandaker & Soh, 2010	Multiagent Human Coalition Formation framework	Knowledge and skills	√	Random or heterogeneous	X
Soh et al., 2006	VALCAM	Social skills and knowledge	√	Jigsaw model	√
Liu et al., 2008	Randomized algorithm	Learning styles	√	Heterogeneou s	√
Paredes et al., 2009	Heuristic	Learning styles	X	Heterogeneou s	X
Ikeda et al., 1997	OGF	Learning goals	√	Matching appropriately according to learning goals	√
Kyprianidou et al., 2009	Undefined	Learning styles	X	Homogeneous and heterogeneous	X
Kreijns et al., 2002	Undefined	Gender, age and ability	√	Heterogeneou s	√

Along with the group formation techniques discussed previously, there is a subcategory of group formation tools, the peer helping. It is a group formation technique considering pairs of partners/colleagues, e.g. (McCalla et al., 1997; Soller, 2001; Bull, 1997; Greer et al., 1998). These systems suggest an appropriate partner for the student based on characteristics, such as knowledge, conversational skills and preferred types of interaction.

2.6. Recommender Tools in Learning Systems

As there is a great amount of information on the World Wide Web and a great variety of information systems available to people in everyday life, it is becoming more difficult to choose what to news to read, books to study, products to buy, music to listen etc. Recommender systems provide a way to relieve us from searching in this maze of information, saving us time and money. Recommender systems are defined as systems that can offer adaptive and intelligent advice to users on what information to receive. Generally speaking, a recommender system reads observed user behavior or opinions from users as input, then aggregates and directs the resulting recommendations to appropriate recipients (Neumann, 2009). They have become fundamental applications in electronic commerce and information access, providing suggestions that effectively prune large information spaces so that users are directed toward those items that best meet their needs and preferences (Burke, 2002). During the last few years, there has been a great interest in applying recommender systems in e-learning environments, as they usually include an extended range of domain related help topics. Hence, the learners become overloaded with information and often confused on what help topics and in which order they should study them.

In the literature, there are two methods of building recommender systems often described as: the Content-based Prediction and the Collaborative/Social Filtering. The Content-based Recommendation Systems export their user recommendation evaluating the preferences and characteristics of the user in association with the description of the system's information. According to the Collaborative/Social Filtering approach, the system recommends the information, that users with similar preferences and characteristics used in the past. Over the last years, the hybrid technique of combining these two methods has been preferred and efficiently applied in a great extent. Both methods have their own advantages but they cannot perform well in many situations (Rojsattarat & Soonthornphisaj, 2003).

Recommender systems have been used for recommending items in a great variety of domains, such as products in e-commerce environments (Prasad, 2005), tourist information (Sánchez-Anguix et al., 2010; Ricci & Werthner, 2002), books (Liao et al., 2010), movies (Jung et al., 2004; Nguyen et al., 2007), TV programs (Blanco-Fernandez et al., 2004; Velusamy et al., 2008; Blanco et al., 2005) music (Nakahara & Morita, 2009; Lampropoulou et al., 2009; Kim et al., 2009), restaurants (Park et al., 2008) and news (Billsus & Pazzani, 2000).

Quite recently, recommender systems have also been developed for recommending learning objects (Lu, 2004; Zaíane, 2002; Wan et al., 2008; Linton et al., 2000; Chen et al., 2005; Tang & McCalla, 2005; Khribi et al., 2008; Furugori et al., 2002; Hummel et al., 2007; Hsu, 2008). Most of them focus on recommendations on learning objects or paths and rarely on adequate colleagues to collaborate with. In Table 2.4 a summarized overview of the existing recommender tools embedded in learning systems is cited.

In (Lu, 2004) a personalized learning material recommendation framework is presented. It implements both content-based and collaborative recommendation using multi-criteria student requirement analysis model to justify a student's need and fuzzy matching method to find suitable learning materials to best meet each student need. The aim of the system is to help students find learning materials they would need to read. The student's characteristics taken into consideration are learning styles, learning material access and achievement of all groups of students.

In (Zaíane, 2002) a recommender agent for on-line learning systems is presented. This agent recommends learning activities based on learners' access history to improve course material navigation using web-mining techniques. It implements both content-based and collaborative techniques taking into account the profiles of on-line learners, their access history and the collective navigation patterns.

Collabo-eNOTE (Wan et al., 2008) is a WEB based intelligent e-NOTEBOOK system that recommends useful notes based on the content-based and collaborative filtering by using learners' reading histories and the contents of notes. The recommendations are generated using the Weighted Slope One algorithm and the COSINE method.

OWL (Linton et al., 2000) is a recommender system to enable continuous knowledge acquisition and individualized tutoring of application software across an organization. It uses the collaborative filtering method recording the expertise of the users per topic of the domain knowledge. The provided recommendations represent tips for each topic.

In (Chen et al., 2005) the authors propose a personalized e-learning system based on Item Response Theory considering both course material difficulty and learner ability to provide individual learning paths for learners. The recommender system is content-based.

The proposed recommender system in (Tang & McCalla, 2005) concerns a web-based learning system, which can adapt itself not only to its users, but also to the open

Web. It finds relevant content on the web and personalizes and adapts this content based on the system's observation of its learners' active assessment and browsing pattern. The recommendation concerns the learning materials (papers) and is both content-based and collaborative. The recommender module is implemented using clustering.

In (Khribi et al., 2008) the authors present an automatic personalization approach of providing online automatic recommendations on learning resources. The recommender uses both content-based and collaborative filtering methods evaluating the learner's recent navigation history and similarities and dissimilarities among learners' preferences and educational content. It is implemented using Web mining and clustering techniques.

COALE (Furugori et al., 2002) is a CSCL environment that includes a personalized active recommendation system. It supports dynamic course organization recommending learning material. The recommendations are generated based on learners' dynamic learning activities (actions and performance). The system uses awareness maps for representing information about the learner and the content.

The system discussed in (Hummel et al., 2007) offers recommendations on learning activities using both content-based and collaborative filtering approaches. The recommendations are based on the available study time, study motive and study domain interest of the learners. These characteristics are fixed metadata, as they are not tracked automatically.

Table 2.4. Overview of Existing Recommender Tools in Learning Systems.

RECOMMENDER SYSTEM	ALGORITHM	RECOMMENDATION CONTENT	CRITERIA	AUTOMATIC RECOGNITION OF CRITERIA VALUES	RECOMMENDATION METHOD	CSCL
Lu, 2004	Multi-criteria and fuzzy matching	Learning materials	Learning styles, learning material access and achievement	X	Content-based and collaborative	X
Zaiane, 2002	Web mining techniques	improve course material navigation	Learners' access history	√	Content-based and collaborative	X
Wan et al.,	COSINE	Useful notes	Learners'	√	Content-based	X

2008	method and Weighted Slope One algorithm		reading histories and the contents of notes		and collaborative	
Linton et al., 2000	Undefined	Advice on domain topics	Evolving expertise	√	Collaborative	X
Chen et al., 2005	Item Response Theory	Individual learning paths	learner ability and course material difficulty	√	Content-based	X
Tang & McCalla, 2005	Clustering	Learning materials (papers)	Active assessment and Browsing pattern	√	Content-based and collaborative	X
Khribi et al., 2008	Web mining and clustering techniques	Learning resources	Navigation history, preferences	√	Content-based and collaborative	X
Furugori et al., 2002	Depth-first and Width-first in Awareness Maps	Learning material	Actions and performanc e	√	Content-based and collaborative	√
Hummel et al., 2007	Undefined	Learning activities	Available study time, study motive and study domain interest	X	Content-based and collaborative	X

2.7. Teacher Leadership

A usually neglected aspect in education is teacher leadership. The learning process can be viewed as a situation where the followed way of leadership should concern every teacher. Most of the times, the teacher plays the role of the leader of his/her students, who play the role of the followers. Teacher leadership is considered essential, however it is often neglected and somehow meets impediments (Gabriel, 2005; Barth, 2001; Wilmore, 2007; York-Barr & Duke, 2004; Suranna & Moss, 1999).

One of the main fields of interest in the organizational and managerial literature is leadership. There are many definitions for the leadership depending on the research field. In (Achua & Lussier, 2009) leadership is defined as "the influencing process of leaders and followers to achieve organizational objectives through change". During the past decades a variety of leadership theories have been proposed, studied and applied in effort of organizing leadership. These theories involve different views of the leader, the follower instances and the variables that affect them. A common classification of leadership theories are: Great Man Theory, Trait Theory (Stogdill, 1974), Behavioral Theories (Blake & Mouton, 1964; Merton, 1957), Participative Leadership (Lewin et al., 1939; Likert, 1967), Situational Theories (Hersey & Blanchard, 1999; Hersey et al., 2007; Vroom & Yetton, 1973; House & Mitchell, 1974), Contingency Theories (Fiedler, 1964; Fiedler, 1963; Fiedler & Garcia, 1987), Transactional Leadership (Dansereau et al., 1975) and Transformational Leadership (Bass, 1985; Burns, 1978; Bass & Avolio, 1994).

The simple nature and general acceptance (Northouse, 2001) of the Hersey-Blanchard Situational Leadership Theory (Hersey & Blanchard, 2007) has motivated us to use it in our learning system. It is not a complex model and the variables used can be traced in a computer-supported environment. There are empirical studies and evaluations that support this theory (Clark, 1981; Hersey et al., 1982; Cairns et al., 1998). The situational leadership model developed by Hersey and Blanchard is perhaps the most widely used model in leadership training in both the public and private sectors (Vasu et al., 1998). Situational leadership has been around for over four decades, has gained acceptance, and is relatively easy to understand (Baker, 2009). This model of situational leadership can be used in day-to-day situations and goals can be achieved effectively and efficiently (Gupta, 2007). [...] The situational leadership model has the benefit of recognizing that leaders confront varying circumstances that are likely to require different combinations of skills (Duke, 2009).

Despite this popularity and effectiveness, the situational leadership theory has not yet been used much in education or in computer supported learning environments. Situational leadership is a well-established concept, but scholars rarely apply it to educational settings (Donahoo & Hunter, 2007). Furthermore, there is research that provides evidence that the situational leadership theory would be effective for use in education. It is suggested that Situational Leadership Theory may be productively applied in training and educational as well as typical management situations (Hersey et al., 1982). Teaching styles are remarkably similar to leadership styles. The Hersey and Blanchard model for sequential development of situational leadership can easily be applied to the classroom instructor (Weber & Karman, 1991). The main purpose of using such a theory is the need of our learning system to provide a tool that would assist the trainer as leader. Furthermore, the system itself, with the embodiment of an Advisor module, constitutes a form of leader role that would also be supported by the adaptation of this theory.

The benefits of using a leadership theory (and especially the situational leadership model) in a learning environment for automatic adaptation of recommendations and advice to learners concern the human nature of the teacher/trainer. The lack of fairness of a trainer/teacher is a frequent case. S/he might like or dislike differently the learners and, hence, offer support that is unequal and not adequate to their needs. Another cause of unfairness could be neglecting those learners that are already of a senior level in skills, disregarding the possible deficiency in self-confidence or motivation. A trainer could, also, be unfair in case s/he has not detected the real problems and therefore needs of the learners. In the absence of fairness, attempts at instruction will not yield any significant amount of student learning (Walbesser, 2002). Fairness can, at a high degree, be ensured by the application of an objective and automatic leadership model that would offer support to the trainees and guidance to the trainer.

According to the Hersey-Blanchard Situational Leadership Theory, leaders should continually adjust their leadership styles depending on the maturity or readiness of the followers. Maturity is a variable defined by the ability and the willingness of the followers. Ability is related to the knowledge, skills and experience of a follower to complete a given task. Willingness concerns the degree of readiness, motivation and self-confidence of a follower to accomplish a given task. Another crucial element of the theory is that the maturity is dependent on each task given to the follower, rather than a global variable. Hersey and Blanchard have defined 4 different levels of maturity and 4 leadership styles (one for each maturity level).

2.8. Conclusions

People have changed through time and so have their educational needs. The everyday stimulus are much more various and complicated than forty, twenty or even ten years ago. Bearing in mind that we are experiencing a technology evolution that has overwhelmed our lives, we should employ these technological attainments to adjust to the new reality and needs. The majority of the scholars and professionals of education highlight the importance of transforming the educational approaches and methods in everyday situations. Regarding the emerge of sociability (especially amongst young people) caused by the rapid growth of Internet applications (social networks, integrated multimodal chat tools etc.) and following the well known and respectful paradigms of social constructivism and collaborative learning, we should consider to revolve to computer technology in order to implement new educational methods and tools. At this aim, this thesis proposes a CSCL system that automatically monitors the trainees and provides them intelligent and adaptive recommendation to improve and support the learning process. The system also offers a useful toolkit for the trainer offering important statistical information about the trainees and recommending optimum group formation and appropriate leadership styles to follow for each trainee and task.

3

AN INTELLIGENT COMPUTER SUPPORTED COLLABORATIVE LEARNING ENVIRONMENT FOR UML: AUTO-COLLEAGUE

3.1. Introduction

The system described in this thesis is a Computer Supported Collaborative Learning Environment for training users in UML. It is called AUTO-COLLEAGUE (AUTOmated COLLaborativE leArning Uml Environment). Trainees learn UML collaboratively under the supervision of the trainer. It is suitable for use both in educational institutes and software houses. UML and relative CASE tools have been very popular during the past decades. Although it has been implemented for UML, it can still be adapted for use for any other domain that can be fractured in separated topics in the form of a graph. Such domains could be programming languages, geography or grammar. The existing professional tools, though effective and useful, are not intended for educational use. They seem to be unfriendly and confusing to inexperienced trainees.

The trainer authors exercises/tests in a multiple-choice format. The trainees, who are organized into groups, may either work collaboratively in a shared workspace or discuss with each other to conclude to a solution to an exercise.

AUTO-COLLEAGUE builds student models of the trainees. The student models describe:

- The knowledge and level of expertise of the trainees using the perturbation (buggy) modelling technique,
- Important personality characteristics, which are associated to the learning and collaboration processes, based on stereotyped user modelling and
- The overall emotional state (positive or negative) of the trainees while collaborating with each other using the OCC theory of emotions.

In specific, the personality related stereotypes used are self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. These stereotypes have never been used in intelligent learning or CSCL environments. Even those learning systems that include relative personality characteristics, such as learning styles, usually evaluate their values using psychometric instruments (e.g. questionnaires) requiring explicit user input. Unfortunately, this may result in misleading data (Lawrence & Martin, 2001; Kolb, 1984; Gonyeau et al., 2006). In AUTO-COLLEAGUE, however, the personality attributes are inferred automatically (implicitly) and silently. This is achieved by tracing and evaluating specific trainee's actions and attributes in ways that resulted after conducting a relative empirical study with experienced trainees.

The overall emotional state of the trainees is predicted adapting the OCC cognitive theory of emotions (Ortony, Clore & Collins, 1988), which is used almost exclusively in emotion perception systems that apply the cognitive approach. According to this theory, emotions (negative or positive) are considered to be reactions to stimulus evoked by certain objects of the environment at a certain moment. The OCC theory of emotions proposes a model of emotion types. The predicted emotions can be categorized as positive or negative. This kind of emotion value contains valuable information for AUTO-COLLEAGUE in order to suggest optimum collaboration schemes. The overall emotional state is the prevailed "sign" after calculating the average of the individual emotion values during collaboration. It is used as an indicator of whether the system should promote a new collaboration between the participated colleagues in the future or not. Actually, this constitutes a novel approach regarding the way that perceived emotions are used. The prediction of student's emotions has already been implemented in learning environments, but they are usually limited to using these emotions for adapting help and/or the expressions of avatars. Emotion perception regarding the collaboration of students has never been done before and, thus, never used for proposing most effective collaboration schemes.

The student models are evaluated to generate intelligent recommendations for the trainees and the trainer. The recommendations are adapted to the needs of the trainees according to the Hersey and Blanchard Situational Leadership Theory, according to which leaders should continually adjust their leadership styles depending on the maturity or readiness of the followers. Maturity is a variable defined by the ability and the willingness of the followers. Ability is related to the knowledge, skills and experience of a follower to complete a given task. Willingness concerns the degree of readiness, motivation and self-confidence of a follower to accomplish a given task. Another crucial element of the theory is that the maturity is dependent on each task given to the follower, rather than a global variable. Hersey and Blanchard have defined 4 different levels of maturity and 4 leadership styles (one for each maturity level). Despite the popularity and adaptation of this theory during the last decades, no learning environment has yet used it. In fact, no leadership theory has been used in learning environments. In general, leadership theories attempt to explain leadership and propose ways of leading people according to their individual traits and needs.

The most important and innovative recommendations offered to the trainers are related to the group formation suggestions. The aim of this facility is to suggest to the trainer the optimum organization of the trainees into groups considering three criteria: (a) the desired and undesired combinations of personality stereotypes in the same group, (b) the desired group structure concerning the levels of expertise and (c) the emotional influence between trainees. The group formation tool processes the Simulated Annealing algorithm to search for the optimum solution. The Simulated Annealing algorithm (Kirkpatrick et al., 1983) is a genetic algorithm that serves as a general optimization technique for solving combinatorial optimization problems. It has never been used in similar cases (group formation tools and learning environments).

With regard to existing group formation tools, most of them automatically group students attempting to achieve homogeneity and/or heterogeneity in the resulted groups (Christodoulopoulos & Papanikolaou, 2007; Graf & Bekele, 2006; de Faria et al., 2006; Wang et al., 2007; Gogoulou et al., 2007a; Ounnas et al., 2009; Martin & Paredes, 2004; Khandaker & Soh, 2010; Paredes et al., 2009; Ikeda et al., 1997). The only exceptions come from (Soh et al., 2006), where the grouping is decided according to the Jigsaw model, and (Ikeda et al., 1997), where the students are matched according to their learning goals. Comparing the student characteristics considered in the group formation process of these systems to ours, none of these uses personality or emotional characteristics similar to ours. Some of them are limited to demographic and knowledge related data (Kreijns et al., 2002; de Faria et al., 2006; Khandaker & Soh, 2010). The majority of them (Kyprianidou et al., 2009; Paredes et al., 2009; Liu et al., 2008; Ounnas et al., 2009; Martin & Paredes, 2004; Christodoulopoulos & Papanikolaou, 2007) use learning styles. However, most of them do not trace the actual students' learning styles automatically, but using scientific instruments (questionnaires/tests) that are not always reliable (Lawrence & Martin, 2001) and miss the possibility of updating their likely to change values (Kolb, 1984; Gonyeau et al., 2006). AUTO-COLLEAGUE, on the other hand, automatically evaluates the personality characteristics and the emotional state of the trainees based on data resulted from empirical studies with experienced trainers.

There are similar CSCL systems designed for training users in UML, such as (Chen et al., 2006; Baghaei & Mitrovic, 2006; Kuriyama et al., 2004; Jondahl & Mørch, 2002). However, none of these or other CSCL systems includes the personality and emotional characteristics used in AUTO-COLLEAGUE. As far as the Hersey and Blanchard Situational Leadership Theory is concerned, there is no other system described in literature that uses it (or any other leadership theory) for adapting the provided advice or the environment.

In summary, the novel features of AUTO-COLLEAGUE are:

- The personality related stereotypes included in the student models and, especially, the way they are automatically traced and evaluated and

- The use of a leadership theory, and specifically the Hersey and Blanchard Situational Leadership Theory, for adapting intelligent recommendations in a learning environment.
- The optimum group formation it proposes to the trainer according to the automatically perceived personality and emotional state of the trainees.

The system has been evaluated in real time using university and school students. The results were quite optimistic and advocating.

3.2. Overview of the System

3.2.1. Kinds of Users

There are two kinds of users in AUTO-COLLEAGUE: the trainer and the trainee. The trainer is the administrator of the system. S/he is the teacher/trainer of the course that supervises the learning and collaboration process of the trainees. His/her role is not formal, as s/he is responsible for crucial duties. These are the parameterizations of the system, advising the trainees according to the data provided by the system and the supervision of the collaboration and learning processes. The trainer is not neglected by AUTO-COLLEAGUE. On the contrary, s/he is supported with intelligent recommendations on the ways s/he should act with the trainees (appropriate leadership style) and the optimum organization of the trainees into groups. Additionally, the system exports and makes available to the trainer a variety of data related to the performance of the trainees, their collaborative activities and the modifications in their student models. In this way, the system provides the trainer not only with tools of tracing the actions of the trainees, but also of being the conductor of the e-class by:

- Re-setting the whole system depending on the needs,
- Monitoring in detail the previous and current states of the trainees,
- Having a more intimate relationship with the trainees, as s/he is informed about their personality state (a chance that s/he may not have in a traditional

class of many student, where s/he may not be able to pay much attention to everybody),

- Organizing the groups in the most effective way
- Being objective towards everyone, as the emotions would not affect him/her in the offered support to the trainees and
- Being acquainted with personality aspects of the trainees that s/he might neglect in case of a dense traditional class.

The trainees are the learners. They may be students or the workers in an organization that attend a training course by their project manager or a trainer. They collaborate with the rest members of their group through a chat system. The advantages of using AUTO-COLLEAGUE are various for the trainees, as they:

- Do not feel alone and unsupported during the learning process,
- Are supported by the trainer and the system in the most effective way (leadership style),
- They feel comfortable in a sited for them group and
- They accomplish the aim of learning.

3.2.2. Main User Interface

The trainees login the system through the form illustrated in figure 3.1. After logging, the system registers the just started session recording the date and time. Then, the main form is appeared (figure 3.2). The chat interface is at the right part of the form. The trainees can send messages to each other by pressing the respective to the type of message button. The types of messages are: greeting, request help, offer help and offer advice. If a trainee wants to contact with someone for personal reasons, s/he will choose the greeting message. The request help message is for asking for help on a UML subject. The offer help button is for responding to a help request message. The offer advice button is for sending a message with a general advice. In the main form, there is also the shares workspace of drawing UML diagrams for practicing purposes. The trainees can share the workspace with their colleagues of the same group. They can save, open and print a workspace or ask for the system to check for errors.

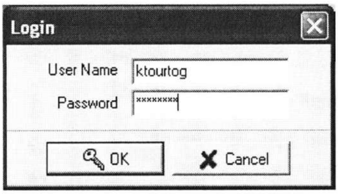


Figure 3.1. Login Form

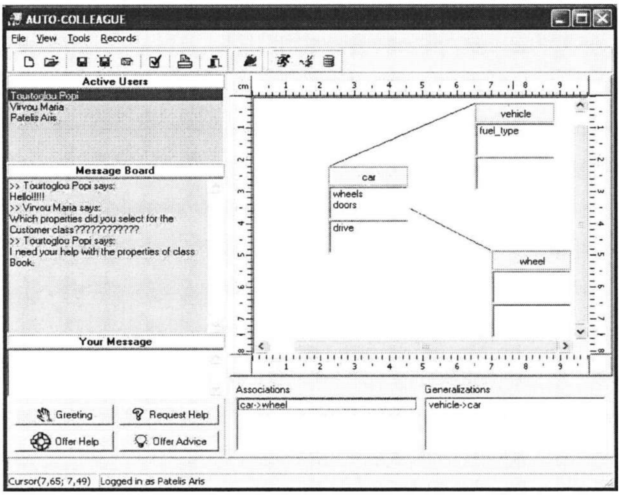


Figure 3.2. Main Form

3.2.3. Solving Tests/Exercises

Apart from the workspace on the main form, the trainee can run the tests/exercises form (figure 3.3). The description of the problem is shown at the upper part of the form. After the trainee studied it carefully, s/he has to draw the correct UML diagram by answering to specific multiple-choice format questions.

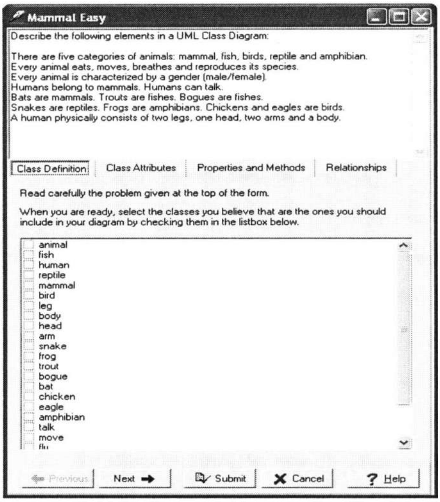


Figure 3.3. Tests/Exercises Form

The first step is to select from a checklist box the classes s/he believes that should be included in the diagram. The checklist box contains the correct and faulty classes that may trick the trainee checking his/her true knowledge.

After selecting the classes, the following step is to press the "next" button (figure 3.4) and fill for each of the previously checked classes the attributes of "Is Abstract" and "Visibility".

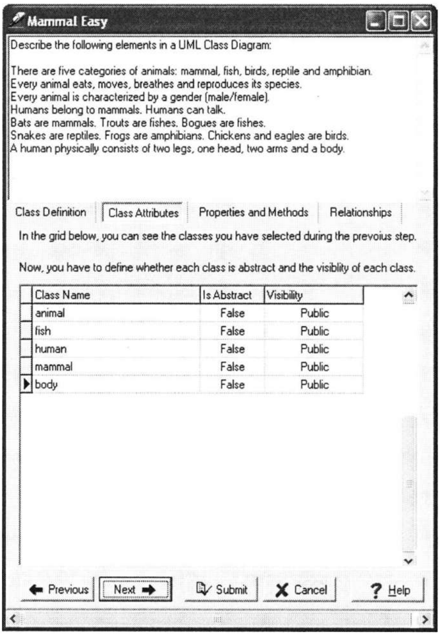


Figure 3.4. Tests/Exercises Form – Class Attributes Step

The next step is to define the properties and methods for every class selected at the first step (figure 3.5). The classes are given in a tree list and the trainee can add properties and methods by right clicking on the appropriate tag. Then the Attribute (figure 3.6) or Method Editor (figure 3.7) will appear. In the Attribute Editor, the trainee must complete the data of the new attribute. Specifically, s/he must select a name for the Attribute by a given list. In this list, there are predefined choices of attribute names. So, the trainee should decide which are the correct ones and additionally select the visibility (public, protected, private), the type (boolean, integer, string, double, char) and the initial value of the new attribute. S/he can also write documentation for the attribute. Similarly in the Method Editor, the trainee must define the method name, visibility (public, protected, private), type (boolean, integer, string, double, char) and the parameters. For the parameters, s/he can press the "New" button to insert a new parameter, the "Edit" button to modify an existing one, the "Delete" button to delete a parameter and the "Clear" button to delete all the parameters. There are, also, the "Move Up" and "Move Down" buttons in case the trainee wants to change the order of the parameters. Pressing the "New" or the "Edit" button, the Parameter Editor appears (figure 3.8). In this form, the name, type (boolean, integer, string, double, char), kind (input, output, input-output) and default value of the parameter are defined. In all the forms described, every control that is yellow colored is mandatory.

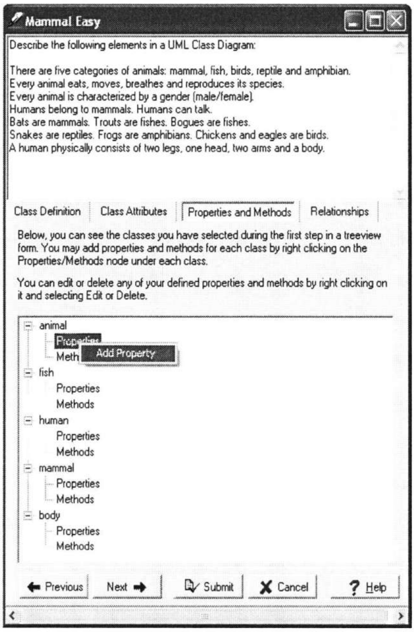


Figure 3.5. Tests/Exercises Form – Properties and Methods Step

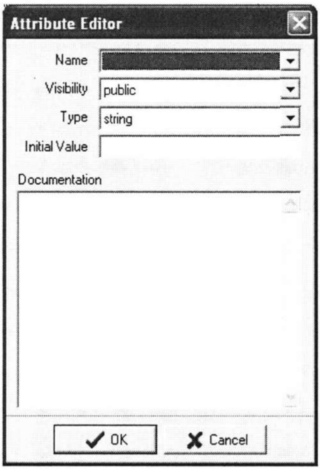


Figure 3.6. Tests/Exercises Form – Properties and Methods Step – Attribute Editor

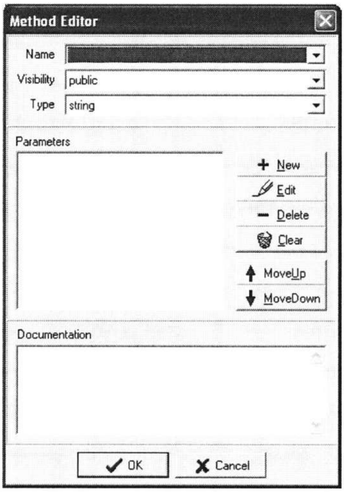


Figure 3.7. Tests/Exercises Form – Properties and Methods Step – Method Editor

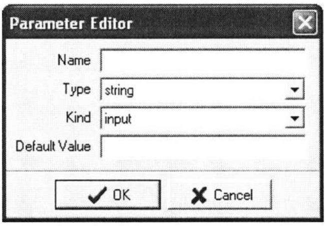


Figure 3.8. Tests/Exercises Form – Properties and Methods Step – Parameter Editor

The final step of this wizard form is to specify the relationships (Generalizations and Associations) of the selected in the first step classes (figure 3.9). There are two different grids for the Generalizations and Associations. The trainer inserts a new record selecting from a list box the start and the end class.

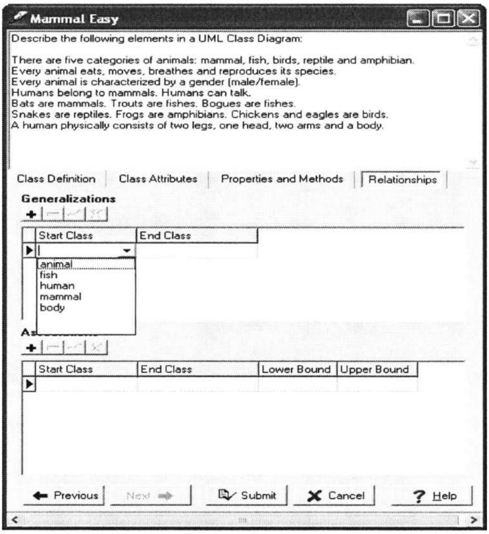


Figure 3.9. Tests/Exercises Form – Relationships Step

Finally, the trainee presses the "Submit" button. Then, the system checks the correct and mistaken answers to give him/her the results and draw the UML diagram, as shown in figure 3.10. The system gives to the trainee a full report on the mistakes made organized by mistake type. Additionally, the described by the trainee diagram is automatically drawn at the lower right part of the form.

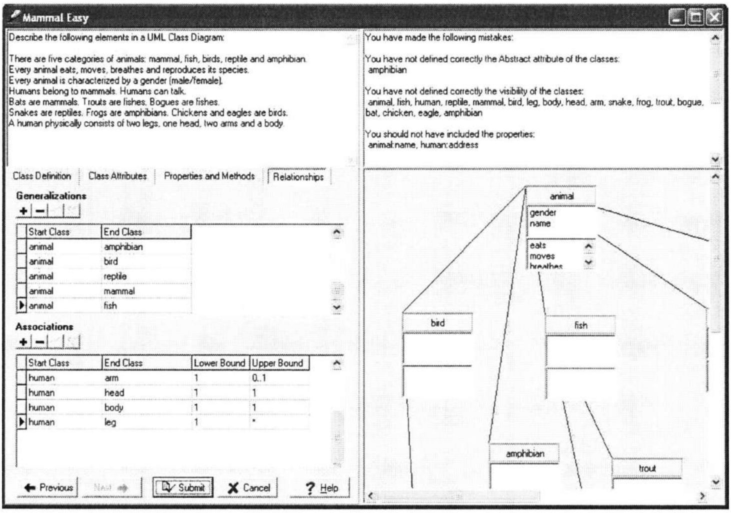


Figure 3.10. Tests/Exercises Form – Results After Submitting Solution

3.2.4. Authoring the Exercises

The trainer through the form illustrated in figure 3.11 authors the exercises described on the exercises/tests form. The problems are shown in a grid at the upper left part of the form. The trainer gives a short description (e.g. "Mammal" and the full description that will appear to the trainees in the "Text" field). Then, the trainer manages the classes, the properties, the methods, the generalizations and the associations of the classes through the respective grid in the same form. For every record, there is a boolean field name "Correct". If it is true ("Yes"), then this record is correct, else it is a false answer. Through this form, the trainer completes the tests data, which the system will process to score the trainees.

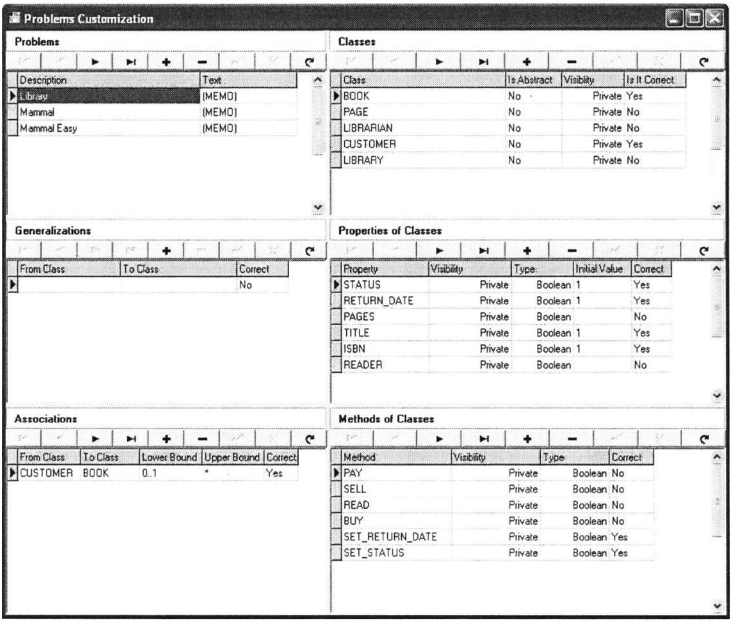


Figure 3.11. Tests/Exercises Customization

3.2.5. Tracing Trainees' Details

The system provides to the trainer a full representation of the state of the trainees, concerning group information, performance, help use history, messages and advice history. This information is shown in the form illustrated in figure 3.12. At first, the trainee selects from the list box at the upper part of the form the trainee whose details s/he wants to trace. The group information page (figure 3.12) contains information about the current group in which the trainee belongs, as well as the rest members of the same group.

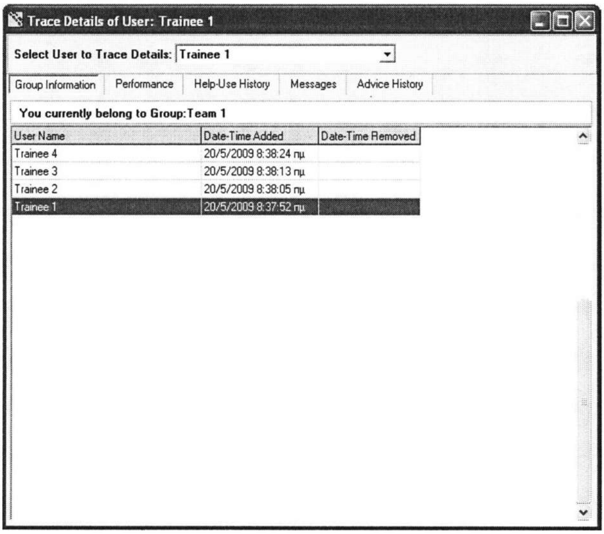


Figure 3.12. Tracing Trainees' Details form

The performance page (figure 3.13) presents information relative to the knowledge on UML. In specific, at the upper part of the form there are two grids showing the mistaken and the correct answers of the trainee. They are ordered by error/correct type showing their frequency. At the lower part of the form, there two grids for the knowledge and the changes in the level of expertise. The knowledge grid lists all the UML topics and the respective degree of knowledge of the trainee in a scale from 0 to 100. The level of expertise grid shows all the level of expertise assignments of the trainee since his/her first use of the system. The sequence field indicates the order of the records starting from the oldest one. The record with sequence equal to 0 is the current state of level of expertise.

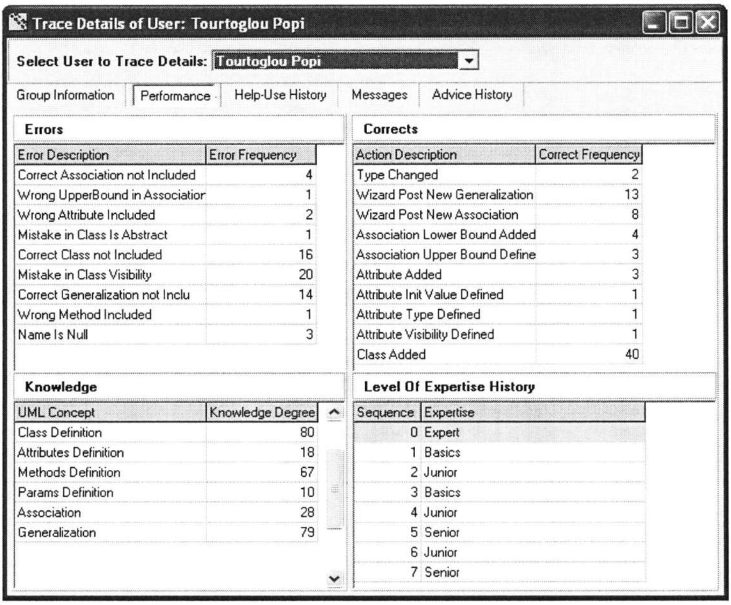
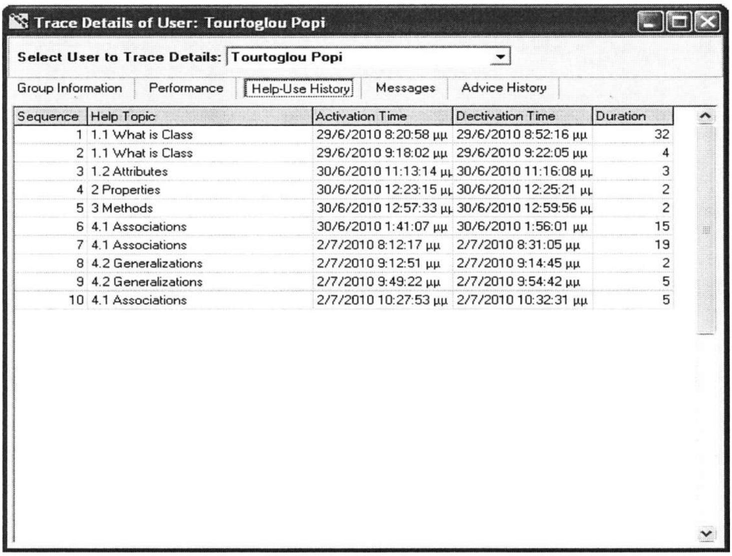


Figure 3.13. Tracing Trainees' Details form – Performance page

The help use history page (figure 3.14) gives information about how the trainee has used the help system. The help system contains information organized in sections. Every section is related to a UML topic. In the grid with the help use records, the trainer is shown which topic the trainee studied, the date-time stamps of beginning and ending studying and the duration in minutes. The records are ascending ordered by sequence.



Trace Details of User: Tourtoglou Popi

Select User to Trace Details: Tourtoglou Popi

Group Information | Performance | Help-Use History | Messages | Advice History

Sequence	Help Topic	Activation Time	Dectivation Time	Duration
1	1.1 What is Class	29/6/2010 8:20:58 μμ	29/6/2010 8:52:16 μμ	32
2	1.1 What is Class	29/6/2010 9:18:02 μμ	29/6/2010 9:22:05 μμ	4
3	1.2 Attributes	30/6/2010 11:13:14 μμ	30/6/2010 11:16:08 μμ	3
4	2 Properties	30/6/2010 12:23:15 μμ	30/6/2010 12:25:21 μμ	2
5	3 Methods	30/6/2010 12:57:33 μμ	30/6/2010 12:59:56 μμ	2
6	4.1 Associations	30/6/2010 1:41:07 μμ	30/6/2010 1:56:01 μμ	15
7	4.1 Associations	2/7/2010 8:12:17 μμ	2/7/2010 8:31:05 μμ	19
8	4.2 Generalizations	2/7/2010 9:12:51 μμ	2/7/2010 9:14:45 μμ	2
9	4.2 Generalizations	2/7/2010 9:49:22 μμ	2/7/2010 9:54:42 μμ	5
10	4.1 Associations	2/7/2010 10:27:53 μμ	2/7/2010 10:32:31 μμ	5

Figure 3.14. Tracing Trainees' Details form – Help-Use History page

The messages page (figure 3.15) shows all the messages related to the selected trainee. The trainer can filter them in the ways listed in the filters group box: This is helpful information, as the trainer may infer the kind of relationships between the trainees.

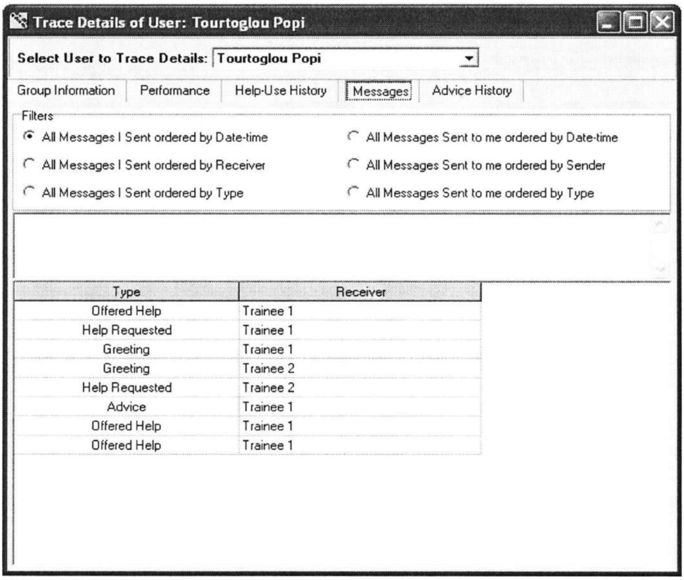


Figure 3.15. Tracing Trainees' Details form – Messages page

The advice history page (figure 3.16) presents all the advice given to the selected trainee by the system. The attributes of each advice record are the type of advice, the date and time stamp, the session and the parameters. The session refers to the session id that the advice message was appeared. There are 4 types of advice depending on what triggered it. In detail, the advice types are the advice triggered by errors, by an upgrade in the level of expertise, by a downgrade in a level of expertise, the assignment of a new stereotype and collaboration proposal. Each advice message can have specific parameters indicating the value of the trigger. So, the upgrade/downgrade in level of expertise type of advice gets as parameter the new level of expertise. The parameter of the error type of advice is the error type. The parameter of the stereotype type of advice is the new stereotype. Finally, the parameter of the collaboration proposal contains the proposed for collaboration trainee. There are cases that the advice messages ask for the opinion of the trainee. S/he has to answer with a "Yes" or "No" button. These answers are registered and shown in the "Responses of User to Given Advice" grid. The data in this grid refreshes as the trainer scrolls the "Advice Given to User History" grid. In case of the collaboration proposal advice type, the trainee may answer to the system if s/he desires to collaborate with the proposed trainee. In the grid at the lower part of the form the rejected for collaboration trainees are listed.

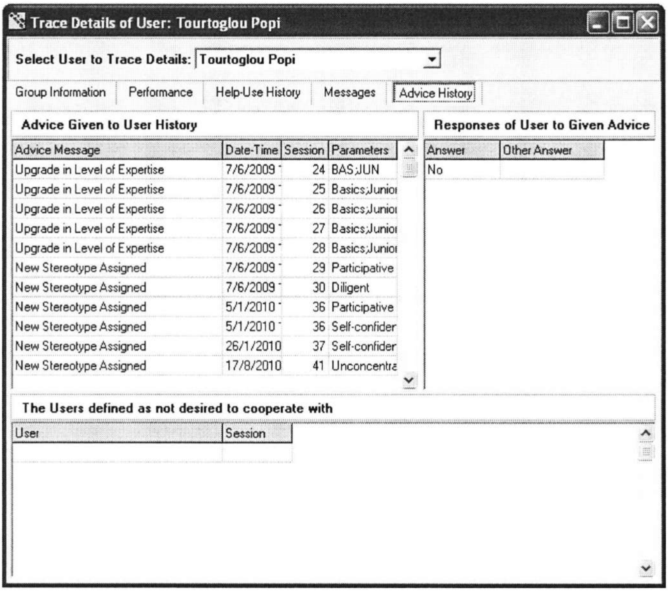


Figure 3.16. Tracing Trainees' Details form – Advice History page

3.3. Architecture of the System

The architecture of AUTO-COLLEAGUE is based on 7 main modules: the Domain Module, the Tracker, the User Modeller, the Help Module, the Collaboration Module, the Advisor and the Optimum Groups Generator. The collaboration diagram between these modules is illustrated in figure 3.17. The role of the Domain Module is to handle the UML knowledge of the trainees and store the problems/tests and their solutions defined by the trainer. The aim of the Tracker is to store every action of the trainee in the database of the system. The User Modeller is responsible for building the student models of the trainees. The task of the Collaboration Module is to handle the collaboration processes of the chat system. The Optimum Group Generator runs the optimum group formation algorithm in order to recommend to the trainer optimum groups of trainees. The Advisor is responsible for generating the intelligent recommendations, adapting their appearance based on the Hersey and Blanchard Situational Leadership Theory and showing them.

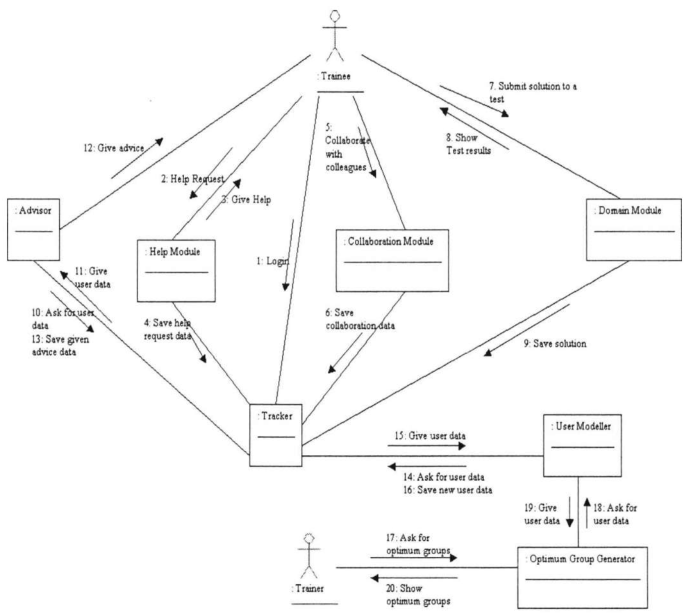


Figure 3.17. Collaboration Diagram of the System

Initially, the trainer logs in the system and the log data (such as date and time and name) are stored by the Tracker. If the trainee needs to view some help topics, then the Help Module is triggered, which afterwards collaborates with the Tracker to save the help request data (the help topic viewed and the date-time). Then, the trainee may need to collaborate with the rest of his/her colleagues of the group. This is achieved through the Collaboration Module that provides him/her with the chat system and, simultaneously, sends the collaboration data (type of dialog, the colleagues of the communication, date-time and messages) to the Tracker to be stored. Following, if the trainee submits a solution to a test, this will be processed by the Domain Module, which will show him/her the errors (if any), the right solution and will forward the trainee's solution data to the Tracker to store it. Periodically, the system is triggered to provide the trainee with advice. This is accomplished by the Advisor, which will ask for specific trainee data from the Tracker, evaluate it and, then, conclude to the advice that will eventually show to the trainee forward to the Tracker to be stored. This specific trainee data is not only the before mentioned data stored by the Tracker. The User Modeller will ask Tracker for trainee data to build the appropriate student models, generate new trainee data and pass it to the Tracker to store it. In case the trainer asks for the optimum groups of trainees, the Optimum Group Generator will get the trainees' data from the User Modeller in collaboration with the Tracker, will evaluate it and produce the optimum groups of learners. This schema of groups of trainees will be shown to the trainer.

In summary, the Domain Module is responsible for storing and processing the problems/tests and their solutions. It also manipulates the UML knowledge. The Tracker keeps track on every action and movement of the user. The Collaboration Module is the component that provides the mechanism that makes AUTO-COLLEAGUE a collaborative environment. The Optimum Group Generator makes the reasoning on finding the most effective organization of trainees into groups. The Advisor is the module that generates and adapts the recommendations to the trainees and the trainer. The User Modeller is the module that builds the student models of the trainees.

The student model is described in three aspects: the *level of expertise*, the *personality* and the *emotional state.* The level of expertise student model is implemented using a combination of the stereotype and the perturbation (buggy) modelling technique. The stereotypes used for this student model are: Basics, Junior, Senior and Expert. The trainees are classified into these stereotypes according to their knowledge on the domain (UML). Their knowledge is described in the system through the buggy student, which is a subset of the domain knowledge (expert model) plus possible faulty knowledge. Therefore, the system uses a domain knowledge library and an error library. More details on the way the knowledge of the trainees is modelled are given in chapter 6.

The personality student model concerns characteristics of the trainees that are related to their ability to learn, communicate and collaborate. The personality student model is built using the stereotype theory, which simulates the way people make assumptions on others, based on relevant information about them. The stereotypes that describe the personality of the trainees are: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. Every stereotype needs to be associated with specific facets and triggers. The facets of a stereotype are the kind of attributes that may characterize a trainee concerning this stereotype. The triggers of a stereotype are the combinations of values of the facets they may indicate that a trainee belongs to this stereotype. The attributes that constitute the triggers and are tracked in order to infer the student stereotypes are: useless mouse movements and clicks frequency, average idle time, number of actions, error frequency, correct frequency, help utilization frequency, advice given frequency, help given to a member/non member of the group, help request from a member/non member of the group, communication frequency and number of upgrades/downgrades in level of expertise. More details on the implementation of the personality-related student model can be found in chapter 5.

The emotional states are automatically predicted using the OCC cognitive theory of emotions (Ortony, Clore & Collins, 1988). According to this theory, emotions (negative or positive) are considered to be reactions to stimulus evoked by certain objects of the environment at a certain moment. These objects can be events, people (quoted as agents) or objects. The type of the aroused emotion is determined by three major factors: the situations that are responsible for the emotion, the person who experiences the emotion and the cognitive appraisal of the situation by the person.

The cognitive appraisal depends on the standards, the goals and the attitudes of the person experiencing the emotion.

3.4. Offering Intelligent Recommendations

The system uses the student models in order to provide intelligent and adaptive recommendations to the trainees and the trainer aiming at:

- Guiding them to the help topics they should study,
- Suggesting appropriate colleagues to collaborate with and
- Leading them following the appropriate leadership style according to the Hersey and Blanchard Leadership Theory.

3.4.1. Recommendations to the Trainees

The recommendations to the trainees concern:

- The next UML topics they should study,
- The appropriate colleagues with whom they should collaborate and
- Supportive/encouraging messages that would increase their performance.

The appearance, content and frequency of the recommendation messages are adapted to the trainee using the Hersey and Blanchard Situational Leadership Theory. The main principle of this theory is that leaders (the trainer and the system in our case) should continually adjust their leadership styles depending on the ability and the willingness of the followers (trainees in our case). The ability and the willingness are variables dependent on the tasks to be accomplished. Hersey and Blanchard have defined four different leadership styles suggesting the most appropriate attitude of the leader towards the followers for increasing individual and group improvement. The ability is calculated using the level of expertise stereotype and the buggy student model. The willingness is defined using the personality-related part of the student model.

The agent concludes to the content of recommendation after evaluating:

- Upgrades/downgrades of the level of expertise,

- Errors,
- Actions
- Preferred colleagues to collaborate with,
- Help topics already studied and
- Successful recommendations already offered to other trainees with similar state or problems.

The next UML help topics that the trainees should study are generated according to the errors made by the trainee. Each error is associated to specific UML concepts indicating missing and/or faulty knowledge. Each action that resulted a correct answer is also associated to specific UML concepts describing correct knowledge. Each UML help topic is associated to relevant UML concepts. In this way, the system can recommend the most appropriate help topics to strategically guide the trainees at improving their knowledge.

The appropriate colleagues with whom the trainee should collaborate are found considering their knowledge, personality and emotional states. The first criterion for this kind of recommendation is to seek for trainees that know the UML topics the trainee has problems with. Then, the system excludes those that (a) the trainee has rejected for collaboration in the past and (b) has been found to have a negative impact on the trainee's emotional state during a previous collaboration. Finally, the system restricts this set to the subset of trainees that (a) have been found to have a positive impact on the trainee's emotional state during a previous collaboration and (b) in order of precedence, belong to the personality-related stereotypes of Willing-to-help, Participative and Diligent.

The aim of the supportive messages is to encourage and motivate the trainees to improve both their learning and collaboration performance. There are standard advice messages depending on the personality-related stereotypes that the trainee is found to belong or not belong to. The system offers this kind of recommendation based on the appropriate leadership style according to the Hersey and Blanchard Situational Leadership Theory. Specifically, the leadership style determines the appearance and frequency of these messages as explained in chapter 8.

3.4.2. Recommendations to the Trainer

The Advisor offers intelligent recommendations to the trainer of the system. Apart from the trainees, the trainer also needs guidance in order to support the trainees. The recommendations to the trainer include:

- Historical/statistical reports and charts of showing the progress of the trainees and
- A group formation tool that proposes optimum organization of the trainees into groups.

The historical/statistical reports and charts constitute a useful toolkit for the trainer, as s/he is able to trace every detail about the trainees that in other cases would miss. These details regard group information, performance, help use history, messages and advice history. But maybe the most important data concern statistical information about the changes on the maturity (ability and willingness) of the trainees per assigned task and the proposed leadership style to follow. In this way, the trainer can draw many conclusions on the performance of the trainees and the effectiveness of the leadership style s/he has followed during time.

The goal of the group formation tool is to suggest to the trainer optimum organization of the trainees into groups. This is done using the Simulated Annealing algorithm, which has never been used in similar cases, is a genetic algorithm that serves as a general optimization technique for solving combinatorial optimization problems. The criteria for the group formation search process are:

- The desired and undesired combinations of personality stereotypes in the same group,
- The desired group structure concerning the level of expertise and
- The observed by the system emotional affect between the trainees.

The desired combinations of stereotypes are the pairs of stereotypes that their coexistence in the same groups would be beneficial for the performance of the individual trainees and of the groups. On the other hand, the undesired combinations of stereotypes are those pairs of stereotypes that the trainer would not like to have together in the same group, as they would be a bad influence to each other. So, the system will try to form groups with as many as possible desire combinations of stereotypes and avoid resulting to groups with the undesired combinations.

The desired group structure concerns the number and kinds of levels of expertise (basics, junior, senior and expert) that should constitute each group. For example, group A should include one senior and two junior trainees. So, the group formation tool will try to satisfy the desired structure depending on the trainees' levels of expertise.

The emotional affect between the trainees is related to the observed emotional state during the collaboration of a trainee with the members of the same group. Specifically, if the emotional states of the majority of the trainees of the same group were found to be positive when in collaboration with the rest members of the group, then the criterion of combining these trainees together will be added. Else, if the emotional states of the majority of the trainees of the same group were negative, the criterion of separating these trainees will be added.

More details on the intelligent recommendations to the trainer can be found in chapter 10.

3.5. Evaluation Experiments

We have performed two evaluation experiments. The first one was conducted in the University of Piraeus among 80 postgraduate students. The aim of this experiment was to evaluate the educational effectiveness of our system after applying the automatic group formation versus a random group formation. The results were:

- 30% of the trainees presented no difference,
- 65% of the trainees presented progress and
- 4% of the trainees presented reduction in their level of expertise comparing the two days of the experiment.

Furthermore, as far as number of errors is concerned:

- 1.25% of the trainees presented no difference
- 90% presented reduction and
- 8.75% presented increase in the number of errors.

The second experiment was conducted in a high school among 70 students of the software engineering class of the last grade. The aim of the evaluation was to have evidence on the successfulness of our choice to choose the SLT, the way of calculating the maturity of the trainees and the adaptation of the intelligent recommendations provided by the system. To evaluate the effect of the use of our system's adaptation of SLT versus a traditional class, we calculated the average increase rate of the ability and willingness (the variables that form the maturity). The resulted difference between the first (use of AUTO-COLLEAGUE) and the second (traditional laboratory course) stage of the experiment was:

- 29% in the average increase rate of ability and
- 16% in the average increase rate of willingness.

These evaluation experiments are discussed further in chapter 11.

3.6. Conclusions

AUTO-COLLEAGUE is a Computer Supported Collaborative Learning system that can be used as a tool for training users in UML. These users can be either students of any educational institute or software house that uses UML. The UML can be easily replaced by almost any other compatible domain knowledge due to the flexibility of the system's implementation. AUTO-COLLEAGUE supports both the trainees and the trainer with intelligent and adaptive recommendations. It uses a hybrid student modelling technique combining buggy and stereotype-based student models to describe and trace the level of expertise, specific personality characteristics of the trainees. It also precedes emotion perception using the OCC theory of emotions in order to infer the overall emotional state (positive or negative) of the trainees while collaborating with each other. The emotional state is stored in the student model and is used in the intelligent group formation suggestions provided to the trainer. The student models are evaluated by the system to adapt the provided recommendations based on the Hersey and Blanchard Situational Leadership Theory, viewing the trainees as the followers and the trainer (as well as the system itself) as the leader. AUTO-COLLEAGUE also suggests optimum group formation of the trainees attempting to resolve the continuous problem of how the trainees of an organization should be organized in the most effective way.

4

STUDENT MODELLING IN AUTO-COLLEAGUE

4.1. Structure of the Student Model

Student modelling is the process of building individual student models, which provide a description of the students. This description may concern a variety of characteristics depending mainly on the ways the system aims to be adapted. In any case, every intelligent and adaptive learning environment uses the student's knowledge representation. Other important and often used characteristics regard psychological (cognitive and affective aspects of the student) and generic information (such as interests and background) about the student. Despite the recognized importance of adding psychological student characteristics in learning environments (Richter & Salvendy, 1995; Murray & Bevan, 1985; Rothrock et al., 2002), there are very few studies that actually use them (Brusilovsky, 2001). Maybe the most typical psychological characteristic found in literature is the learning style. The term "learning styles" refers to the concept that individuals differ in regard to what mode of instruction or study is most effective for them (Pashler et al., 2009).

In this thesis, we introduce a new approach in the student characteristics included in student models. In the implementation of our system, we describe the students similarly to the way a human teacher would try to consciously or unconsciously understand their individual features. More specifically, a teacher would certainly evaluate the performance of the students concerning the curriculum to be taught through questions, exercises and tests. But s/he would not be limited to these domain dependent data. The teacher would also attempt to recognize main personality characteristics of the students aiming at adapting his/her guidance. Usually, the teacher tries to understand the students' emotions while interacting with them in order to approach them accordingly. In some other cases where group work is involved, the teacher would additionally observe the emotional influence between the students, aiming at arranging groups in the most effective way. Taking these human tactics into consideration, we incorporated these student data in our student models, which describe the student entity in three aspects: the *level of expertise*, the *personality* and the *emotional state*. The structure of the student model is shown in figure 4.1.

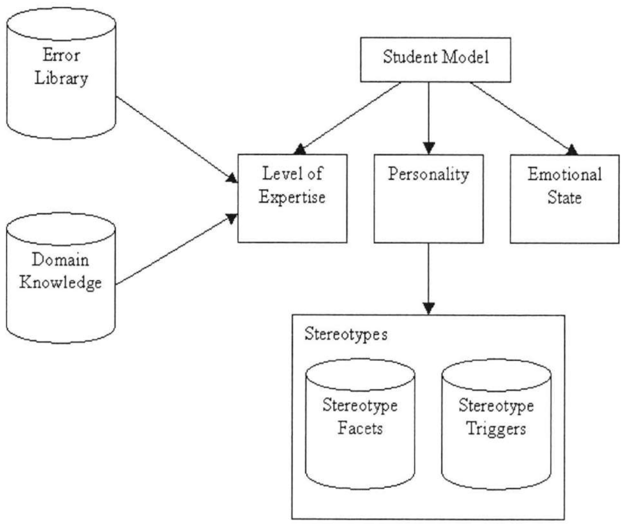


Figure 4.1. Structure of the Student Model.

4.2. How the Student Model is Built

Most of the systems that include psychological features of the students do not evaluate them automatically. Instead, they use relative questionnaires and psychometric instruments (Carver et al., 1999; Shang, Shi & Chen, 2001; Bajraktarevic, Hall & Fullick, 2003; Wolf, 2003; Papanikolaou et al., 2003; Brown & Brailsford, 2004) or explicitly receive them as input (de Bra & Calvi, 1998; Stash et al., 2006; Grigoriadou et al., 2001). However, the use of such psychometric instruments needs caution, as in some cases reliability can be low (Lawrence & Martin, 2001) and learning styles are likely to change over time (Kolb, 1984; Gonyeau et al., 2006).

To overcome these hazards, the student models in AUTO-COLLEAGUE are updated automatically and frequently. The system traces the student's actions and their consequences in order to infer the tracked student characteristics described in the student model. A user model can be built using both methods. There are several student-modelling techniques, such as the overlay model, the perturbation (or buggy) model, stereotypes, the constraint-based model, fuzzy logic/fuzzy sets and Bayesian networks. In AUTO-COLLEAGUE, we have used a combination of the perturbation (buggy) and the stereotype-based student modelling techniques. A buggy model describes not only the correct knowledge and the missing knowledge (like overlay model), but also the faulty knowledge a student may have on the domain. To achieve this, additionally to the domain knowledge, it maintains a bug library where the possible misconceptions (bugs) are predefined. The stereotype-based method simulates the way people make assumptions on others, based on relevant information about them.

In specific, the level of expertise of the students is described using both of these methods. The personality-related data are represented via stereotypes. The emotional states are automatically predicted using the OCC cognitive theory of emotions (Ortony, Clore & Collins, 1988). According to this theory, emotions (negative or positive) are considered to be reactions to stimulus evoked by certain objects of the environment at a certain moment. The OCC theory of emotions proposes a model of emotion types. In this model, emotion types are categorized according three objects that can be the stimulus for emotions: events, people and objects.

The level of expertise describes the knowledge level of the trainee on the domain, which is UML. There are four stereotypes in this category: Basics, Junior, Senior and Expert. Each of these stereotypes is linked to a subset of the expert model/knowledge described using the perturbation technique. The personality related stereotypes are: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. The attributes tracked in order to infer the student stereotypes are: useless mouse movements and clicks frequency, average idle time, number of actions, error frequency, correct frequency, help utilization frequency, advice given frequency, help given to a member/non member of the group, help request from a member/non member of the group, communication frequency and number of upgrades/downgrades in level of expertise.

4.3. How Student Models are Used

The system uses the student models in order to provide intelligent and adaptive recommendations to the trainees and the trainer.

4.3.1. For Recommendations to the Trainees

The recommendations to the trainees concern (a) the next UML topics they should study, (b) the appropriate colleagues with whom they should collaborate and (c) supportive/encouraging messages that would increase their performance. The appearance, content and frequency of the recommendation messages are adapted to the trainee using the Hersey and Blanchard Situational Leadership Theory. The main principle of this theory is that leaders (the trainer and the system in our case) should continually adjust their leadership styles depending on the ability and the willingness of the followers (trainees in our case). The ability and the willingness are variables dependent on the tasks to be accomplished. Hersey and Blanchard have defined four different leadership styles suggesting the most appropriate attitude of the leader towards the followers for increasing individual and group improvement. The ability is calculated using the level of expertise stereotype and the buggy student model. The willingness is defined using the personality-related part of the student model. The aspects of the student model evaluated for generating each of the types of recommendations are cited in table 4.1.

Table 4.1. Associations between trainees' recommendation and aspects of student model.

Recommendation Type	**Aspects of Student Model**
Next UML topics that should be studied	The level of expertise stereotype and the buggy student model
Appropriate colleagues to collaborate	• The level of expertise stereotype and the buggy student model. • Personality. • Emotional state.
Supportive/encouraging messages	• The level of expertise stereotype and the buggy student model. • Personality.

The next UML help topics that the trainees should study are generated according to the errors made by the trainee. Each error is associated to specific UML concepts indicating missing and/or faulty knowledge. Each action that resulted a correct answer is also associated to specific UML concepts describing correct knowledge. Each UML help topic is associated to relevant UML concepts. In this way, the system can recommend the most appropriate help topics to strategically guide the trainees at improving their knowledge.

The appropriate colleagues with whom the trainee should collaborate are found considering their knowledge, personality and emotional states. The first criterion for this kind of recommendation is to seek for trainees that know the UML topics the trainee has problems with. Then, the system excludes those that (a) the trainee has rejected for collaboration in the past and (b) has been found to have a negative impact on the trainee's emotional state during a previous collaboration. Finally, the system restricts this set to the subset of trainees that (a) have been found to have a positive impact on the trainee's emotional state during a previous collaboration and (b) in order of precedence, belong to the personality-related stereotypes of Willing-to-help, Participative and Diligent.

The aim of the supportive messages is to encourage and motivate the trainees to improve both their learning and collaboration performance. There are standard advice messages depending on the personality-related stereotypes that the trainee is found to belong or not belong to. The system offers this kind of recommendation based on the appropriate leadership style according to the Hersey and Blanchard Situational Leadership Theory. Specifically, the leadership style determines the appearance and frequency of these messages as explained in chapter 8.

4.3.2. For Recommendations to the Trainer

The recommendations to the trainer include (a) leadership style suggestion and (b) a group formation tool that proposes optimum organization of the trainees into groups. The aspects of the student model evaluated for generating each of these recommendations are cited in table 4.2.

Table 4.2. Associations between trainer's recommendation and aspects of student model.

Recommendation Type	Aspects of Student Model
Leadership Style Suggestion	• The level of expertise stereotype and the buggy student model. • Personality.
Group Formation Tool	• The level of expertise stereotype and the buggy student model. • Personality. • Emotional state.

AUTO-COLLEAGUE offers to the trainer a useful toolkit of historical/statistical reports and charts regarding group information, performance, help use history, messages and advice history. But maybe the most important data concern statistical information about the changes on the maturity (ability and willingness) of the trainees per assigned task and the proposed leadership style to follow. In this way, the trainer can draw many conclusions on the performance of the trainees and the effectiveness of the leadership style s/he has followed during time.

The goal of the group formation tool is to suggest to the trainer optimum organization of the trainees into groups. This is done using the Simulated Annealing algorithm, which has never been used in similar cases, is a genetic algorithm that serves as a general optimization technique for solving combinatorial optimization problems. The criteria for the group formation search process are:

- The desired and undesired combinations of personality stereotypes in the same group,
- The desired group structure concerning the level of expertise and
- The observed by the system emotional affect between the trainees.

The desired combinations of stereotypes are the pairs of stereotypes that their coexistence in the same groups would be beneficial for the performance of the individual trainees and of the groups. On the other hand, the undesired combinations of stereotypes are those pairs of stereotypes that the trainer would not like to have together in the same group, as they would be a bad influence to each other. So, the system will try to form groups with as many as possible desired combinations of stereotypes and avoid resulting to groups with the undesired combinations.

The desired group structure concerns the number and kinds of levels of expertise (basics, junior, senior and expert) that should constitute each group. For example, group A should include one senior and two junior trainees. So, the group formation tool will try to satisfy the desired structure depending on the trainees' levels of expertise.

The emotional affect between the trainees is related to the observed emotional state during the collaboration of a trainee with the members of the same group. Specifically, if the emotional states of the majority of the trainees of the same group were found to be positive when in collaboration with the rest members of the group, then the criterion of combining these trainees together will be added. Else, if the emotional states of the majority of the trainees of the same group were negative, the criterion of separating these trainees will be added.

4.4. Conclusions

In this chapter, we explained which characteristics are incorporated in the student models used in AUTO-COLLEAGUE, how these student models are built and how they are used. In specific, the student models describe the trainee in three aspects: the *level of expertise*, the *personality* and the *emotional state*. The student modelling techniques implemented are perturbation and stereotypes. Especially for the emotional state, we have adapted the OCC theory of emotions. The student models are used for generating intelligent recommendations to the trainees and the trainer. We have, also, applied the principles of the Hersey and Blanchard Situational Leadership Theory for adapting the recommendations according to the trainees' ability and willingness for each assigned task. The next two chapters are intended to explain in more detail how the personality-related stereotypes and the buggy models of the trainees' knowledge are implemented and used.

5

REPRESENTATION OF STUDENT'S PERSONALITY USING STEREOTYPES

5.1. Introduction

Stereotype-based student modelling is a technique for building student models. It simulates the way people build and use stereotypes in everyday life making assumptions about others using relative information. Stereotype-based reasoning takes an initial impression of the student and uses this to build a detailed student model based on default assumptions (Kay, 2000a).

It is a popular method used in adaptive and intelligent learning environments, such as generalised user modeling tools (Vergara, 1994; Paiva & Self, 1994; Brajnik & Tasso, 1994; Kay, 1995; Finin, 1989; Piyawat & Norcio, 2001), recommender systems (Rich, 1979a; Ardissono et al., 2004; Shapira et al., 1997; Kurapati & Gutta 2002; Krulwich, 1997; Chin 1989; Fink et al., 1997; Gena, 2001) and especially in intelligent learning and tutoring environments (Jeremic et al., 2009; Hatzilygeroudis & Prentzas, 2004; Eklund & Brusilovski, 1999; Kabassi et al., 2006; Wei et al., 2005; Virvou & Moundridou, 2001; Surjono & Maltby, 2003; Koutsojannis et al., 2001; Hatzilygeroudis & Prentzas, 2004; Lee & Baba, 2005; Virvou & Moundridou, 2000;

Virvou & Tsiriga, 2001a; Virvou & Tsiriga, 2001b). The user characteristics described in the stereotypes of these systems are associated mainly to knowledge, skills, generic data and preferences. However, in AUTO-COLLEAGUE, the stereotypes used are appropriate for a learning environment and are related to the level of expertise and the personality characteristics that affect the learning and collaboration processes. The selection of these personality characteristics is the outcome of extended research. Another difference presented in the use of stereotypes in AUTO-COLLEAGUE is that the definitions of stereotypes are not hard coded. The trainer of the system may change them through the relative forms offered.

For a system to use stereotype-based student models, it is necessary to define the stereotypes, which are consisted of the facets and the triggers. Facets are the characteristics that describe the stereotype. Triggers are the facet-value pairs that constitute the satisfaction/dissatisfaction conditions for a user to belong to the stereotype. The user model is formed by the stereotypes assigned to the specific user and their satisfied triggering conditions. In AUTO-COLLEAGUE, the facets are implemented using fuzzy sets. The triggers were selected after an empirical study and are implemented using a rule-based subsystem.

5.2. Theoretical Background for Choosing Stereotypes for a Learning Environment

The most commonly used classification of personality traits is the Five Factor Model of Personality (Norman, 1963), also known as the "Big Five" (Goldberg, 1990). The five-factor model of personality is a hierarchical organization of personality traits in terms of five basic dimensions: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience (Mccrae & John, 1992). According to a study presented in (John, 1989), the adjectives to describe Extraversion are: active, assertive, energetic, enthusiastic, outgoing and talkative. Agreeableness can be reflected by the adjectives: appreciative, forgiving, generous, kind, sympathetic and trusting. Conscientiousness can be described by: efficient, organized, planful, reliable, responsible and thorough. Neuroticism can be represented by: anxious, self-playing, tense, touchy, unstable and worrying. Openness can be described by: artistic, curious, imaginative, insightful, original and wide interests.

In line with the above personality taxonomy of the five-factor model, we chose the personality traits that would be more suitable for an educational environment in which students work into groups. These are: participative (Extraversion factor), willing to help (Agreeableness factor), diligent, sceptical, efficient (Contentiousness factor), hurried, unconcentrated (Neuroticism factor) and self-confident (Openness factor).

5.3. The Stereotypes Used in AUTO-COLLEAGUE

The stereotypes used in AUTO-COLLEAGUE are related to the knowledge on the domain (level of expertise) and the behaviour during the collaborative learning process (personality).

The level of expertise describes the knowledge level of the trainee on the domain, which is UML. There are four stereotypes in this category: Basics, Junior, Senior and Expert. Each of these stereotypes is linked to a subset of the expert model/knowledge.

The personality related stereotypes are: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. The self-confident trainee believes in him/herself and his/her skills. When a person has self-confidence, s/he maintains a positive attitude even if his/her knowledge and skills are not of a high level or even if probably s/he actually is not highly esteemed by his/her colleagues. The diligent trainee has earnest and persistent application to the training task and makes steady efforts during the learning process. The participative trainee seems to like collaborating with others and has an active presence in the task elaboration. The willing to help trainee demonstrates good disposal to help his/her colleagues. Sceptical is the trainee that seems to need more than the average time to process the data of the problem. The sceptical trainee tends to make unreasonable mistakes and (relatively to his/her knowledge) the progress in his/her skills could have been faster. The hurried trainee usually submits the answers to problems quickly without examining their correctness and effectiveness. This results to frequent errors. The unconcentrated trainee seems to lose his/her abstraction during the training task and perhaps is engaged with other irrelevant tasks at the same time. This kind of characteristic leads to frequent errors and increase in the average time needed to complete a task. The efficient trainee appears to successfully fulfill the demands of the training task. This kind of trainee always submits correct solutions/diagrams after a usual – or even lower than the usual – average amount of time.

5.4. Facets

Facets are the attributes of the trainees, which are calculated and evaluated by the system, in order to assign the trainees with the appropriate stereotypes. The facets we decided to use in AUTO-COLLEAGUE are these that can provide us with clues about the used stereotypes. In particular, these facets are: useless mouse movements and clicks frequency, average idle time, number of actions, error frequency, correct frequency, help utilization frequency, advice given frequency, help given to a member/non member of the group, help request from a member/non member of the group, communication frequency and number of upgrades/downgrades in level of expertise.

The facets are described using fuzzy sets. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristic) function, which assigns to each object a grade of membership ranging between zero and one (Zadeh, 1965). In fuzzy sets, an element is not strictly a member or not a member of a set, but can also be only partially in the set, which means it is present in the set to some extent (Kavcic, 2004). Hence, a set is called fuzzy when its membership function takes values in the unit interval [0,1] rather than in the {0,1} as in the classical logic (Kavcic, 2004).

In our implementation, for every facet, three values are stored: Low-Limit, Medium-Limit and High-Limit. They correspond to the degrees that the system presumes that an actual facet value of a trainee is of low, medium or high degree. These limits are used in the definition of the membership function of the fuzzy sets describing the facets. The membership function is defined as:

$$\mu_{F_i}(x) = \begin{cases} 0, \mathrm{x} \leq \mathrm{LowLimit} \\ \dfrac{\mathrm{MediumLimit\text{-}x}}{\mathrm{MediumLimit\text{-}LowLimit}}, \mathrm{LowLimit<x} \leq \mathrm{MediumLimit} \\ \dfrac{\mathrm{HighLimit\text{-}x}}{\mathrm{HighLimit\text{-}MediumLimit}}, \mathrm{MediumLimit<x} \leq \mathrm{HighLimit} \\ 1, \mathrm{HighLimit<x} \end{cases} \tag{5.1}$$

For every facet Fi (i=1,2..n, where n is the amount of facets used in the system) let U be the positive real numbers representing the total times a trainee acted correspondingly to the facet Fi. Then the fuzzy set Fi is defined as a set of ordered pairs:

$$F_i = \{\langle x, \mu_{F_i}(x) \rangle \mid x \in U\} \tag{5.2}$$

For example, the facet communication frequency that is the frequency of sending greeting messages per session is defined to have: Low-Limit=0, Medium-Limit=6 and High-Limit=12. If a trainee is found to have sent 10 such messages (x=10), then according to the membership function (Medium-Limit<x≤High-Limit) the value of the communication frequency facet for the trainee will be approximately 0.333.

For implementation purposes, we have correlated every of these four ranges of values with values 1,2,3,4 correspondingly. In detail, value 1stands for no value, value 2 stands for low value, value 3 stands for medium value and value 4 stands for high value. This is useful for the implementation of the triggers, explained in the next section.

5.5. Triggers

5.5.1. Empirical Study for the Specification of Triggers

In order to choose the most appropriate triggers for our learning system, we conducted an empirical study, in which 22 experienced software engineering trainers participated. The 9 of these trainers were project managers of 2 software houses that, among other duties, they train software engineers in the Borland Delphi programming language, the C# (in Microsoft Visual Studio) and MS SQL Server. There were, also, 8 teachers in the last grade of greek high schools that teach the software engineering course and the rest 5 trainers were scientific collaborators of the University of Piraeus, experienced in training students in UML and programming languages.

The aim of this empirical study was to decide which are the conditions of the facet values that would trigger each stereotype (concerning the stereotypes of personality, not the level of expertise). Therefore, the trainers were asked to fill in a table with the combinations of facet values for every stereotype. For example, in table 5.1 the answers of a trainer for the hurried stereotype are shown. F1 is the useless mouse movements and clicks frequency, F2 the average idle time, F3 the number of actions, F4 the error frequency, F5 the correct frequency, F6 the help utilization frequency, F7 the advice given frequency, F8 the help given to a member of the group, F9 the help given to a non-member of the group, F10 the help request from a member of the group, F11 the help request from a non-member of the group, F12 the communication frequency, F13 the number of upgrades in level of expertise and F14 the number of downgrades in level of expertise. In this way, she states that the conditions that should be satisfied for a trainee to belong to this stereotype would be: the value of the useless mouse movements and clicks frequency is medium, the value of the average idle time is low, the value of the number of actions is high, the value of the error frequency is high, the value of the correct frequency is low and the value of the help utilization frequency is low.

Table 5.1. Example of answers of a trainer about the triggers

HURRIED														
VALUE	*F1*	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*F9*	*F10*	*F11*	*F12*	*F13*	*F14*
No							X	X	X	X	X	X	X	X
Low		X			X	X								
Medium	X													
High			X	X										

The results of this study were evaluated in two levels. At the first level we concluded to the facets we should include in the triggering conditions for each stereotype. We calculated the rates of the selected facets per stereotype and decided to include only those that had a percentage of selection over 15%. These results are shown in table 5.2.

Table 5.2. Results Showing the Rates of the Selected Facets per Stereotype

FACET	NUMBERS OF SELECTION (%)							
	SCEPTICAL	HURRIED	UNCONCENTRATED	EFFICIENT	SELF-CONFIDENT	DILIGENT	PARTICIPATIVE	WILLING-TO-HELP
F1	100	100	100	5	9	14		
F2	100	100	100	100	100	100		
F3	100	95	100	100		100		14
F4	86	91	100	100				
F5	86	95	100	100				
F6	91	86	77	9	14	5		
F7					100			100
F8					100		100	100
F9					100		100	100
F10		9	18		100		100	
F11		9	18		100		100	
F12	95		95		5	5	100	9
F13			64	100		100		
F14			14	100		100		

At the second level, we calculated the average values of the selected facets with a percentage over 15%. These results are shown in table 5.3 and constitute the final results of the evaluation of the empirical study. These are the conditions of facets values per stereotype that form the main triggers of the stereotypes.

Table 5.3. Results Showing the Average Facet Values per Stereotype

FACET	AVERAGE FACET VALUES							
	SCEPTICAL	HURRIED	UNCONCENTRATED	EFFICIENT	SELF-CONFIDENT	DILIGENT	PARTICIPATIVE	WILLING-TO-HELP
F1	low	medium	high					
F2	medium	low	high	low	low	low		
F3	medium	high	low	medium		high		
F4	medium	high	high	low				
F5	medium	low	low	high				
F6	medium	low	low					
F7					medium			medium
F8					medium		medium	medium
F9					medium		medium	medium
F10			low		low		medium	
F11			low		low		medium	
F12	low		high				medium	
F13			low	high		medium		
F14				low		low		

5.5.2. Implementation of Triggers

The Triggers in AUTO-COLLEAGUE are implemented in a Rule-Based subsystem (Ligeza, 2006). We found it appropriate to use this technique as the triggering conditions do not constitute a large problem area and can be written in the if-then structure. Moreover, the rule-based technique meets our need to use a structure that could be easily updated even at runtime by the trainer of the system.

The basic modules of a Rule-Based system are the rule-base, the working memory and the inference engine. The rule-base stores all the triggering conditions cited in table 5.3 in if-then structure. The condition is written in the If section and the stereotype to be triggered is written in the then section. For example, for the Hurried stereotype the rules/conditions in the rule-base are listed in figure 5.1. The working memory is the student data derived from the system's database. This data concerns the student's facet values. The inference engine examines the facet values of the student at a specific moment and checks if these match with any of the conditions of the rules stored in the rule base. If it finds any matching rule, the inference engine fires/triggers the stereotype of the corresponding condition. The inference method used is forward chaining. This means that the inference engine will continue to search for matching conditions, taking into consideration the new data derived from previous triggered rules-stereotypes.

```
If  (F1=medium)  and
    (F2=low)     and
    (F3=high)    and
    (F4=high)    and
    (F5=low)     and
    (F6=low)     then
    AssignStereotype(Hurried)
```

Figure 5.1. The rules in the rule-base for the Hurried Stereotype

The use of the forward chaining inference method was necessary for the Triggering subsystem. The main triggers are those derived from the empirical study explained in the previous section and shown in table 5.3. However, there are other triggers too that do not concern only the facet values, but also the causality of the activation of another stereotype. For example, there are two triggers for the *efficient* stereotype. The first trigger is the one described in table 5.3 and related to the facet values. The second trigger is related to the inference that a trainee may belong to the *efficient* stereotype because s/he already belongs to the *expert* stereotype.

The triggers for the level of expertise stereotypes are implemented similarly in the same subsystem. The only difference is the parameters of the condition sections. They do not include the facets discussed in the previous section, but the knowledge level on the domain that is derived from the buggy student model of knowledge discussed in chapter 6.

5.6. The User Interface for Constructing the Stereotypes

The stereotypes, their facets and triggers are not hard coded. The trainer can change any of them through the form of the stereotypes construction. This form is illustrated in figure 5.2.

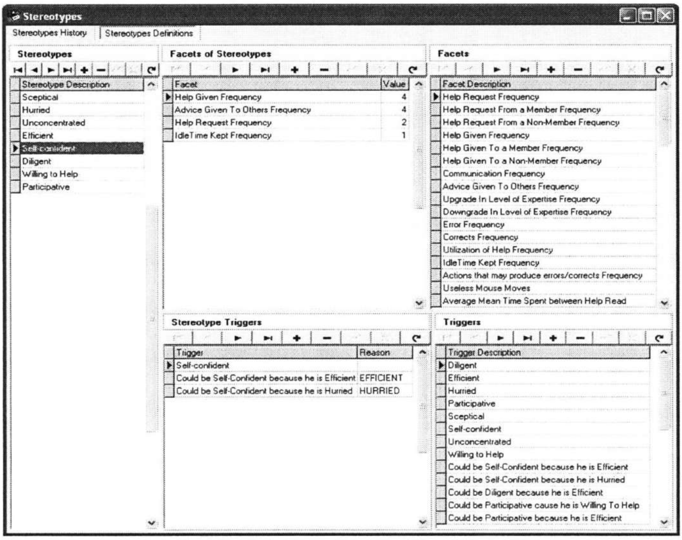


Figure 5.2. The form of defining the stereotypes, facets and triggers

At the left part, the trainer may view and modify the stereotypes. At the right part, all the facets and triggers are listed. The trainer may change, modify, add or delete facets and triggers. Whenever the trainer scrolls through the stereotypes, on the middle part of the form s/he can view, add or delete facets and triggers of the current stereotype. In this way, the trainer can adjust the parameters of the student models as necessary according to the needs of his/her trainees.

5.7. Building the Stereotype-based Student Model

A stereotype-based student model encapsulates the stereotypes assigned to the trainee and the inferences that caused these assignments. The class diagram of the stereotype-based student model is cited in figure 5.3, showing the structure of the student model.

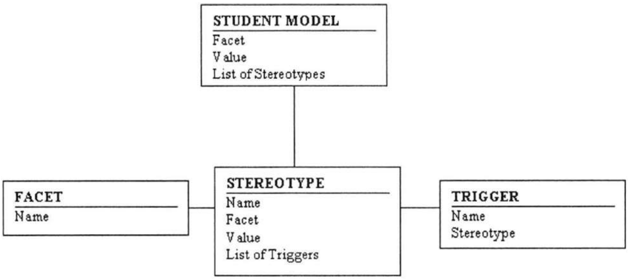


Figure 5.3. Class Diagram of the Stereotype-based Student Model

For the system to build the stereotype-base student model, it includes two agents: the Tracker and the Student Modeller. The Tracker tracks the actions of the trainee and assigns him/her with the appropriate facet values. The Student Modeller searches for satisfied triggering conditions based on the assigned facet values of the trainee. If such conditions are found, then the Student Modeller assigns to the student model of the trainee the respective stereotype as well as the facet value pairs that matched with the trigger (inferences that caused this assignment) along with a rating. This rating is a real number between 0 and 1. It is calculated per trainees and per task as described in the pseudocode cited in figure 5.4, where number_of_satisfied_facets is the number of the facets that satisfy the triggering conditions of the stereotype, total_number_of_facets is the total number of facets of the trigger, facet_rate is the participation rate of each facet value condition in the rating formation (e.g. if the total number of facets is 5, then the facet_rate will be 0.2) and rating is the rating of the trainee belonging to the stereotype for a specific task. For example, if a trainee has been assigned with the facet values as follows: (F1, F2, F3, F4, F5, F6, F7) = (medium, high, medium, medium, medium, medium, low), then the system will calculate for the self-confident stereotype that the total_number_of_facets is 7, the number_of_satisfied_facets is 5 (F3-F7), facet_rate is 14.28 (100/7) and rating is 0,714. In other words the probability that the trainee belongs to the self-confident stereotype is 71.4%.

```
if number_of_satisfied_facets = total_number_of_facets then
     rating = 1
else
 begin
     facet_rate = 100/total_number_of_facets;
     rating = facet_rate * number_of_satisfied_facets/100;
 end
```

Figure 5.4. Pseudocode for the stereotypes rating calculation.

5.8. How Personality-Related Stereotypes are Used in the System

The personality-related stereotypes are used for generating the most important intelligent recommendations to them and to the trainer of the system. Basically, the appearance, content and frequency of the recommendation messages are adapted to the trainee using the Hersey and Blanchard Situational Leadership Theory, which is based on measuring the ability and willingness on the assigned tasks. The willingness is calculated using the *self-confident* and *diligent* stereotypes. In specific, the recommendations related to the personality-related stereotypes concern:

- The appropriate colleagues with whom they should collaborate,
- Supportive/encouraging messages that would increase their performance and
- The group formation tool that proposes optimum organization of the trainees into groups.

The appropriate colleagues with whom the trainee should collaborate are extracted taking into consideration the criteria of UML knowledge, previous rejections of collaboration, the emotional influences during collaboration and the belonging to the personality-related stereotypes of Willing-to-help, Participative and Diligent.

The supportive messages, whose aim is to encourage and motivate the trainees to improve both their learning and collaboration performance, are generated after evaluating their personality-related stereotypes. There are standard advice messages depending on the personality-related stereotypes that the trainee is found to belong or not belong to. The system offers this kind of recommendation based on the appropriate leadership style according to the Hersey and Blanchard Situational Leadership Theory. Specifically, the leadership style determines the appearance and frequency of these messages as explained in chapter 8.

The group formation tool uses as criterion the desired and undesired combinations of personality stereotypes in the same group. The desired combinations of stereotypes are the pairs of personality stereotypes that their coexistence in the same groups would be beneficial for the performance of the individual trainees and of the groups. On the other hand, the undesired combinations of stereotypes are those pairs of personality stereotypes that the trainer would not like to have together in the same group, as they would be a bad influence to each other. So, the system will try to form groups with as many as possible desire combinations of stereotypes and avoid resulting to groups with the undesired combinations.

5.9. Conclusions

The personality-related stereotypes used in AUTO-COLLEAGUE are in accordance with the Five Factor Model of Personality, but were chosen to fit to a collaborative learning environment. In specific, these stereotypes are: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. The triggers used to infer these stereotypes were selected after an empirical study conducted among experienced trainers. These triggers are rules/conditions between the values of the facets: useless mouse movements and clicks frequency, average idle time, number of actions, error frequency, correct frequency, help utilization frequency, advice given frequency, help given to a member/non member of the group, help request from a member/non member of the group, communication frequency and number of upgrades/downgrades in level of expertise. The facets are implemented using fuzzy sets and the triggers using the rule-based technique. The trainer can change any of the stereotypes, their facets and triggers. This accommodation facilitates the flexibility of our system to be adjusted to any preference or need of the trainer according to his/her trainees' special features or observations.

6

REPRESENTATION OF THE EXPERT AND BUGGY STUDENT MODEL

6.1. Introduction

The student's knowledge is represented using perturbation (buggy) modelling. The buggy student models are extensions of the overlay student models, according to which the student's knowledge is described as a subset of the expert's knowledge. The expert's knowledge is the domain knowledge structured in topics/concepts. Overlay models use weight variables upon each concept representing in this way the degree of knowledge for each topic. The extension introduced in buggy models concerns the observation that the common case is that knowledge is not always a scaled variable of the topics. In other words, knowledge is not analyzed only in conceptions and missing conceptions. Instead, students may have misconceptions or mal knowledge that cannot be represented in an overlay model. This functionality was added in buggy student models that integrate a bug library containing the possible misconceptions on the domain aiming at describing more accurately the knowledge state of the student. As buggy student models take into consideration the mal knowledge a student may have on the domain knowledge, they represent the knowledge of the student as a union of a subset of the expert knowledge and a subset of the mal knowledge (figure 6.1).

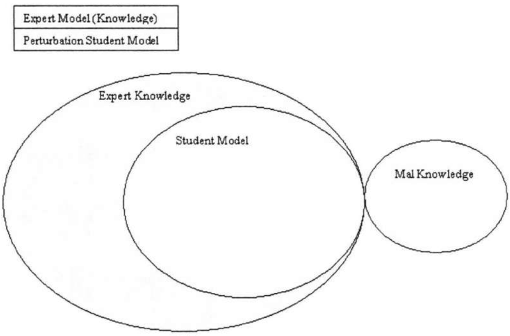


Figure 6.1. The perturbation/buggy model structure

In this figure, the expert knowledge (also called expert model) describes the full structure of knowledge on the domain. The mal knowledge illustrates the faulty knowledge a student may have on the domain in the form of an error library. Taking into consideration the faulty knowledge along with the correct can redound to the successfulness of the system's assumptions on the exact knowledge and on the reasons that caused such misconceptions.

Perturbation (Buggy) modelling is a common technique for adaptive environments, such as (Brown & Burton, 1978; Brown & Van Lehn, 1980; Faraco et al., 2004; Labidi & Sergio, 2000; Sleeman & Smith, 1981; Soloway & Johnson, 1984; Sleeman, 1987; Hoppe, 1994; Murray, 2003; Teixeira et al., 2002). In AUTO-COLLEAGUE, the expert knowledge and the buggy student model is represented using a directed graph.

6.2. Representation of the Expert and the Buggy Student Model

The expert knowledge is described by the UML topics and their dependencies, which indicate the prerequisite knowledge on the UML topics. It is represented using a directed graph (a part of which is shown in figure 6.2). Each node in the diagram represents a topic of the domain knowledge (UML). The edges between these nodes (topics) indicate their dependencies.

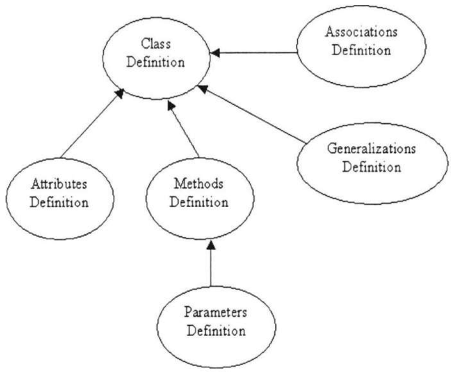


Figure 6.2. Sample of the directed graph of the expert knowledge

The directed graph of the expert knowledge is a pair G=(T, D). The elements of the set T are the nodes of the graph, in our case the UML topics. The set D is a set of ordered pairs of the vertices/directed edges of the graph, or else the dependencies between the UML topics that represent the prerequisite knowledge. Let n, m, i, j and k be positive integers, then T is the set of topics $T=\{T_1, T_2, \ldots, T_n\}$ and D is the set of dependencies between the topics $D=\{D_1, D_2, \ldots, D_m\}$. Each of D_i (where $1 \leq i \leq m$) is defined as an ordered pair of elements of T: $D_i=(T_j, T_k)$. This definition means that there is the D_i dependency between the T_j and the T_k UML topics. The dependency indicates that the system will assume the existence of knowledge of the T_j topic if the knowledge of the T_k topic already exists.

The buggy model is described by a graph similarly to the expert knowledge. There is only one difference: there is a weight assigned to each node (UML topic). This weight is a positive real number in [0, 1] and expresses the degree of knowledge on the relative topic. The expert knowledge graph does not include such an indicator, as it is supposed to be the maximum (that is 1) for every node/topic.

6.3. Representation of the Mal Knowledge - The Error Library

The error library illustrates the mal knowledge. It includes the error types, the associations of the error types with the UML topics and all the errors made by the student. In order to make evaluations on the student's knowledge based on errors, it is necessary to define all the possible error types. Each of these error types is associated with one or more UML topics with a specific weight. This describes that making a specific error type means that there is misknowledge of specific topic(s) in specific degree(s). The degree is the weight and is a constant variable that can get one of the values low, medium or high. For example, the Wrong Association Included type of error is linked to the Association UML topic with weight equal to high. The error library, also, keeps historical records of all the errors of the student with a date-time stamp and session details.

6.4. Building the Buggy Student Model

The buggy student model is built by an agent that evaluates the knowledge of the trainee and assigns it to the respective student model. This agent traces the errors of the trainee as well as the correct actions, associates them to the corresponding topics and updates the student model. The architecture and interrelations of this process is shown in figure 6.3.

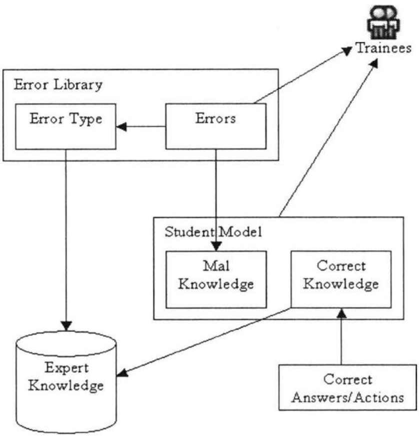


Figure 6.3. Architecture and Interrelations of Building the Buggy Student Model

The agent processes an algorithm for every UML topic in order to calculate its degree of knowledge and assign it to the student model. The algorithm takes as input the actions and the errors of the trainee that are associated with the topic. The output of the algorithm is the degree of knowledge on the topic and is a positive real number in [0, 1]. This degree is used for assigning the weight value in the graph of the buggy student model. The algorithm is processed for every UML topic to calculate the corresponding weights and update the student model as a subset of the expert knowledge.

The first step of the algorithm is to calculate the total weight of the actions made for the specific UML topic. Like the error types explained previously, there are also the action types associated with the UML topics bearing a weight. The weight can get one of the values low, medium or high and describes the degree of knowledge the trainee has on a topic if the action does not produce error(s). The calculation is cited in equation 6.1, where k is the number of types of actions, $ACTIONS_i$ is the number of actions of the i^{th} type of action, $WEIGHT_i$ is the weight of the i^{th} type of action. The total weight (ACTIONS_TOTAL_WEIGHT) is calculated by summing for every type of action (related to the UML topic) the products of the number of actions made with their weights.

$$ACTIONS\_TOTAL\_WEIGHT = \sum_{i=1}^{k} ACTIONS_i * WEIGHT_i \quad (6.1)$$

The second step is to calculate in similar way the total weight of the errors made by the trainee for the specific UML topic. The calculation is cited in equation 6.2, where m is the number of error types, $ERRRORS_i$ is the number of errors of the i^{th} type of error and $WEIGHT_i$ is the weight of the i^{th} error type. This total weight (ERRORS_TOTAL_WEIGHT) is found by summing for every type of error (related to the UML topic) the products of the number of these errors made with their weights.

$$ERRORS\_TOTAL\_WEIGHT = \sum_{i=1}^{m} ERRORS_i * WEIGHT_i \quad (6.2)$$

The final step is to calculate the degree of knowledge for that UML topic (equation 6.3). It is calculated by subtracting the total weight of errors from the total weight of actions and then dividing the result with the total weight of actions.

$$DEGREE = \frac{ACTIONS\_TOTAL\_WEIGHT - ERRORS\_TOTAL\_WEIGHT}{ACTIONS\_TOTAL\_WEIGHT} \quad (6.3)$$

For example, there are 4 types of actions associated with the UML topic Attributes Definition:

- Attribute Added (weight=high),
- Attribute Type Defined (weight=low),
- Attribute Visibility Defined (weight=low) and
- Attribute Initial Value Defined (weight=low).

There are 2 associated with the UML topic Attributes Definition types of errors:

- Wrong Attribute Included (with weight =high),
- Correct Attribute Not Included (with weight =high),

- Error in Attribute Type (with weight =low),
- Error in Attribute Visibility (with weight =low) and
- Attribute Initial Value (with weight =low).

A trainee is fount to have made totally 24 actions related to the Attributes Definition UML topic. In specific:

- 6 actions of the Attribute Added action type,
- 6 actions of the Attribute Type Defined action type,
- 6 actions of the Attribute Visibility Defined action type and
- 6 action of the Attribute Initial Value Defined action type.

He has, also, made 5 errors:

- 2 mistakes of the Wrong Attribute Included mistake type,
- 1 mistake of the Attribute Initial Value mistake type and
- 2 mistakes of the Mistake in Attribute Type mistake type.

According to the formulas, we have:

- ACTIONS_TOTAL_WEIGHT = 6 (actions of the Attribute Added action type) * 3 + 6 (actions of the Attribute Type Defined action type) * 1 + 6 (actions of the Attribute Visibility Defined action type) * 1 + 6 (actions of the Attribute Initial Value Defined action type) * 1 = 36.
- MISTAKES_TOTAL_WEIGHT = 2 (mistakes of the Wrong Attribute Included mistake type) * 3 + 1 (mistake of the Attribute Initial Value mistake type) * 1 + 2 (mistakes of the Mistake in Attribute Type mistake type) * 1 = 9.
- DEGREE = (36 – 9) *10/ 36 = 0.75.

This means that the system assumes that the trainee knows the Attributes Definition UML topic in a degree of 0.75.

6.5. How Buggy Student Models are Used in the System

The buggy student models, which provide a detailed representation of the trainees' knowledge and level of expertise, are used for generating the intelligent recommendations to them and to the trainer of the system. The appearance, content and frequency of the recommendation messages are adapted to the trainee using the

Hersey and Blanchard Situational Leadership Theory, which is based on measuring the ability and willingness on the assigned tasks. The ability is calculated using the buggy student models and their correspondent levels of expertise. In specific, the recommendations related to the buggy student models concern:

- The next UML topics they should study,
- The appropriate colleagues with whom they should collaborate,
- Supportive/encouraging messages that would increase their performance and
- The group formation tool that proposes optimum organization of the trainees into groups.

The next UML topics the trainees should study are exclusively related to the knowledge of the trainees, as there are associations that indicate each UML help topic with relative topics of the UML domain knowledge stored in the system. The appropriate colleagues with whom the trainee should collaborate are found by firstly seeking for trainees that know the UML topics the trainee has problems with. The supportive messages, whose aim is to encourage and motivate the trainees to improve both their learning and collaboration performance, are generated after evaluating their personality-related stereotypes, but the frequency and appearance are adjusted to their appropriate leadership style as estimated using the Hersey and Blanchard Situational Leadership Theory (ability=knowledge). The group formation tool uses as criterion the desired group structure, which concerns the number and kinds of levels of expertise (basics, junior, senior and expert) that should constitute each group. For example, group A should include one senior and two junior trainees. So, the group formation tool will try to satisfy the desired structure depending on the trainees' levels of expertise that are updated trough their buggy student models.

6.6. Conclusions

In AUTO-COLLEAGUE, the student's knowledge is represented using perturbation (buggy) student modelling. Buggy student models are used to represent the knowledge of the student not only as a snapshot of the expert (domain) knowledge, which could be interpreted as knowledge and missing knowledge. Buggy student models additionally represent possible faulty knowledge. This is achieved through building and evaluating a bug library, which contains possible mistake types and their associations to the domain topics of the expert knowledge. In AUTO-COLLEAGUE, the expert knowledge and the buggy student model is represented using a directed graph. In order to build the buggy student models, the system traces the errors of the trainees as well as the correct actions and associates them to the corresponding topics. The buggy student models are used in generating every intelligent recommendation of the system. They are also the main values used in measuring the ability of the trainees per assigned task in order to find the appropriate leadership style according to the Hersey and Blanchard Situational Leadership Theory.

7

EMOTION PERCEPTION USING THE OCC THEORY OF EMOTIONS

7.1. Introduction

Emotions bear valuable information that can potentially improve the efficiency of computer software. As described in the literature (Damasio, 1994), (Izard, 1984), emotions lead to rational behaviours and, therefore, can provide important information for making inferences about a user reactions. Consequently, these inferences can be used further for decision making based on emotions. Emotion recognition has already been applied in learning environments for animated pedagogical agents (Gratch & Marsella, 2001; Jaques & Vicari, 2007; Lester et al., 1999; Craig et al., 2004; Jaques et al., 2004; Elliott et al., 1999; Nkambou, 2006) and affective system responses, support and adaptation (Katsionis & Virvou, 2005; Moridis & Economides, 2008b; Poel et al., 2004; Leontidis et al., 2009; Conati & Zhou, 2004). However, as emphasized in (Dillenbourg et al., 2009): "affective and motivational aspects that influence collaborative learning have been neglected by experimental CSCL researchers".

AUTO-COLLEAGUE includes an emotion recognition agent that infers the overall emotional state of the trainees adapting the OCC Theory of emotions (Ortony, Clore & Collins, 1988). This theory is a de facto in emotion recognition systems in a variety of fields (Karunaratne & Yan, 2001; Liu & Pan, 2005; Paiva et al., 2004; Dias & Paiva, 2005; Bartneck, 2002; Ochs, 2005; Allbeck & Badler, 2002; Van Dyke Parunak et al., 2001; van Breemen & Bartneck, 2003; Streit et al., 2004; Zong et al., 2000) and, recently, in intelligent learning environments (Moridis & Economides, 2008b; Jaques & Vicari, 2007; Katsionis & Virvou, 2004; Conati & Zhou, 2004; Chalfoun et al., 2006; Jaques et al., 2004; Elliott et al., 1999; Chaffar & Frasson, 2006). An important novelty presented in this thesis concerns the use of perceived emotions in the generation of recommendations to the trainees and the trainer. Both of these kinds of recommendation are related to suggesting optimum collaboration patterns between the trainees taking into consideration, among other characteristics, the emotional influence of the trainees during previous collaborations.

7.2. The OCC Theory of Emotions

According to the OCC Theory of Emotions, emotions (negative or positive) are considered to be reactions to stimulus evoked by certain objects of the environment at a certain moment. These objects can be Events, People (quoted as agents) or Objects. The type of the aroused emotion is determined by three major factors:

- The situations that are responsible for the emotion,
- The person who experiences the emotion and
- The cognitive appraisal of the situation by the person.

The cognitive appraisal depends on the standards and the goals of the person experiencing the emotion.

The OCC Theory of Emotions proposes a model of emotion types. In this model, emotion types are categorized according the three objects that can be the stimulus for emotions (events, agents and objects). Specifically, according to this model, emotions are Valenced Reactions to: Consequences of Events, Actions of Agents and Aspects of Objects. The global structure of emotion types is illustrated in Figure 7.1.

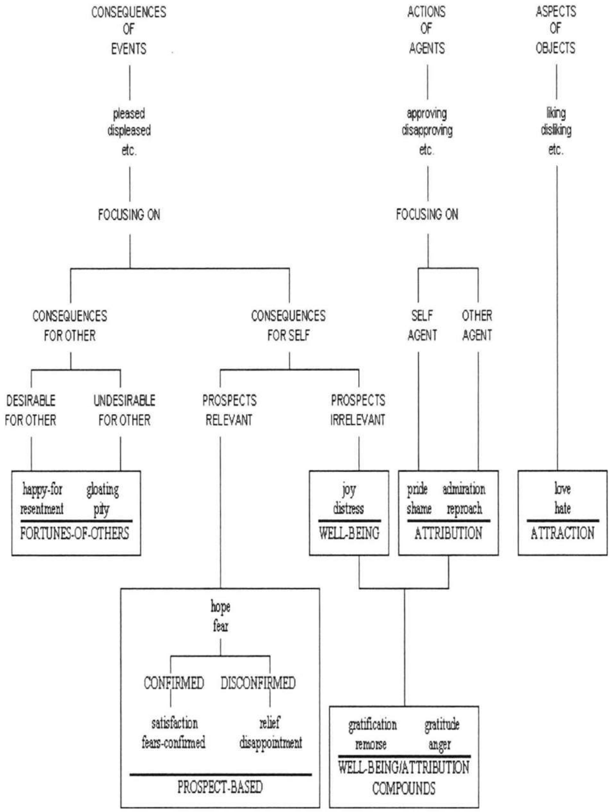


Figure 7.1. Global Structure of Emotion Types

The Events will cause Event-Based Emotions (such as pleased, displeased). The Event-Based Emotions are concerned to be goal-based emotions. These emotions are further categorized into two branches based on who is the receiver of the consequences of the emotions:

- If the emotion consequences are for another person: Fortunes of Other emotions. In this emotion category the desirability of the event (if the person wanted the event to happen) affects the emotion:
    - If the event is desirable, then the emotion will be positive (such as happy for, gloating).
    - If the event is undesirable, then the emotion will be negative (such as resentment, pity).
- If the emotion consequences are for the person who experiences the emotion, then there are two different categories depending on the relevancy of the prospect for the event (if the person expected or not the event to happen): the Prospects Relevant and Prospects Irrelevant categories. The Prospect Irrelevant emotions are extended to the Well Being emotions, which can be either positive (such as joy) or negative (such as distress). The Prospect Relevant (expected to happen) emotion type (such as hope, fear) will be classified relatively to whether the event is confirmed or not. In specific:
    - Confirmed (expected to happen and it did happen): the emotions are such as satisfaction (wanted to happen) or fear confirmed (did not want to happen),
    - Disconfirmed (expected to happen and it did not happen): the emotions are such as relief (did not want to happen) or disappointment (wanted to happen).

The Actions of Agents will cause Attribution Emotions (such as approving, disapproving). The Attribution Emotions are standards-based emotions. This emotion type is categorized depending on whether the action concerns the person who experiences the emotion (Self Agent) or someone else (Other Agent):

- Self-Agent: the emotions may be positive (such as pride) or negative (such as shame).
- Other-Agent: the emotions may be positive (such as admiration) or negative (such as reproach).

The Aspects of Objects will cause Attraction Emotions, which can be positive (such as love) or negative (such as hate). The Attraction Emotions are attitudes-based emotions.

7.3. The Emotion Categories Used in AUTO-COLLEAGUE

In AUTO-COLLEAGUE, we have applied only a part of the model of the OCC Theory, that is the emotion categories adequate for a collaborative learning environment. As the Event-Based Emotions are goal-based emotions and the Attribution Emotions are standards-based emotions, we have defined certain goals, and standards that affect the appraisal of emotions of the users in such a learning environment.

Specifically, the identified goals concerning the Prospect-Based and Well-Being emotions (that correspond to the Prospects Relevant and Prospects Irrelevant types) are cited in Table 7.1. The goal "I learn/have progress" concerns the performance of the trainee and in what degree s/he presents progress in knowledge. The goal "My team has progress" refers to the fact that the rest members of the same group have also achieved improvement in their level of expertise. Normally, the trainee would expect these two goals to be achieved (Prospects Relevant). If they are confirmed, then the produced emotion will be satisfaction (positive emotion). If they are disconfirmed, then the produced emotion will be disappointment (negative emotion). The goal "I have a good relationship with my colleagues" is associated to the degree that the trainee seems to match with the rest members of the group and have a harmonious collaboration. As the main aim when using educational software is to learn, these goals are not direct. So, the trainee does not expect them to happen (Prospects Irrelevant). However, if these goals are achieved, then the produced emotion will be joy (positive). If these goals are not achieved, then the produced emotion will be distress (negative).

Table 7.1. Goals (for Event-Based Emotions)

PROSPECT RELEVANT	I learn/I have progress
	My team has progress.
PROSPECT IRRELEVANT	I have a good relationship with my colleagues

The identified standards (cited in Table 7.2) concern the Attribution Emotions that is the Self Agent and Other Agent Actions type. The standard "I am useful to my group" concerns the desirability of the trainee to contribute to his/her colleagues and the group work. The standard "I am a very good student/employer" refers to the need of the trainee to be good at what s/he is trying to achieve (that is knowledge). The standard "I am the best in my group" is related to the desire of the trainee to distinguish from the group. These 3 standards are associated with the Self-Agent Actions, as they are related to the trainee. If they are accomplished, then the produced emotion will be pride/gratification (positive). If they are not accomplished, then the emotion will be shame/disappointment (negative). The standard "Others admire me for my capabilities" refers to the need of the trainee to be admired by others. The standard "I help others" refers to the wish of the trainee to offer help and advice to others and share the attained knowledge and experience. The standard "I belong to a group" is associated to the need of feeling a member of a group and have a common group target struggling to accomplish. The standard "I am being helped" is related to the need of the trainee to feel that s/he is not alone and that others can offer him/her help when needed. The standard "Others ask for my help" refers to the need of feeling useful. These 5 standards are associated with the Other-Agent Actions, as they are affected by the actions of other people. If they are accomplished, then the produced emotions will be pride/gratification (positive). If they are not accomplished, then the emotion will be shame/disappointment (negative).

Table 7.2. Standards (for Attribution Emotions)

SELF AGENT ACTIONS	I am useful to my group
	I am a very good student/employer
	I am the best in my group
OTHER AGENT ACTIONS	Others admire me for my capabilities
	I help others
	I belong to a group
	I am being helped
	Others ask for my help

7.4. Traced Characteristics for Predicting the Appraisal of Emotions

In order to infer if these identified goals and standards are likely to be accomplished and, hence, the relative emotions to be triggered, the system traces specific characteristics of the trainees. These characteristics are related to the performance of the trainees, as well as the kind and frequency of their participation in the chat system. In detail, the traced characteristics are: the frequency of sending/receiving messages and the upgrades in the level of expertise.

7.4.1. Messages

There are 4 types of messages:

- Request help: the trainee sends a message asking for help in a specific topic.
- Offer help: the trainee sends a message answering to a received request help message.
- Offer Advice: the trainee sends a message providing general advice on a topic.
- Greeting: the trainee sends a message with personal content.

Three values are stored for every message type: Low-Limit, Medium-Limit and High-Limit. Each of these values corresponds to the degrees that the system presumes that the frequency of the types of messages of a trainee is considered of low, medium or high degree. For example, the frequency of sending greeting messages is defined to have: Low-Limit=0, Medium-Limit=6 and High-Limit=12. If a trainee is found to have sent 10 such messages, then the value of the greeting messages frequency for the trainee will be high.

7.4.2. Upgrades in Level of Expertise

The level of expertise is described using the stereotype-based student modelling technique. There are 4 stereotypes for the level of expertise: Basics, Junior, Senior and Expert. Every stereotype is associated with specific degrees of knowledge per UML topic. The system classifies the trainee into one of the level of expertise stereotypes after evaluating his/her performance on UML while using the environment. It takes into consideration the actions that led to correct and mistaken answers. Then, the system can simply count the upgrades/downgrades in the level of expertise.

7.5. How the Traced Characteristics Influence the Appraisal of Emotions

The associations between the identified goals and the values of the traced characteristics are:

- **I learn/I have progress:** *Upgrade in level of expertise:* if the trainee is found to have made at least 1 upgrade in his/her level of expertise, this means that s/he has progress.
- **My team has progress:** *Team members' upgrade in level of expertise:* if all the members of the trainee's group are found to have at least 1 upgrade in their level of expertise, this means that the trainee's team has progress.
- **I have a good relationship with my colleagues:** *Frequency of greeting messages:* if the frequencies of the greeting messages received and sent are high, then the trainee probably has a good relationship with his/her colleagues.

The associations between the **standards** and the values of the traced characteristics are:

- **I am useful to my group:** *Frequency of advice messages and offer help messages:* if the frequencies of advice messages and offer help messages sent are high, then the trainee is likely to believe that s/he is useful to the group.
- **I am a very good student/employer:** *Belonging in the highest level of expertise:* if the trainee is found to belong to the highest level of expertise (expert), then s/he will feel that s/he is very good at what s/he is trying to accomplish.
- **I am the best in my group:** *Level of expertise is the highest in the group:* if the level of expertise of the trainee is the highest among all others' in the same group, then s/he will believe that s/he has achieved to be the best in the group.
- **Others admire me for my capabilities:** *Frequency of received help request messages:* if the frequency of help request messages received are high, then the trainee may feel that others admire him/her to ask for his/her help.
- **I help others:** *Frequency of offer help messages sent* and *frequency of advice messages sent*: if the frequencies of offer help messages and advice messages sent to colleagues are high, then it is likely that the trainee will believe that s/he can help others.
- **I belong to a group:** *Frequency of all types of messages sent and received*: if the frequency of al types of messages sent and received are high, then the trainee is possible to feel that s/he in fact belongs to the group.
- **I am being helped:** *Frequency of offer help messages received*: if the frequency of offer help messages received by others is high, then the trainee will feel that s/he is being helped by the rest of the group and that s/he is not alone.
- **Others ask for my help:** *Frequency of request help messages received*: if the frequency of request help messages received by colleagues is high, then the trainee will feel s/he has accomplished to be asked for his/her help.

Depending on the emotion type of the identified goals/standards, the generated emotions will be:

- **Prospect Relevant:** I learn/I have progress, My team has progress:

   - Positive: Satisfaction.
   - Negative: Dissatisfaction.
- **Prospect Irrelevant:** I have a good relationship with my colleagues:
   - Positive: Joy
   - Negative: Distress.
- **Self-Agent Actions:** I am useful to my group, I am a very good student/employer, I am the best in my group, Others ask for my help:
   - Positive: Pride, Gratification.
   - Negative: Shame, Remorse.
- **Other-Agent Actions:** Others admire me for my capabilities, I help others, I am being helped:
   - Positive: Pride, Gratification.
   - Negative: Shame, Remorse.
- **Other-Agent Actions:** I belong to a group:
   - Positive: Gratification.
   - Negative: Remorse.

7.6. Inferring the Emotional Influence of the Trainees

The aim of the system is to record whether the trainee is experiencing more positive emotions than negative emotions or the opposite. The flow chart of this process is illustrated in Figure 7.2. The system traces the values of the aforementioned characteristics and makes inferences about the possibility that the trainee will accomplish the associated goals and standards as described above. If the characteristics' values for the trainee satisfy positively the associated goal/standard, then the system assumes that the trainee will be triggered emotionally in a positive way. In the opposite case (the characteristics' values satisfy negatively the associated goal/standard), the system will assume that the trainee is likely to have negative emotions. Then, it calculates the difference between the positive and negative amount of emotions. If the result is negative, then the system will conclude that the trainee has generally negative feelings. Else (the difference is a positive value), the system will infer that the overall emotions of the trainee are positive.

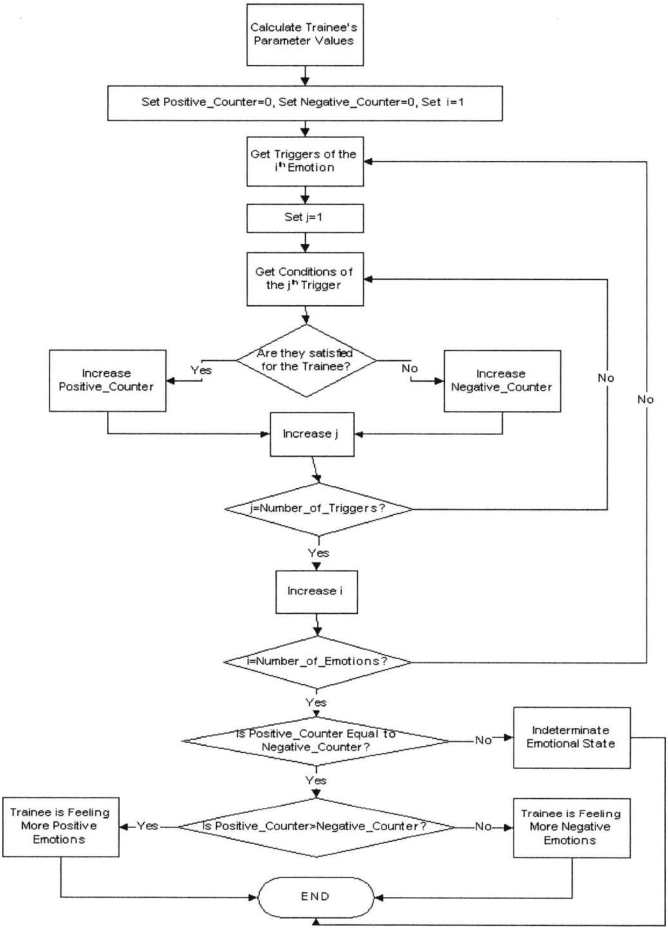


Figure 7.2. Flow Chart of Identifying the Overall Emotional State of the Trainee

The identified overall emotional state of the trainee is stored in his/her student model and is evaluated by the system in relation to who were the trainees that collaborated with him/her at the time the process of emotion perception was executed.

7.7. How Perceived Emotions are Used in the System

As already explained, the perceived emotions are used to infer the overall emotional states (positive or negative) of the trainee and his/her colleagues. Then, the system concludes to whether it should recommend the repetition of this collaboration schema or not. In specific, the emotional states are taken into consideration for generating recommendations about:

- The appropriate colleagues to collaborate with and
- The optimum organization of the trainees into groups (group formation tool).

Recommendation of Appropriate Colleagues to Collaborate With

The recommendation of appropriate colleagues with whom the trainee should collaborate is provided to trainees after considering the criteria of knowledge, personality and emotional states. First of all, the recommended colleagues should know the UML topics the trainee has problems with. From this set of colleagues, the system excludes those that:

- The trainee has rejected for collaboration in the past and
- Has been found to have a negative impact on the trainee's emotional state during a previous collaboration.

Finally, the system restricts this set to the subset of trainees that

- Have been found to have a positive impact on the trainee's emotional state during a previous collaboration and
- In order of precedence, belong to the personality-related stereotypes of Willing-to-help, Participative and Diligent.

Recommendation of Optimum Organization of the Trainees into Groups

This kind of recommendation is offered to the trainer and concerns the optimum organization of the trainees into groups according to the following criteria:

- The desired and undesired combinations of personality stereotypes in the same group,
- The desired group structure concerning the level of expertise and
- The observed by the system emotional affect between the trainees.

The desired combinations of stereotypes are the pairs of stereotypes that their coexistence in the same groups would be beneficial for the performance of the individual trainees and of the groups. On the other hand, the undesired combinations of stereotypes are those pairs of stereotypes that the trainer would not like to have together in the same group, as they would be a bad influence to each other. So, the system will try to form groups with as many as possible desire combinations of stereotypes and avoid resulting to groups with the undesired combinations.

The desired group structure concerns the number and kinds of levels of expertise (basics, junior, senior and expert) that should constitute each group. For example, group A should include one senior and two junior trainees. So, the group formation tool will try to satisfy the desired structure depending on the trainees' levels of expertise.

The emotional affect between the trainees is related to the observed emotional state during the collaboration of a trainee with the members of the same group. Specifically, if the emotional states of the majority of the trainees of the same group were found to be positive when in collaboration with the rest members of the group, then the criterion of combining these trainees together will be added. Else, if the emotional states of the majority of the trainees of the same group were negative, the criterion of separating these trainees will be added.

A more detailed description on the extraction of these recommendations is given in chapter 10.

7.8. Conclusions

A substantial novelty of the CSCL system presented in this thesis is that it automatically predicts the overall emotional state of the trainees. The emotions are perceived adapting a part of the OCC cognitive model of emotions, which has been a de facto in affective software. Until now, the influence of emotions is a neglected issue in learning environments and CSCL systems. The few existing affective learning environments use the predicted emotions to improve the mood and positive emotions of the students by representing affective states through avatars or generating affective messages. In our implementation, the perceived emotions are used for inferring the most effective collaboration between the trainees and group formation.

8

ADAPTING INTELLIGENT RECOMMENDATIONS USING THE HERSEY AND BLANCHARD SITUATIONAL LEADERSHIP THEORY

8.1. Introduction

Any teacher or trainer who wants to be successful must obtain leadership role and capabilities, as s/he has to manage a group of people, whom s/he needs to influence, guide, support and inspire (Gabriel, 2005; Barth, 2001; Wilmore, 2007; York-Barr & Duke, 2004; Suranna & Moss, 1999). Therefore, after researching in literature, we have decided to use the Situational Leadership Theory (SLT) in order to adapt the intelligent advice offered by our learning system to the trainees and the trainer. This decision was supported by related studies on SLT that advocated on its use (Clark, 1981; Hersey et al., 1982; Cairns et al., 1998), its simple features (Weber & Karman, 1991; Baker, 2009; Gupta, 2007) and general acceptance (Duke, 2009; Vasu et al., 1998). In our approach, the follower role is applied to the trainee and the leader role is applied to the trainer and the system (as the system also has a trainer's role through the provided recommendations). The system continually evaluates the maturity of the trainees per task and associates them (again per task) with the respective leadership style. These inferences on maturity and leadership styles are used to adapt the advice given to the trainees and the trainer.

In AUTO-COLLEAGUE, the trainees are offered advice regarding their change in performance, the problematic domain topics (that is in UML), the help topics they should study and the appropriate colleagues with whom they should collaborate. In this case, the system plays in some way the role of the trainer who guides them during the learning process. The appearance and frequency of this advice is adapted to the trainee according to the SLT.

The trainer of the system, also, receives intelligent recommendations, the content of which concerns the leadership style that s/he should follow for each trainee according to his/her maturity level per task. In addition, the trainer is given analytical statistical and historical reports on the changes in the maturity (ability and willingness) per assigned task of the trainees.

In this chapter, we describe the way that the definitions of the SLT have been calculated in our system. The ways that the maturity of the trainees has been used in AUTO-COLLEAGUE is described in detail in chapter 8.

One of the main problems in applying the SLT is the great possibility that the trainee of the group will not be able to aptly define the maturity of every trainee and, therefore, be precise in the appropriate leadership style to follow. The maturity is a combination of the ability and willingness of the follower/trainee for each assigned task. In AUTO-COLLEAGUE, we challenge this difficulty defining the maturity through calculating objective measurable trainees' features related separately to the ability and the willingness.

8.2. The Hersey and Blanchard Situational Leadership Theory

One of the main principles of the Hersey and Blanchard Situational Leadership Theory (SLT) is that the leadership style that a leader should adopt should not be the same for everyone and for every task. The leader should be flexible depending on each follower readiness/maturity and on each task assigned to the follower. The readiness or maturity is defined as variable that is both follower and task specific. Its value is affected by two parameters: the ability and the willingness. The ability refers to the knowledge, skills and experience of the follower. The willingness is related to the self-confidence and motivation the follower has in order to accomplish an assigned task. There are four levels of maturity: R1, R2, R3 and R4. In case a follower belongs to the R1 level, s/he is unable and unwilling or insecure (low ability, low willingness). If s/he is classified into the R2 level, this means s/he is unable, though willing and motivated (low ability, high willingness). The R3 level entails that the follower is able, but unwilling or insecure (high ability, low willingness). Followers that belong to the R4 level are those that are able and willing and motivated (high ability, high willingness).

Accordingly to these four levels of maturity of the follower, the leader should follow the corresponding leadership style. Hersey and Blanchard have defined four leadership styles. Every leadership style is influenced by two different leadership dimensions: the Task Behaviour and the Relationship Behaviour. The task behaviour concerns the not bi-directional communication the leader has with the follower in order to give him/her strict directions on the task. The relationship behaviour refers to the bi-directional communication the leader has with the follower in effort to support him/her in a more socio-emotional way and simultaneously get feedback. Depending on the leadership style, the extent of acting these two behaviours ranges from low to high values.

These four leadership styles are: Telling, Selling, Participating and Delegating. Following the Telling leadership style means that the leader will describe to the follower in great detail the steps for accomplishing the assigned task and supervise him/her intimately (high task behaviour and low relationship behaviour). The Selling leadership style means that the leader should still provide guidance and support, but in a more indirect way (high task behaviour and high relationship behaviour). According to the Participating style, the leader should provide less direction to the follower and at the same time focus on their relationship (low task behaviour and high relationship behaviour). In conformance with the Delegating leadership style, the leader should leave responsibilities to the follower and supervise him/her less and quietly (low task behaviour and low relationship behaviour).

8.3. Measuring the Maturity

8.3.1. Calculating the Ability

The ability of a trainee on a specific task is calculated using an algorithm that is processed for every UML topic related to the task. This algorithm is the same used for building the buggy student model of the trainee as explained in detail in chapter 6. Every task is related to specific UML topics. For calculating the ability, the system firstly finds all the UML topics with which the specific task is associated and, then, runs the algorithm for each topic. The algorithm takes as input the actions and the errors of the trainee that are associated with the topic. The output of the algorithm is the degree of knowledge on the topic and is a positive real number in [0, 1]. This degree is used for assigning the weight value in the graph of the buggy student model. The result of the algorithm expresses the ability of the trainee on the specific topic for which it is processed. Finally, the system calculates the average of all the topic abilities. This average expresses the ability of the trainee on the task. A schematic representation of the ability calculation for a specific task is illustrated in figure 8.1.

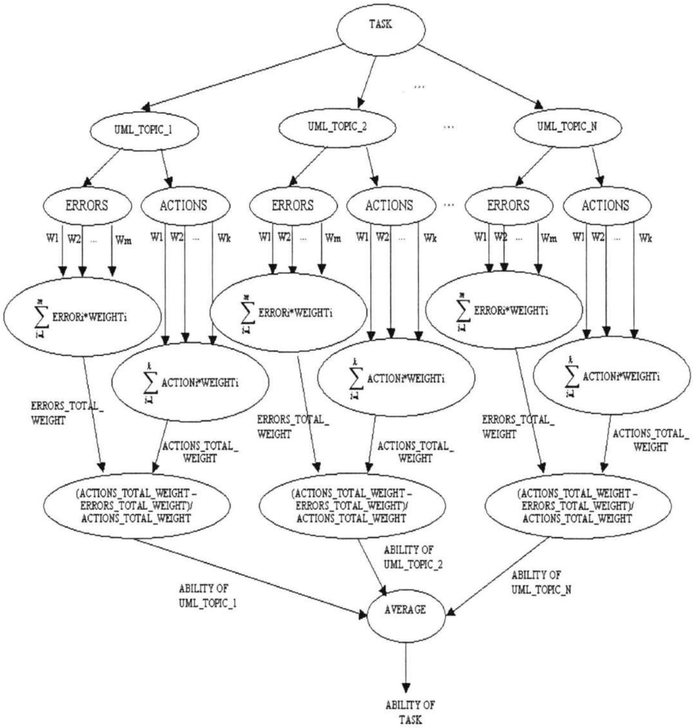


Figure 8.1. Schematic Representation of the Ability Calculation for a Specific Task

8.3.2. Calculating the Willingness

The calculation of the willingness of the trainees should be based on the observation of personality traits related to the self-confidence and motivation the trainee shows working to complete a task. For this reason, the willingness is calculated using the self-confident and diligent personality-related stereotypes of the student models. The self-confident trainee believes in him/herself and his/her skills. When a trainee has self-confidence, s/he maintains a positive attitude even if his/her knowledge and skills are not of a high level or even if probably s/he actually is not highly esteemed by his/her colleagues. The diligent trainee has earnest and persistent application to the training task and makes steady efforts during the learning process. The triggers of these stereotypes are shown in table 8.1 and are the outcome of the empirical study presented in chapter 5.

Table 8.1. Triggers of the willingness stereotypes

Facet	Self-confident	Diligent
F1: useless mouse movements and clicks frequency	Low	Medium
F2: average idle time	Medium	Low
F3: Number of actions	Medium	High
F4: error frequency	Medium	High
F5: correct actions frequency	Medium	Low
F6: Help utilization frequency	Medium	Low
F7: communication frequency	Low	

The triggers are the conditions between facet-value pairs that activate the stereotype. There is, also, a rating upon each trigger indicating the degree of the probability that a trainee belongs to the corresponding stereotype depending on the facet values. This rating is a real number between 0 and 1. It is calculated per trainees and per task as described in chapter 5. After the system calculates the ratings for both of the stereotypes, it calculates their average rating that forms the willingness of the trainee for the specific task. The willingness is a real number between 0 and 1. If the average rating is below 0.5, the willingness of the trainee on this task is defined as low. In the opposite case, the willingness of the trainee on this task is defined as high. The process of the calculation of the willingness of a trainee for a specific task is cited in figure 8.2, where STEREOTYPE_C is the self-confident stereotype, STEREOTYPE_D is the diligent stereotype, RATING_C is the rating for the self-confident stereotype and RATING_D is the rating for the diligent stereotype.

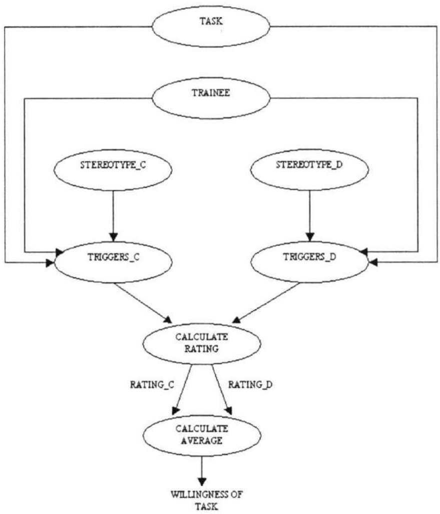


Figure 8.2. Schematic Representation of the Willingness Calculation.

8.3.3. Calculating the Maturity

The maturity of a trainee on a specific task is calculated based on his/her ability and willingness on the task, as shown on table 8.2. If both ability and willingness are low, the maturity level is R1. If the ability is low and the willingness is high, the maturity level is R2. If the ability is high and the willingness is low, the maturity level is R3. If both ability and willingness are high, the maturity level is R4.

Table 8.2. Calculation table of maturity based on ability and willingness of trainee in a specific task.

Maturity Level	**Ability**	**Willingness**
R1	low	low
R2	low	high
R3	high	low
R4	high	high

8.4. How Leadership Styles are Used in the System

The appropriate leadership styles estimated by the system are used for (a) adapting the recommendations offered to the trainees and (b) providing to the trainer assistance in leading and handling the trainees.

8.4.1. Adapting the trainees' recommendations

The system, which plays the role of the leader, follows the respective leadership style depending on the maturity of the trainees (who play the role of the followers) using the SLT by adapting specific parameters of the recommender system. These parameters are:

- The Advisor Interval,
- The Error Triggering Frequency and
- The Modality of Messages.

The Advisor Interval is a time parameter that defines how frequently the recommender system will be searching for satisfied conditions that trigger the offering of recommendations. These conditions are: (a) specific frequency of errors made (Error Triggering Frequency parameter), (b) change in the knowledge (ability) and (c) change in the diligent/self-confident stereotype (willingness). When at least one of these conditions is satisfied, recommendation messages are shown to the trainee. The content of these messages varies depending on the kind of the satisfied condition.

In case of specific frequency of errors made (Error Triggering Frequency parameter), the trainee is given a series of messages. The first message informs the trainee on the errors kind and frequency. The second message recommends to the trainee the help topics s/he should study. The third message proposes to the trainee adequate colleagues with whom s/he should collaborate.

In case of change in the diligent/self-confident stereotype, the trainee is informed about this, as it may influence his/her future behaviour and progress. For instance, informing a trainee about his/her progress in knowledge will possibly increase his/her self-confidence and diligence.

The Modality of Messages parameter defines whether the recommendation message will be modal or not. This is useful for minimizing the possibility of the ignoring the recommendation.

If the trainee belongs to the R1 maturity level (low ability, low willingness), the appropriate leadership style is the Telling. The recommender system should have high task behaviour and low relationship behaviour towards the trainees. Therefore, the Advisor Interval is defined as 4 minutes (which is a low interval) and the Error Triggering Frequency is 1. The messages are modal, so that the trainees cannot ignore them. In this way, the recommender system will support the trainee frequently with many descriptive help messages.

If the trainee belongs to the R2 maturity level (low ability, high willingness), the appropriate leadership style is the Selling. The recommender system should have high task behaviour and high relationship behaviour towards the trainees. Therefore, the Advisor Interval is defined as 4 minutes (which is a low interval) and the Error Triggering Frequency is 2. The messages are modal, so that the trainees cannot ignore them. Additionally, the recommender system will provide the trainee with encouraging messages. For example, if s/he is not found to belong to the self-confident stereotype, the recommender system will send supportive messages that will possibly encourage him/her.

If the trainee belongs to the R3 maturity level (high ability, low willingness), the appropriate leadership style is the Participating. The recommender system should have low task behaviour and high relationship behaviour towards the trainees. Therefore, the Advisor Interval is defined as 8 minutes (medium interval) and the Error Triggering Frequency is 3. The messages are not modal. Additionally, the recommender system will provide the trainee with encouraging messages.

If the trainee belongs to the R4 maturity level (high ability, high willingness), the appropriate leadership style is the Delegating. The recommender system should have low task behaviour and low relationship behaviour towards the trainees. Therefore, the Advisor Interval is defined as 15 minutes (high interval) and the Error Triggering Frequency is 5. The messages are not modal.

8.4.2. Leadership Style Toolkit for the Trainer

AUTO-COLLEAGUE offers to the trainer a toolkit of statistical/historical information about the changes on the maturity (ability and willingness) of the trainees per assigned task. The trainer is able to review and track the assigned tasks per trainee. Descriptive data are shown, such as the description, the beginning and finishing date and time of the task and the score achieved by the trainee in a scale from 0 to 100. The trainer may also view the updates in the maturity values of the trainees either for each task or for all tasks (average). In this way, the trainer can draw many conclusions on the performance of the trainees and the effectiveness of the leadership style s/he has followed over time. Furthermore, there is an explanative static form with description on the way that s/he should behave per leadership style. This form is useful for the trainer as s/he can consult it about the way of leadership at any time.

8.5. Conclusions

A main contribution of this thesis is related to the novel use of the Hersey and Blanchard Situational Leadership Theory for adapting intelligent recommendations in a learning environment. As the system can be viewed as a leader in the learning process, it seems appropriate to use a leadership theory for guiding the trainees at achieving knowledge and qualities necessary for successful collaboration and learning. The Hersey and Blanchard Situational Leadership Theory provides a simple and computational way for inferring the multi-dimensional trainees' states (defined by the maturity variable), as well as a discrete leadership style to follow. The proposed tactics of each defined leadership style can also be applied in a learning environment quite easily. Maybe the most complicated and liable to misleading results task is the calculation of the maturity. In AUTO-COLLEAGUE, the maturity is calculated in two stages as explained in SLT: defining the ability and evaluating the willingness. The ability is defined using the buggy student model that represents the knowledge of the trainee. The willingness is evaluated using the self-confident and diligent personality-related stereotypes. Then, according to the estimated maturity, the system chooses the most adequate leadership style, which imposes specific rules of offering the recommendations.

9

Adaptive and Intelligent Recommendations to Trainees Based on the Hersey and Blanchard Situational Leadership Theory

9.1. Introduction

AUTO-COLLEAGUE offers adaptive and intelligent recommendation to the trainees based on their student models, which describe them in three aspects: the level of expertise, the personality and the emotional state. The level of expertise describes the knowledge level of the trainee on each domain topic. The personality-related stereotypes used in AUTO-COLLEAGUE are in accordance with the Five Factor Model of Personality, but were chosen to fit to the needs of a collaborative learning environment. These personality-related stereotypes are: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. The emotional states (positive or negative) are automatically predicted using the OCC cognitive theory of emotions (Ortony, Clore & Collins, 1988).

There are three types of recommendations provided to the trainees: (a) the next

UML topics they should study, (b) the appropriate colleagues with whom they should collaborate and (c) supportive/encouraging messages that would increase their performance. The appearance, content and frequency of the recommendation messages are adapted to the trainee and the assigned task using the Hersey and Blanchard Situational Leadership Theory. This constitutes a novelty of our system, as there is no other learning environment to have used this theory or any other leadership theory before. The recommender system of AUTO-COLLEAGUE is built based on both content-based and collaborative recommendation methods. The recommendations are content-based since the system evaluates relative information about the trainees, such as upgrades/downgrades of the level of expertise, the errors, the actions, the preferences in collaboration and the help topics already studied. In addition, the recommendations are collaborative as the system consults the successful recommendations offered to other trainees with similar state or problems. A recommendation is considered to be successful if the receiver trainee had overcome his/her problems in UML after following the steps described by it.

9.2. Overview of the Recommendations

The recommendations to the trainees concern (a) the next UML topics they should study, (b) the appropriate colleagues with whom they should collaborate and (c) supportive/encouraging messages that would increase their performance. The appearance, content and frequency of the recommendation messages are adapted to the trainee using the Hersey and Blanchard Situational Leadership Theory.

The main principle of this theory is that leaders (the trainer and the system in our case) should continually adjust their leadership styles depending on the maturity of the followers (trainees in our case). The maturity is analysed in two variables: the ability and the willingness, which are dependent on the tasks to be accomplished. Hersey and Blanchard have defined four different leadership styles suggesting the most appropriate leadership style of the leader towards the followers for increasing individual and group improvement. The ability is calculated using the level of expertise stereotype and the buggy student model. The willingness is defined using the personality-related part of the student model. There are four levels of maturity: R1, R2, R3 and R4. In case a follower belongs to the R1 level, s/he is unable and unwilling or insecure (low ability, low willingness). If s/he is classified into the R2 level, this means s/he is unable, though willing and motivated (low ability, high willingness). The R3 level entails that the follower is able, but unwilling or insecure (high ability, low willingness). Followers that belong to the R4 level are those that are able and willing and motivated (high ability, high willingness). Accordingly to these four levels of maturity of the follower, the leader should follow the corresponding leadership style. Hersey and Blanchard have defined four leadership styles. Every leadership style is influenced by two different leadership dimensions: the Task Behaviour and the Relationship Behaviour. The task behaviour concerns the not bi-directional communication the leader has with the follower in order to give him/her strict directions on the task. The relationship behaviour refers to the bi-directional communication the leader has with the follower in effort to support him/her in a more socio-emotional way and simultaneously get feedback. Depending on the leadership style, the extent of acting these two behaviours ranges from low to high values.

The next UML help topics that the trainees should study are generated according to the errors made by the trainee following both recommendation generation methods: the content-based and the collaborative filtering. The content-based method traces the errors of the trainee to find the problematic topics. Each error is associated to specific UML concepts indicating missing and/or faulty knowledge. Each action that resulted a correct answer is also associated to specific UML concepts describing correct knowledge. Each UML help topic is associated to relevant UML concepts. Based on the collaborative-filtering method, the system gets the recommended topics to trainees that made the same errors in the past and had a successful outcome. The outcome is regarded as successfulness when the trainee had opened the recommended help topics and did not make the same error types during the next test.

The appropriate colleagues with whom the trainee should collaborate are found considering their knowledge, personality and emotional states. The first criterion for this kind of recommendation is to seek for trainees that know the UML topics the trainee has problems with. Then, the system excludes those that (a) the trainee has rejected for collaboration in the past and (b) has been found to have a negative impact on the trainee's emotional state during a previous collaboration. Finally, the system restricts this set to the subset of trainees that in order of precedence, belong to the personality-related stereotypes of Willing-to-help, Participative and Diligent.

The aim of the supportive messages is to encourage and motivate the trainees to improve both their learning and collaboration performance. There are standard advice messages depending on the personality-related stereotypes that the trainee is found to belong or not belong to. These messages are shown in table 9.1. The system offers this kind of recommendation based on the appropriate leadership style according to the Hersey and Blanchard Situational Leadership Theory. The leadership style determines the appearance and frequency of these messages as explained in chapter 8.

Table 9.1. Supportive messages according to personality-related stereotype.

STEREOTYPE	BELONGS	DOES NOT BELONG
Self-confident		You should not have low self-confidence without reason!
Diligent		You should work harder!
Participative		Why not participate more?
Willing to help		You should be more willing to help your colleagues!
Sceptical	There is no need to hesitate so much!	
Hurried	You should take your time! Do not rush to answer.	
Unconcentrated	You seem to be unconcentrated. Be more focused!	

9.3. Generating the Recommendations

In the background, there is an agent that continuously searches for new (a) upgrades/downgrades in level of expertise, (b) personality-related stereotypes updates in the student model of the trainees and (c) errors. Any such update will trigger the recommender system to generate recommendations.

9.3.1. Recommender System Triggered by Updates in Level of Expertise and Personality

In case of upgrade/downgrade in level of expertise, the recommender system will inform the trainee about the update in the student model. Such informative messages could motivate the trainee. This kind of messages will appear only if the maturity level of the trainee is either R2 or R3 (which impose low relationship behaviour).

In case of a new assignment in the personality-related stereotypes of the trainee, the recommender system will generate a supportive message according to table 9.1. These supportive messages will appear only if the maturity level of the trainee is either R2 or R3 (which impose low relationship behaviour).

9.3.2. Recommender System Triggered by Errors

In case of errors, the recommender system searches for errors the trainee made for a specific amount of times (defined by the Error Triggering Frequency parameter). In this case, the trainee is given a series of messages. The activity diagram of this process is shown in figure 9.1. Firstly, the trainee is informed about the error s/he was found to have made and for how many times. At the end of this message the system asks the trainee if s/he agrees with that. If the trainee answers negatively, then there is no other message. If the trainee answers positively, then a second message is shown that suggests a UML help topic to be studied and a colleague with whom s/he should collaborate. At the end of the message the trainee is asked again for his/her opinion about the collaboration suggestion. If the trainee answers positively, then no other message is shown. If the trainee answers negatively, the system will inform the recommended trainee about this rejection and will search again for a suitable colleague. The search will continue until eventually the trainee answers positively or until no other suitable partner is found.

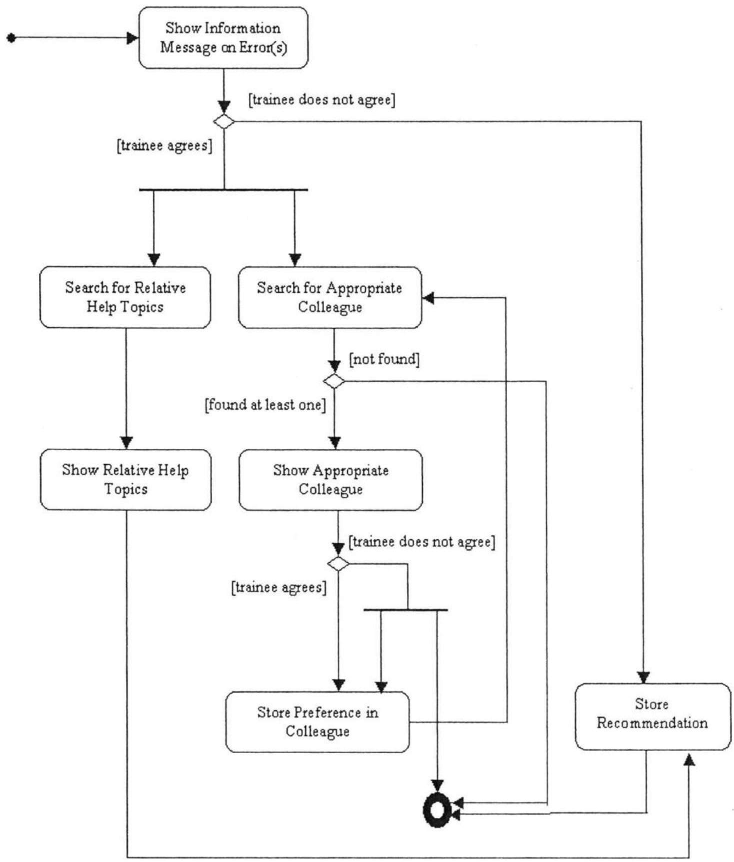


Figure 9.1. Activity Diagram of the recommendation extraction when triggered by error.

Searching for Relative UML Topics to Study

The next UML help topics that the trainees should study are generated based on the content-based recommendation method and the collaborative filtering method.

Following the content-based method, the recommender system uses the errors made by the trainee to infer which are the domain topics that s/he has problems with. Each potential error is linked to one or more error types. Each error type is associated to specific UML topics indicating missing and/or faulty knowledge. Such error types are: Wrong Class Included, Method not Included and Circular Association. For example, the Wrong Class Included is associated to the Class Definition UML topic, describing that this error type possibly indicated lack of knowledge of this UML topic. Each action that resulted a correct answer is also associated to specific UML concepts describing correct knowledge. In addition, every UML topic is linked to the relative help topics. The recommender system uses this structure to search for the help topics to recommend to the trainee based on the error type that triggered it.

Based on the collaborative filtering method, the recommender system repeats recommendations that had a successful outcome at the performance of trainees with the same problems in the past. A recommendation is considered as successful when the trainee studied the recommended topics and did not make the same error types during the next test. For the system to be able to track such information, all the errors, their respective recommendation messages and topics opened (with date-time stamps) in the help system are recorded in the database. The process is as follows: The recommender system searches for trainees that made the same errors (defined by error type) in the past. Then, it retrieves the recommendations shown to these trainees based on the content-based method at that time. The system has already registered whether the trainees had studied the recommended topics. So, the next step is to restrict the found set of trainees to those trainees that indeed opened the recommended topics. Afterwards, the system searches in the database whether these trainees had made the same error types in the next test (after opening the recommended topics and if there was a next test). If such cases are found, the system gathers these recommended topics and compares them to the topics generated using the content-based method. Finally, the recommender system concludes to recommend the common UML topics (in other words, the intersection of the two sets: the one resulted from the content-based and the one resulted from the collaborative-filtering method).

Searching for Appropriate Colleagues to Collaborate With

The system searches for appropriate colleagues using as criteria their knowledge, their personality-related stereotypes and their emotional states. The activity diagram of the recommendation extraction is shown in figure 9.2.

At first the system seeks for trainees that know the UML topics that the trainee has problems with, based on the error type made. Then, the system excludes those that (a) the trainee has rejected for collaboration in the past and (b) has been found to have a negative impact on the trainee's emotional state during a previous collaboration. If the result set of trainees is null, then the system returns to the firstly generated set of trainees that know the UML topics that the trainee has problems with. This is done, as possibly the trainee is not collaborative having the negative tendency to reject everybody. Finally, the system restricts this set to the subset of trainees that in order of precedence belong to the personality-related stereotypes of Willing-to-help, Participative and Diligent.

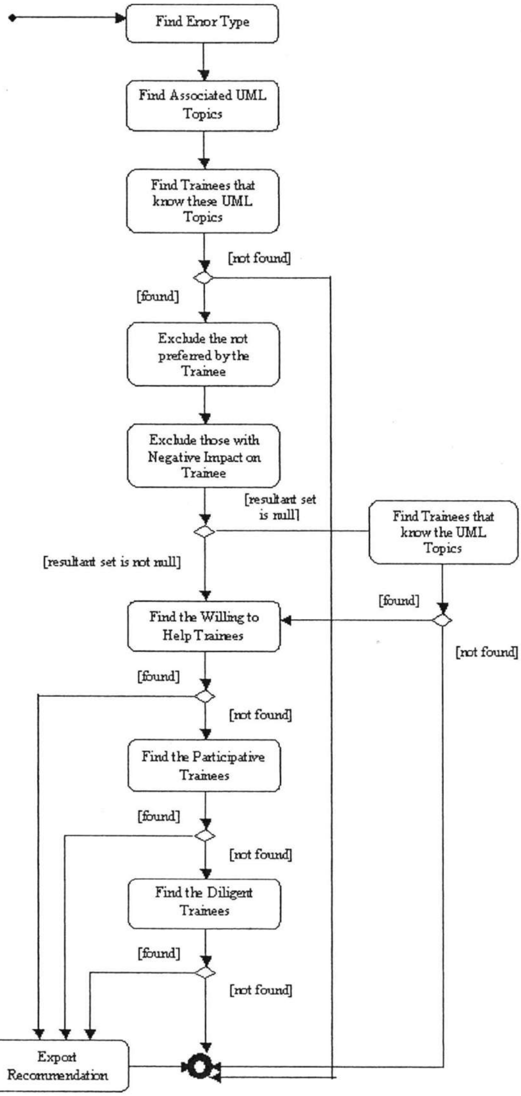


Figure 9.2. Activity Diagram of the Recommendation Extraction.

9.4. Adaptivity of Recommendations based on the Hersey and Blanchard Leadership Theory

The recommender system, playing the role of the leader, follows the respective leadership style depending on the maturity of the trainees (who play the role of the followers) using the Hersey and Blanchard Situational Leadership Theory. This is implemented through adapting specific parameters of the system: (a) the Advisor Interval, (b) the Error Triggering Frequency and (c) the Modality of Messages. The Advisor Interval is a time parameter that defines how frequently the recommender system will be searching for satisfied conditions that trigger the recommender system. The Error Triggering Frequency defines which is the amount of the same error made that would trigger the recommender system. The Modality of Messages indicates whether the recommendation messages will be modal or not. The leadership styles for each trainee and task are evaluated after calculating the respective maturity as explained in chapter 8.

If the trainee belongs to the R1 maturity level (low ability, low willingness), the appropriate leadership style is the Telling. The recommender system should have high task behaviour and low relationship behaviour towards the trainees. Therefore, the Advisor Interval is defined as 4 minutes (which is a low interval) and the Error Triggering Frequency is 1. The messages are modal, so that the trainees cannot ignore them. In this way, the recommender system will support the trainee frequently with many descriptive help messages. As low relationship behaviour should be applied, there will be no supportive messages.

If the trainee belongs to the R2 maturity level (low ability, high willingness), the appropriate leadership style is the Selling. The recommender system should have high task behaviour and high relationship behaviour towards the trainees. Therefore, the Advisor Interval is defined as 4 minutes (which is a low interval) and the Error Triggering Frequency is 2. The messages are modal, so that the trainees cannot ignore them. Additionally, the recommender system will provide the trainee with supportive messages.

If the trainee belongs to the R3 maturity level (high ability, low willingness), the appropriate leadership style is the Participating. The recommender system should have low task behaviour and high relationship behaviour towards the trainees. Therefore, the Advisor Interval is defined as 8 minutes (medium interval) and the Error Triggering Frequency is 3. The messages are not modal. Additionally, the recommender system will provide the trainee with supportive messages (high relationship behaviour).

If the trainee belongs to the R4 maturity level (high ability, high willingness), the appropriate leadership style is the Delegating. The recommender system should have low task behaviour and low relationship behaviour towards the trainees. Therefore, the Advisor Interval is defined as 15 minutes (high interval) and the Error Triggering Frequency is 5. The messages are not modal. As low relationship behaviour should be applied, there will be no supportive messages.

The parameterisations of these features depending on the leadership style are summarized in table 9.2.

Table 9.2. Summary of parameterizations depending on leadership style.

Leadership Style	Advisor Interval	Error Triggering Frequency	Modality of Messages
S1	low	1	yes
S2	low	2	yes
S3	medium	3	no
S4	high	5	no

9.5. Example of Adaptive and Intelligent Recommendation to Trainee

We will now present an example of offering recommendation to a trainee, George, whose leadership style should be S3. This means that the Error Triggering Frequency for him is 3 (according to the table 9.2). The Recommendation Agent has been triggered by the occurrence of 3 errors associated to the Attributes Definition UML topic that George has made. The Advisor searches for the appropriate to the problematic UML concepts help topics to suggest to the trainee. Then, the agent searches for the most appropriate colleague and concludes to John who knows the specific UML topic and is found to be *Willing-to-help*. The first message shown to George is illustrated in figure 9.3.

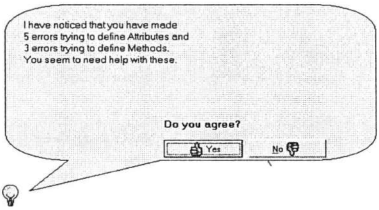


Figure 9.3. First Message of the Recommendation Agent triggered by errors

After George pressed the "Yes" button, the next message, which is illustrated in figure 9.4, was shown and George disagreed and pressed the "No" button.

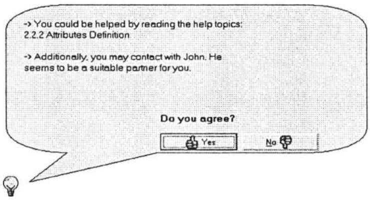


Figure 9.4. Second Message of the Recommendation Agent.

The next message is illustrated in figure 9.5. Its purpose is to register the opinion of the trainee. George decides to check the first checkbox.

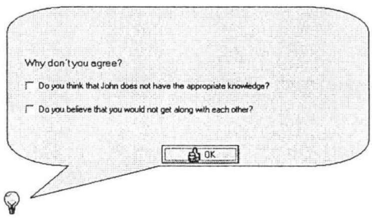


Figure 9.5. Third Message of the Recommendation Agent.

The agent repeats then the search to find another suitable colleague. There was no appropriate colleague with the Participative stereotype found, so the agent chooses Mary who was found to be Diligent. The next message is illustrated in figure 9.6, to which George answered positively.

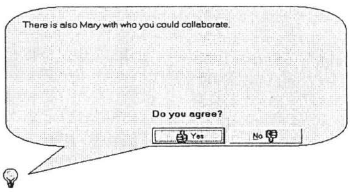


Figure 9.6. Fourth Message of the Recommendation Agent.

9.6. Conclusions

In this chapter, we describe the recommendations provided to the trainees and the methods of their generation. There are three types of recommendations: (a) the next UML topics they should study, (b) the appropriate colleagues with whom they should collaborate and (c) supportive/encouraging messages that would increase their performance. The appearance, content and frequency of the recommendation messages are adapted to the trainee and the assigned task using the Hersey and Blanchard Situational Leadership Theory. This constitutes a novelty of our system, as there is no other learning environment to have used this theory or any other leadership theory before. The recommendations are generated using both the content-based and the collaborative-filtering approaches.

10

Adaptive and Intelligent Recommendations to the Trainer Using the Hersey and Blanchard Situational Leadership Theory, the OCC Theory of Emotions and the Simulated Annealing Algorithm

10.1. Introduction

Not always the role of the human trainer is supported in learning environments. In AUTO-COLLEAGUE, we decided to facilitate the role of the trainer providing him/her intelligent recommendations. These recommendations include (a) leadership style suggestions and (b) a group formation tool that proposes optimum organization of the trainees into groups.

The generation of the leadership style suggestions are based on the Hersey and Blanchard Situational Leadership Theory. This kind of recommendation viewing the trainer/teacher as a leader has never been implemented in learning environments. The system concludes to the most effective leadership style after calculating the maturity of the trainees for each assigned task. The maturity is a very crucial variable of this theory and very complicated to evaluate, as it is task specific and calculated considering both ability and personality related characteristics.

The aim of the optimum group formation is to suggest the most effective organization of the trainees into groups. CSCL systems facilitate collaborative learning enabling students to work collaboratively into groups. An important but often neglected aspect in Computer-Supported Collaborative Learning is the formation of learning groups (Mühlenbrock, 2005). There are many studies that highlight the importance of group formation in collaborative learning tools (Daradoumis et al., 2002; Inaba et al., 2000). However, there are few experimental studies that provide automatic group formation. Most of them are stand-alone group formation tools (Christodoulopoulos & Papanikolaou, 2007; Graf & Bekele, 2006; Cavanaugh et al., 2004; Wang et al., 2007; Gogoulou et al., 2007a; Martin & Paredes, 2004; Ounnas et al., 2009; Khandaker & Soh, 2010; Paredes et al., 2009; Kyprianidou et al., 2009) and few of them are integrated tools in CSCL systems (Soh et al., 2006; Liu et al., 2008; Ikeda et al., 1997; de Faria et al., 2006; Kreijns et al., 2002). The majority of the existing group formation tools do not evaluate in real-time the criteria values (student characteristics) of their group formation algorithm. They receive it as input by the instructor of the systems or evaluate them based on scientific instruments, such as psychometric tests (Christodoulopoulos & Papanikolaou, 2007; Graf & Bekele, 2006; Cavanaugh et al., 2004; Wang et al., 2007; Gogoulou et al., 2007a; Martin & Paredes, 2004; Ounnas et al., 2009; Paredes et al., 2009; Kyprianidou et al., 2009). On the other hand, in our system the criteria values are evaluated in real-time using the student models of the trainees.

The group formation tool is generated using the Simulated Annealing algorithm, which has never been used in relative environments. It is a genetic algorithm that serves as a general optimization technique for solving combinatorial optimization problems. The criteria for searching and matching the trainees in groups are:

- The desired and undesired combinations of personality-related stereotypes in the same group,
- The desired group structure concerning the levels of expertise and
- The observed by the system emotional affect between the trainees.

The desired/undesired combinations of stereotypes are the pairs of personality-related stereotypes that their coexistence in the same groups would have a positive/negative influence on the performance of the individual trainees and of the groups. The default combinations are the outcome of an empirical study. The desired group structure concerns the number and kinds of levels of expertise (basics, junior, senior and expert) that should constitute each group. The emotional affect between the trainees is related to the observed emotional state during the collaboration of a trainee with the members of the same group. AUTO-COLLEAGUE includes an emotion recognition agent that infers the overall emotional state of the trainees adapting the OCC Theory of emotions (Ortony, Clore & Collins, 1988).

10.2. Providing Leadership Style Suggestions

AUTO-COLLEAGUE uses the Hersey and Blanchard Situational Leadership Theory (SLT) in order to infer the most effective leadership styles according to the trainees' individual needs and characteristics. A key element of SLT is the way of identifying these individual characteristics of the followers. This is achieved using a trainee and task specific variable, which is referred as maturity. Its value is affected by two parameters: the ability and the willingness. The ability refers to the knowledge, skills and experience of the follower. The willingness is related to the self-confidence and motivation the follower has in order to accomplish an assigned task. There are four levels of maturity: R1 (low ability, low willingness), R2 (low ability, high willingness), R3 (high ability, low willingness) and R4 (high ability, high willingness). Each maturity level is associated with one of the defined leadership styles: Telling, Selling, Participating and Delegating.

In our system, the maturity of a trainee on a specific task is defined after calculating separately his/her ability and willingness on the task. The ability is calculated using the knowledge of trainee as described in his/her buggy student model. The willingness is calculated using the self-confident and diligent personality-related stereotypes of the student models. Calculating the average of these stereotypes' ratings assigned during working on a specific task, the system finds the willingness of the trainee on a specific task. Then, the system concludes to the maturity value. If both ability and willingness are low, the maturity level is R1. If the ability is low and the willingness is high, the maturity level is R2. If the ability is high and the willingness is low, the maturity level is R3. If both ability and willingness are high, the maturity level is R4.

AUTO-COLLEAGUE offers to the trainer a toolkit of statistical/historical information about the changes on the maturity (ability and willingness) of the trainees per assigned task. This form is illustrated in figure 10.1. At the upper part of the form the grid showing all the trainees and their assigned tasks are shown. The fields of the tasks are the date and time of beginning and of finishing the task (if finished), the description of the task and the score achieved by the trainee in a scale from 0 to 100. The updates in the maturity values for the trainee selected from the grid are shown at the lower part of the form. The trainer can choose through the radio buttons whether s/he wants this statistical information on maturity refers to the task selected from the tasks' grid or to the average of all tasks. The fields shown in the maturity grid are the maturity level (R1, R2, R3 or R4), the ability (real number between 0 and 1), the willingness (real number between 0 and 1), the date and time that the update in maturity was recorded and the appropriate leadership style to follow. In addition, the same records of maturity are given in a graph with two series: the ability and the willingness series. In this way, the trainer attains a full representation of the changes in the maturity of the trainee through time for a specific task or for all of the tasks.

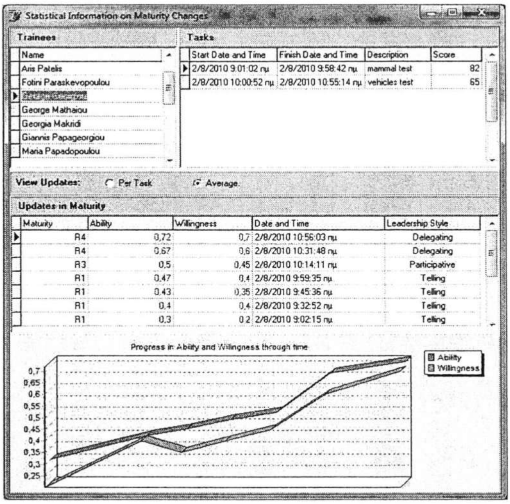


Figure 10.1. Form of showing statistical information on maturity changes (advice to trainers).

Through this form, the trainer can draw many conclusions on the performance of the trainees and the effectiveness of the leadership style s/he has followed during time. Furthermore, there is another form (figure 10.2) with description on the way that s/he should behave per leadership style. This form is useful for the trainer as s/he can consult it about the way of leadership at any time.

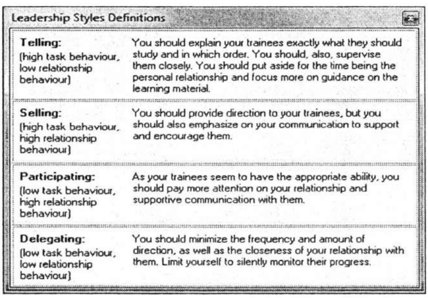


Figure 10.2. Form of Leadership Style Definitions for the Trainer.

10.3. Optimum Group Formation of Trainees

10.3.1. Criteria

The group formation tool recommends the most effective organization of the trainees into groups according to:

- The desired and undesired combinations of personality-related stereotypes in the same group,
- The desired group structure concerning the level of expertise and
- The observed by the system emotional affect between the trainees.

The desired combinations of stereotypes are the pairs of stereotypes that their coexistence in the same groups would be beneficial for the performance of the individual trainees and of the groups. On the other hand, the undesired combinations of stereotypes are those pairs of stereotypes that the trainer would not like to have together in the same group, as they would be a bad influence to each other. So, the system will try to form groups with as many as possible desired combinations of stereotypes and avoid resulting to groups with the undesired combinations. The default combinations (shown in figure 10.3) are the outcome of an empirical study presented in chapter 10. However, the trainer may define the desired and undesired combinations of personality-related stereotypes through the form illustrated in figure 10.3.

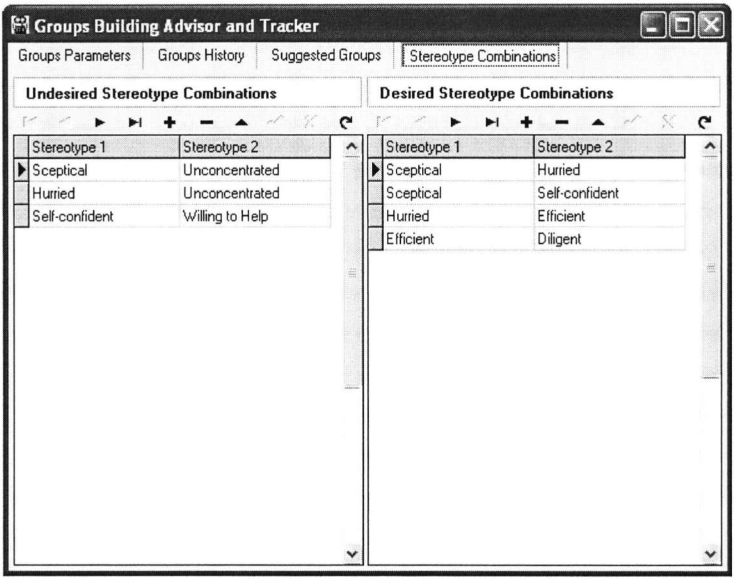


Figure 10.3. Form of Defining the Desired and Undesired Combinations of Personality-Related Stereotypes.

The desired group structure concerns the number and kinds of levels of expertise (basics, junior, senior and expert) that should constitute each group. For example, group A should include one senior and two junior trainees. So, the group formation tool will try to satisfy the desired structure the most, depending on the trainees' levels of expertise. The form of defining the desired structures of groups is illustrated in figure 10.4. The groups are defined at the upper left part of the form and the structure for each group at the right part.

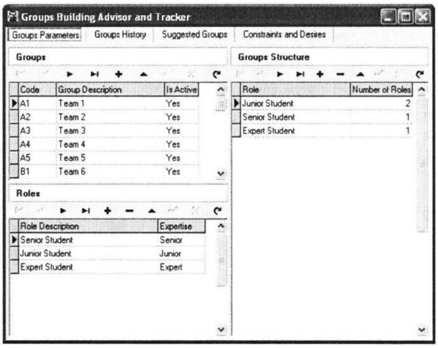


Figure 10.4. Form of defining the desired level of expertise structures of groups.

The emotional affect between the trainees is related to the observed emotional state during the collaboration of a trainee with the members of the same group. Specifically, if the emotional states of the majority of the trainees of the same group were found to be positive when in collaboration with the rest members of the group, then the criterion of combining these trainees together will be added. Else, if the emotional states of the majority of the trainees of the same group were negative, the criterion of separating these trainees will be added.

The form of the group formation tool (figure 10.5) is available only to the trainer of the system. The trainer may choose to form groups according to both of the criteria described above or according only to the desired level of expertise structures of groups by pressing the corresponding button (at the bottom of the right part of the form in figure 10.5). At the left part of the form, the suggested by the system groups are listed in hierarchical tree view, where the roots are the teams. At the right part of the form, an evaluation report is shown. In this report, 4 evaluation characteristics of the current group suggestion are listed. Failed Combinations are the number of the combinations between trainees that that the system should not make according to the searching criteria. The Failed Groups refer to the number of the groups that Failed Combinations are included. In similar way, Successful Combinations state the number of successful combinations between trainees according to the searching criteria. Successful Groups refer to the number of the groups that Successful Combinations are included. The existence of failed combinations may be the outcome of failure in the search algorithm, but the most common reason is the lack of available trainees with characteristics that would fit in the searching criteria. However, the trainer can manually change the formation of the groups by adding, deleting or moving the trainers after consulting their individual student models.

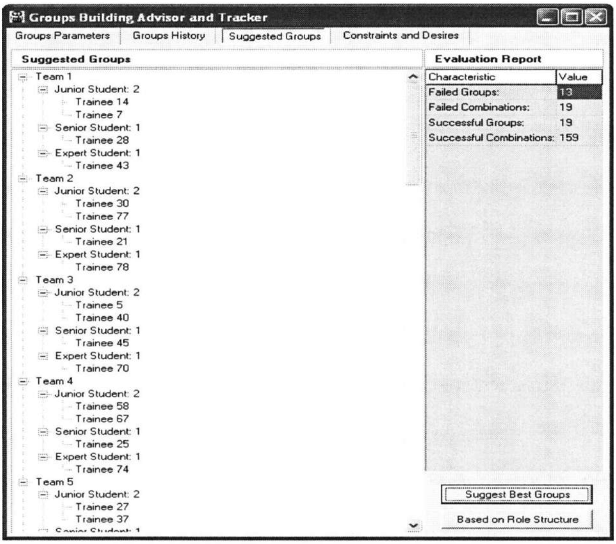


Figure 10.5. Form of the Group Formation Tool.

10.3.2. Empirical Study for Defining Appropriate Desired/Undesired Combinations of Stereotypes

We have conducted an empirical study on finding the most effective combinations between the user stereotypes. The empirical study included 50 experienced trainers. They were given a questionnaire in which they had to answer to questions concerning the desired combinations and undesired combinations of the personality-related stereotypes used in our system. The given questions were related to the ways they organize the trainees in their classes according to the individual characteristics they have traced. The trainers were also asked to justify their answers. The results are illustrated in figures 10.6 and 10.7.

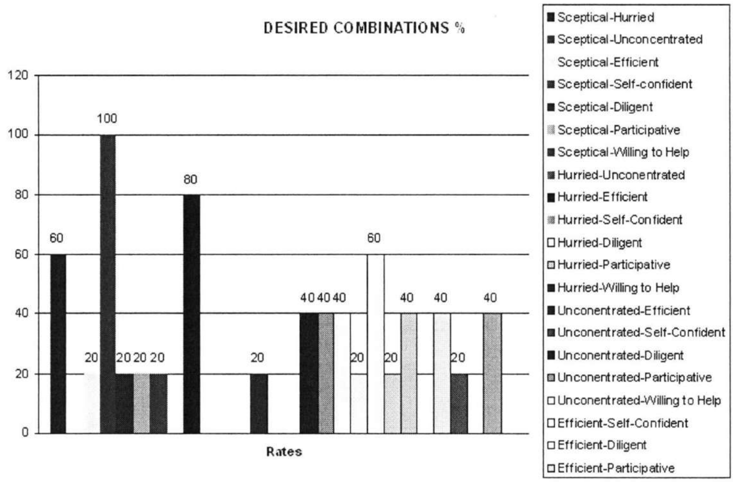


Figure 10.6. Results on Desired Combinations.

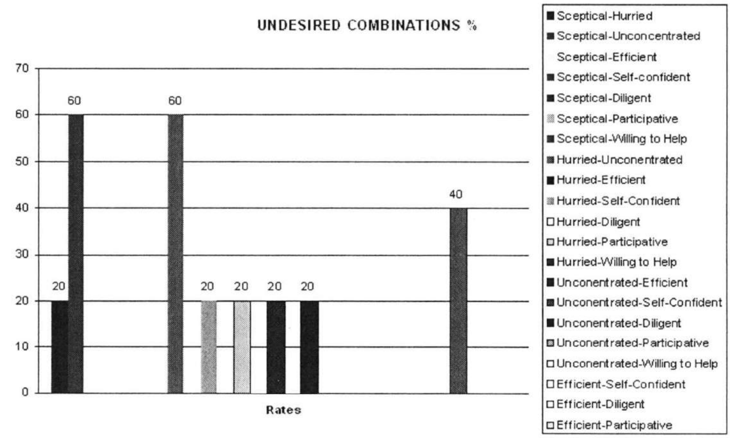


Figure 10.7. Results on Desired and Undesired Combination of Personality-Related Stereotypes.

In AUTO-COLLEAGUE, we decided to use as default combinations of stereotypes those with value more than 50%.

10.3.3. Using the Simulated Annealing Algorithm

The Simulated Annealing Algorithm

The search for the best solution is implemented using the Simulated Annealing (SA) algorithm (Kirkpatrick et al., 1983), which is a genetic algorithm that serves as a general optimization technique for solving combinatorial optimization problems. Simulated Annealing is motivated by the desire to avoid getting trapped in poor local optima, and hence, occasionally allows "uphill moves" to solutions of higher cost, doing this under the guidance of a control parameter called the temperature (Johnson et al., 1989).

The temperature is used in the acceptance probability that the algorithm evaluates to decide if a solution is acceptable. The initial value of the temperature is high and then reduced during the progress of the algorithm. There are, also, two maximum limits of repeats of the algorithm without finding a better solution per temperature value. The first limit indicates that the temperature must change. The second limit represents the termination criterion for the algorithm. The termination criterion can also be: temperature=0, instead of using a limit. The initial value of the temperature and its changes are controlled by the so-called cooling schedule/strategy. The cost of each solution generated is calculated by the objective/cost function.

The flow chart for the process of finding optimum groups of learners based on SA is illustrated in figure 10.8. The first step of the algorithm is to start with an initial solution. Then, this solution is evaluated using an objective/cost function. If the cost of the new solution is lower than the cost of the current solution, then the current solution is updated to the new solution. If not, then an additional criterion is applied based on the probability $p=\exp(-(\delta f)/T)$, where δf is the difference between the costs of the new solution and the initial solution. If p is larger than a random number between 0 and 1, then the current solution is updated to the new solution. Then, the algorithm will be repeated to this point until the temperature is to be changed (according to the cooling schedule). The next step will be to change the temperature and decide whether the search should be terminated according to the termination criteria. If the search should not be terminated, the algorithm is repeated.

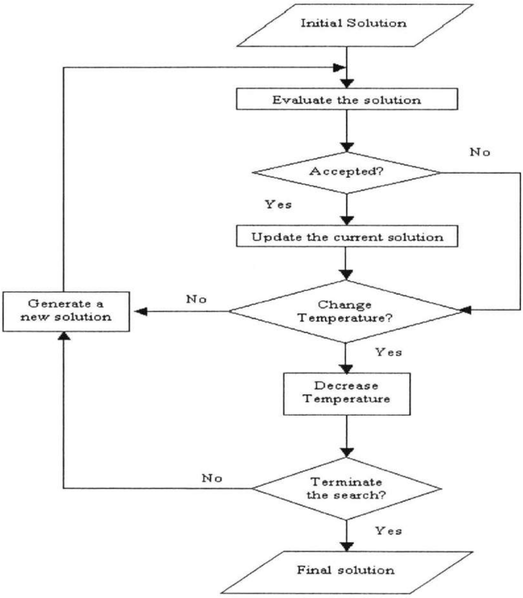


Figure 10.8. Flow chart for finding optimum groups based on SA

In order to apply the SA algorithm, it is necessary to define the configuration space, the method of finding the neighbourhoods, the objective function and the cooling schedule/strategy.

Configuration Space

The configuration space is the set of possible solutions. In our case, the possible solutions are all the possible organizations of the students into groups that satisfy the criteria related to the defined groups' structures, the desired and undesired combinations of personality-related stereotypes. If G is a finite set of the groups and U is a finite set of the students, then the solution space is the finite set O of P(GXU).

Finding Neighbourhoods

The method of finding the neighbourhoods concerns the way the next solution is calculated. In our implementation, there is a generator of random changes/perturbations in the combinations of students to form groups. This means that the next solution (the neighbour) will be the current solution with a random change/perturbation.

The initial solution given by the generator is a random grouping of the learners. It organizes all the trainees into groups according to the desired level of expertise structures of groups defined by the trainer of the system. For example, if there are 6 defined teams with specific levels of expertise, the generator will try to form 6 groups of learners with these levels of expertise. However, there may not be the adequate number of learners to meet the requirements of the groups' structure criterion in the configuration space. In this case, the generator will place the appropriate trainees to the groups it can and, then, complete the rest of the groups' members randomly (without considering their levels of expertise). Every next solution is generated after a random change (of the current solution) in the group membership of two learners randomly selected. This random change is, also, called perturbation of the current solution.

Objective/Cost Function

The objective/cost function refers to the method of evaluating the cost of the solution. The result of this function expresses how much it would cost to follow a solution. The greater the cost is, the more disadvantageous the solution will be Therefore, the algorithm condition of accepting a solution is satisfied when its cost is lower than the cost of the current solution. In our implementation, the objective/cost function returns an evaluation degree of the solution and is defined as:

$$f_{cost} : P(GXU) \to [-1,1], f_{cost}(x) = -\frac{f_{SC}(x) - f_{FC}(x)}{f_{TC}(x)}$$

$$f_{SC} : P(GXU) \to \mathbb{N}\,,\ f_{FC} : P(GXU) \to \mathbb{N}\,,\ f_{TC} : P(GXU) \to \mathbb{N} \tag{10.1}$$

where x is the solution, $f_{SC}(x)$ returns the number of successful combinations of the solution x, $f_{FC}(x)$ returns the number of failed combinations of the solution x and $f_{TC}(x)$ returns the total number of combinations of the solution x.

The successful/failed combinations are the combinations that are/are not in line with the desired combinations of stereotypes and the level of expertise structure of the groups defined by the trainer. The total number of combinations is not the sum of the successful and failed combinations, as the solution may include combinations that are neither successful nor failed.

The result of $f_{cost}(x)$ is a real number between –1 and 1. For example, if in the solution x there have been made 8 successful and 3 failed combinations out of a total of 12 combinations, then the result of the $f_{cost}(x)$ will be calculated as:

$$f_{cost}(x) = -\frac{8-3}{12} = -0.41\,. \tag{10.2}$$

Cooling Schedule

The cooling schedule/strategy is very important for the efficiency of the algorithm and is related to the definition of an initial temperature T for the algorithm and the ways of decreasing it during the searching. The most simple and commonly used cooling schedule is the exponential. According to it, T_{i+1}=a.T_i, where *a* is a constant, usually selected to be between 0.5 and 1. We have chosen to use a=0.9. A method commonly used for determining the initial value of the temperature is by calculating the formula:

$$T_0 = \frac{-\delta f^{+}}{\ln(p_0)}, \tag{10.3}$$

where T_0 is the initial temperature, δf^{+} is the average increase in cost for a number of random transitions (in our case random rearrangements of students into groups), and p_0 is the initial acceptance probability. A usual value used for p_0 is 0.8. For 15 random solutions, we found that the average increase in cost δf^{+} was approximately 4. Therefore, T_0 was calculated to be approximately 18.

10.4. Conclusions

In this chapter, we describe the intelligent recommendations offered to the trainer. These recommendations may be a useful toolkit for the often disregarded in similar learning environments trainer. The recommendations include (a) leadership style suggestions and (b) a group formation tool that proposes optimum organization of the trainees into groups.

The generation of the leadership style suggestions are based on the Hersey and Blanchard Situational Leadership Theory. This kind of recommendation viewing the trainer/teacher as a leader has never been implemented in learning environments. The system concludes to the most effective leadership style after calculating the maturity of the trainees for each assigned task. The maturity is a very crucial variable of this theory and very complicated to evaluate, as it is task specific and calculated considering both ability and personality related characteristics.

The aim of the optimum group formation is to suggest the most effective organization of the trainees into groups. The implemented grouping method is differentiated from other related group formation tools in:

- The criteria taken into consideration,
- The grouping method and
- The grouping algorithm.

The considered criteria are related to the desired and undesired combinations of knowledge, personality-related stereotypes in the same group. The affectivity of the group formation tool constitutes a major contribution of this thesis, as there is no other such tool to have use emotions for matching people. The criteria values for each trainee are evaluated automatically using student modelling techniques and the OCC theory for emotions. The grouping algorithm used is the Simulated Annealing algorithm (Kirkpatrick et al., 1983), which has not been used in similar situations.

11

EVALUATION EXPERIMENTS OF AUTO-COLLEAGUE

11.1. Introduction

In effort of checking the performance of AUTO-COLLEAGUE and make decisions on further improvements and extensions, we conducted two evaluation experiments with real users.

The first experiment was conducted in the University of Piraeus among 80 postgraduate students. The aim of this experiment was to evaluate the educational effectiveness of our system after applying the automatic group formation versus a random group formation.

The second experiment was conducted in a high school among 70 students of the software engineering class of the last grade. The aim of the evaluation was to have evidence on the successfulness of our choice to choose the Hersey and Blanchard Situational Leadership Theory, the way of calculating the maturity of the trainees and the adaptation of the intelligent recommendations provided by the system. To evaluate the effect of the use of our system's adaptation of the Hersey and Blanchard

Situational Leadership Theory versus a traditional class, we calculated the average increase rate of the ability and willingness (the variables that form the maturity).

11.2. Evaluating the Group Formation Tool

The aim of the evaluation experiment was to study the educational effectiveness of the intelligent recommendation to the trainer, that is the group formation tool.

The experiment took place in the University of Piraeus among 80 postgraduate students during the Software Engineering course. These postgraduate students were registered in the system as the trainees and the teacher of the course was registered as the trainer. The experiment consisted of two parts. At the first part the students were organized into 20 groups of 4 trainees in alphabetical order. At the second part the students were reorganized according to the proposed groups of trainees according to the results of the group formation tool.

Our purpose was to observe the effect that the recommended groups had on the performance of the trainees as individuals as well as groups. For this reason, the values of specific characteristics of the students during the first and the second part of the experiment were examined. These characteristics, which are related to the facets of stereotypes, are useless mouse movements and clicks frequency, average idle time, number of actions, error frequency, correct frequency, help utilization frequency, advice given frequency, help given to a member/non member of the group, help request from a member/non member of the group, communication frequency and number of upgrades/downgrades in level of expertise.

The trainees preceded two different tests, one during each part of the experiment. These tests were given in a wizard form as illustrated in figure 11.1.

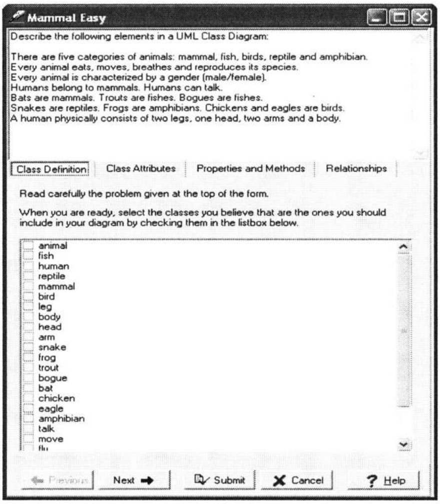


Figure 11.1. Test of the First Day of Experiment

Before giving these tests, the trainees attended two lessons of basics on UML. The second test was slightly more difficult than the first one, so that the degree of difficulty would not influence the results of the experiment. Additionally, the second test should be more difficult as the trainees would have more experience on UML after the first part of the experiment. The experienced teacher of the software engineering course authored these tests. The initial assignment of the level of expertise of all users was basics in both of the days of the experiment.

As the trainees were trying to solve the tests, they could send text messages to the members of their group. In this way they collaborated with each other and, simultaneously, the system traced these interactions to build their student models.

During the first day of the experiment, the 80 trainees were organized into 20 groups of 4 in alphabetical order. Every trainee was considered by the system as junior. Team 1 included Trainee1, Trainee2, Trainee3 and Trainee4. Team 2 included Trainee 5, Trainee6, Trainee7 and Trainee8 and so forth until Team 20.

For the second day, 20 teams of specific structure of roles were defined in the system. The structure of teams 1, 2, 3, 4 and 5 was: two juniors, one senior and one expert. The structure of teams 6, 7, 8, 9 and 10 was: one junior, two seniors and one expert. The structure of teams 11, 12, 13, 14 and 15 was: two juniors, two seniors and no expert. Finally, the structure of teams 16, 17, 18, 19 and 20 was: one junior, one senior and two experts. Furthermore, the desired and undesired combinations between stereotypes were defined as explained in chapter 10.

For the organization of the trainees into optimum groups, the administrator of the system ran the Groups Building form and started the group formation process. In the Evaluation Report, the results of the group organization are listed: 13 Failed Groups, 19 Failed Combinations, 19 Successful Groups and 159 Successful Combinations. In Table 11.1, we have listed the groups, the trainees, the level of expertise and the stereotypes that the system assigned them, the failed and the successful combinations related to their level of expertise (related to the role structure of the group) and the failed and the successful combinations related to the stereotypes.

Table 11.1. Trainees' Properties and Evaluation Results per Group After Optimum Group Suggestion

GROUP	TRAINEE	LEVEL OF EXPERTISE	STEREOTYPES	RELATED ON LEVEL OF EXPERTISE		RELATED ON STEREOTYPES		TOTAL	
				FAILED COMBINATIONS	SUCCESSFUL COMBINATIONS	FAILED COMBINATIONS	SUCCESSFUL COMBINATIONS	FAILED COMBINATIONS	SUCCESSFUL COMBINATIONS
Team 1	Trainee14	junior	sceptical, diligent	0	4	0	4	0	8
	Trainee7	junior	Hurried, participative						
	Trainee28	senior	self-confident						
	Trainee43	expert	participative, sceptical						
Team 2	Trainee30	junior	unconcentrated, diligent	0	4	0	3	0	7
	Trainee77	junior	unconcentrated						
	Trainee21	senior	efficient, diligent						
	Trainee78	expert	efficient, participative, willing to help						
Team 3	Trainee5	junior	hurried, participative, unconcentrated	1	3	1	6	2	9
	Trainee40	junior	sceptical, diligent						
	Trainee45	senior	efficient, self-confident						
	Trainee70	senior	efficient						
Team 4	Trainee58	junior	sceptical	0	4	0	3	0	7
	Trainee67	junior	hurried, participative						
	Trainee25	senior	self-confident, willing to help, participative						
	Trainee74	expert	diligent, efficient						
Team 5	Trainee27	junior	participative, unconcentrated	0	4	1	3	1	7
	Trainee37	junior	hurried, participative, diligent						

	Trainee17	senior	efficient						
	Trainee63	expert	diligent, willing to help, participative						
Team 6	Trainee1	junior	hurried, participative, diligent	1	3	0	7	1	10
	Trainee23	senior	hurried						
	Trainee31	senior	efficient, diligent						
	Trainee38	senior	efficient, sceptical						
Team 7	Trainee41	junior	unconcentrated, hurried, self-confident	0	4	1	4	1	8
	Trainee18	senior	sceptical						
	Trainee8	senior	efficient, participative						
	Trainee16	expert	efficient, participative						
Team 8	Trainee3	junior	unconcentrated, participative, diligent	0	4	2	3	2	7
	Trainee47	senior	self-confident, diligent, sceptical						
	Trainee9	senior	willing to help, participative, self-confident						
	Trainee22	expert	efficient						
Team 9	Trainee20	junior	unconcentrated, hurried	1	3	1	4	2	7
	Trainee52	senior	self-confident, willing to help						
	Trainee65	senior	sceptical, diligent, participative						
	Trainee72	senior	efficient, participative						
Team 10	Trainee66	junior	participative	0	4	0	5	0	9
	Trainee36	senior	sceptical, diligent						
	Trainee55	senior	hurried, diligent						
	Trainee26	expert	self-confident, willing to help, diligent, efficient						
Team 11	Trainee49	junior	participative, self-confident	0	4	0	2	0	6
	Trainee64	junior	hurried						
	Trainee10	senior	efficient, participative						
	Trainee75	senior	diligent, self-confident						
Team 12	Trainee54	junior	sceptical, diligent	0	4	1	4	1	8
	Trainee80	junior	participative, diligent						
	Trainee60	senior	self-confident, diligent						
	Trainee76	senior	willing to help, efficient						
Team 13	Trainee4	junior	sceptical, participative	0	4	1	6	1	10
	Trainee42	junior	hurried, self-confident, diligent						
	Trainee53	senior	willing to help, participative, diligent, self-confident						
	Trainee59	senior	efficient, diligent						
Team 14	Trainee15	junior	unconcentrated, participative, hurried	0	4	2	5	2	9
	Trainee12	junior	diligent, sceptical, self-confident						
	Trainee33	senior	diligent, willing to help, participative						
	Trainee79	senior	sceptical, participative, efficient						
Team 15	Trainee51	junior	participative, hurried	0	4	1	7	1	11

	Trainee56	junior	hurried, diligent, willing to help						
	Trainee68	senior	efficient, hurried						
	Trainee71	senior	self-confident, diligent, participative, sceptical						
Team 16	Trainee6	junior	unconcentrated, diligent	0	4	1	5	1	9
	Trainee34	senior	diligent, participative						
	Trainee11	expert	self-confident, participative, efficient						
	Trainee57	expert	efficient, willing to help, diligent						
Team 17	Trainee29	junior	hurried, participative	1	3	0	4	1	7
	Trainee32	senior	efficient, self-confident, participative						
	Trainee48	senior	self-confident, diligent, participative						
	Trainee24	expert	self-confident, efficient						
Team 18	Trainee39	junior	sceptical, participative	0	4	0	6	0	10
	Trainee62	senior	willing to help, hurried, diligent						
	Trainee13	expert	efficient, participative, diligent						
	Trainee61	expert	efficient, sceptical						
Team 19	Trainee50	junior	unconcentrated, hurried	1	3	0	3	1	6
	Trainee46	senior	self-confident, diligent						
	Trainee69	senior	participative, diligent						
	Trainee44	expert	self-confident, efficient						
Team 20	Trainee35	junior	participative, willing to help	2	2	0	2	2	4
	Trainee73	junior	hurried, unconcentrated						
	Trainee19	senior	diligent, participative, willing to help						
	Trainee2	senior	efficient, willing to help						
			TOTAL	7	73	12	86	19	159

In order to evaluate the effect of this organization of the trainees, we gathered the values of some critical trainee characteristics during the first and the second day of the experiment. These characteristics are cited in table 11.2 and figure 11.2 and concern the upgrades of the trainees in the level of expertise and the number of errors they made. The upgrades in the level of expertise express the progress of the trainee in UML. They indicate the times that the system assigned the trainee to a better level of expertise stereotype.

Table 11.2. Values of Trainees' Characteristics per Day of Experiment.

	Upgrades In Level Of Expertise		Number of Errors	
	Day 1	Day 2	Day 1	Day 2
Trainee1	1	2	12	7
Trainee2	2	2	10	9
Trainee3	1	1	18	21
Trainee4	1	2	15	9
Trainee5	0	1	24	15
Trainee6	0	0	25	22
Trainee7	1	1	14	12
Trainee8	2	2	10	8
Trainee9	2	2	11	10
Trainee10	2	3	12	1
Trainee11	3	3	2	4
Trainee12	1	1	23	22
Trainee13	3	3	4	3
Trainee14	1	1	22	20
Trainee15	0	0	28	25
Trainee16	3	1	2	18
Trainee17	2	1	10	17
Trainee18	2	2	12	10
Trainee19	2	0	13	27
Trainee20	1	1	21	19
Trainee21	2	2	14	13
Trainee22	3	1	3	14
Trainee23	2	1	9	13
Trainee24	3	3	2	2
Trainee25	2	3	9	2
Trainee26	3	2	5	9
Trainee27	1	1	14	12
Trainee28	2	2	13	11
Trainee29	1	1	18	15
Trainee30	1	1	16	16
Trainee31	2	2	8	6
Trainee32	2	3	9	1
Trainee33	2	2	7	7
Trainee34	2	2	10	8
Trainee35	1	1	15	16
Trainee36	2	1	10	9
Trainee37	1	0	20	23
Trainee38	2	1	14	19
Trainee39	1	1	16	17
Trainee40	1	0	19	24
Trainee41	0	1	22	13
Trainee42	1	1	18	17
Trainee43	3	3	5	1
Trainee44	3	3	5	2
Trainee45	2	1	12	14

Trainee46	2	2	8	6
Trainee47	2	2	14	13
Trainee48	2	0	12	21
Trainee49	1	2	18	8
Trainee50	1	0	20	22
Trainee51	1	2	15	10
Trainee52	2	3	6	1
Trainee53	2	0	12	21
Trainee54	1	1	17	15
Trainee55	2	2	11	9
Trainee56	1	1	12	10
Trainee57	3	2	5	10
Trainee58	1	3	18	3
Trainee59	2	3	6	2
Trainee60	2	0	12	21
Trainee61	3	3	4	3
Trainee62	2	1	7	14
Trainee63	3	3	4	0
Trainee64	1	1	20	18
Trainee65	2	2	8	6
Trainee66	1	1	19	13
Trainee67	1	1	17	14
Trainee68	2	3	8	1
Trainee69	2	3	9	0
Trainee70	2	0	12	25
Trainee71	2	2	12	11
Trainee72	2	1	10	14
Trainee73	1	0	20	21
Trainee74	3	2	4	8
Trainee75	2	1	11	13
Trainee76	2	3	6	2
Trainee77	1	0	19	24
Trainee78	3	3	4	1
Trainee79	2	1	12	13
Trainee80	1	1	19	18

After analyzing these results, we calculated that:

- 30% of the trainees presented no difference,
- 65% of the trainees presented progress and
- 4% of the trainees presented reduction in their level of expertise comparing the two days of the experiment.

Furthermore, as far as number of errors is concerned:

- 1.25% of the trainees presented no difference
- 90% presented reduction and
- 8.75% presented increase in the number of errors.

As a conclusion, it seems that the organization into groups that the system proposed is effective for the majority of the trainees that participative in the experiment.

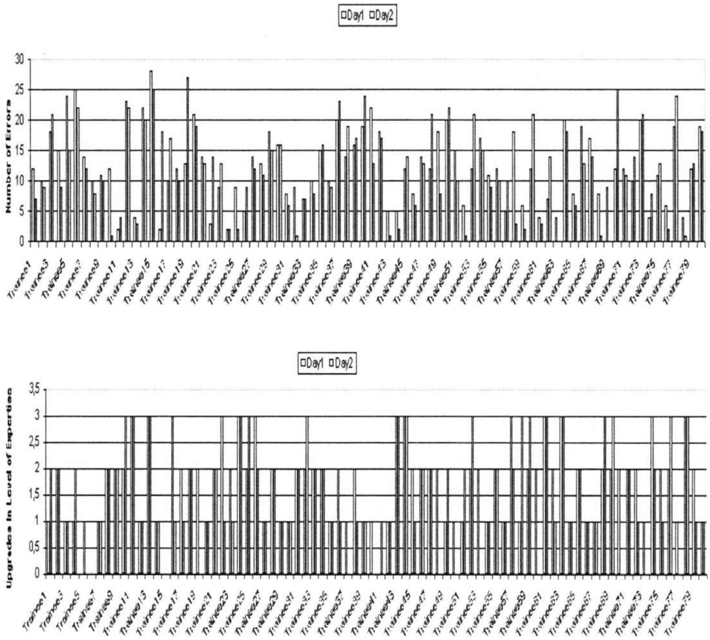


Figure 11.2. Values of Trainees' Characteristics per Day of Experiment

11.3. Evaluating the Adaptation of the Hersey and Blanchard Situational Leadership Theory

The aim of the evaluation was to have evidence on the successfulness of:

- Our choice to choose the SLT,
- Our way of calculating the maturity of the trainees and
- The adaptation of the intelligent advice provided by the system.

We found that we could draw such conclusions by calculating the trainees' performance concerning their maturity (ability, willingness) during a task. The ideal case for a trainee would be to begin with the R1 maturity level and end up to the R4 maturity level. Therefore, we decided to compare this kind of results between a traditional class and a class where AUTO-COLLEAGUE would be used.

The evaluation experiment was conducted with the participation of 70 students of the software engineering class of the last grade of a Greek high school in Athens. The students were organized into 14 groups of 5 trainees in alphabetical order. The teacher of the class was assigned as the trainer. She was an experienced trainer, who has worked as a teacher of Informatics for the last 9 years. She has also studied the SLT in order to be able to apply the system's advice on leadership style effectively. We wanted the trainer to be the most objective as possible, so we selected trainees that had not been taught by her in the past.

Before the experiment the students attended one traditional preliminary course on the basics of UML class diagrams and activity diagrams. The trainer was asked to complete the estimated willingness values of the trainees in a given report form selecting a number between 0 and 10. These values were the initial willingness values assigned to the trainees for the experiment. At the end of this course, the trainees had two tests on the teaching material separately on UML class diagrams and UML activity diagrams. The results on these tests were the initial ability values assigned to the trainees for the experiment's stages.

The experiment was conducted in 2 stages. During the first stage the trainees attended a laboratory course on UML using AUTO-COLLEAGUE. During the second stage they attended a traditional laboratory course. We decided to place AUTO-COLLEAGUE at the first stage in order to avoid socio-emotional influences to the trainer caused by an earlier contact with the trainees, something that would affect her objectiveness. The trainer and the trainees were the same in both stages of the experiment. The trainees were assigned one task in UML class diagrams in the first stage and one task of similar difficulty in UML activity diagrams in the second stage. These tasks were exercises/tests on drawing UML diagrams given the description of a situation and were authored by the trainer. We decided to use different teaching material for the 2 stages of the experiment, because, in a different case, the increase rates in ability and willingness of the second stage would be affected by the progress already achieved by the trainees during the first stage.

During the first stage the ability and willingness variables were calculated by the system. During the second stage the trainer defined these values in a report form we gave her. The difference between the values of ability at the end and at the beginning of each stage was recorded to find the increase rate in the ability for each trainee per stage of the experiment. Similarly, the difference between the values of willingness at the end and at the beginning of each stage was tracked to calculate the increase rate in the willingness of each trainee per stage of experiment. An indicative sample of these results is shown in table 11.3. We, also, calculated the average of increase rates in ability and willingness separately for all the trainees per stage. The results are presented in table 11.4 and figure 11.3.

Table 11.3. Sample of calculated ability and willingness values per stage.

	Stage 1						Stage 2					
	Ability			Willingness			Ability			Willingness		
Trainee	**Initial**	**Ending**	**Increase %**	**Initial**	**Ending**	**Increase %**	**Initial**	**Ending**	**Difference %**	**Initial**	**Ending**	**Difference %**
Trainee 1	0.42	0.71	**29%**	0.3	0.5	**20%**	0.38	0.52	**14%**	0.3	0.4	**10%**
Trainee 2	0.68	0.82	**14%**	0.4	0.82	**42%**	0.62	059	**-3%**	0.4	0.3	**-10%**
Trainee 3	0.53	0.63	**10%**	0.6	0.69	**9%**	0.61	0.67	**6%**	0.6	0.6	**0%**

Table 11.4. Average increase rates in ability and willingness per stage

Stage 1		Stage 2		Difference between the 2 Stages	
Ability	Willingness	Ability	Willingness	Ability	Willingness
87%	79%	58%	63%	29%	16%

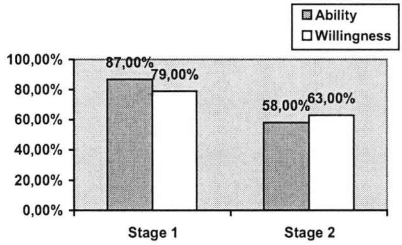


Figure 11.3. Average Increase Rates in Ability and Willingness per Stage of Experiment

The difference between the first (use of AUTO-COLLEAGUE) and the second (traditional laboratory course) stage of the experiment in the average increase rate of ability was 29% and of willingness was 16%. These results indicate the successfulness of AUTO-COLLEAGUE on both the ability and willingness in comparison with the educational outcome of a traditional class. Though quite satisfying, the difference in the average increase rate of the willingness was much less than this of ability claiming that perhaps we should reconsider the way of calculating the willingness values of the trainees or add additional stereotypes that affect willingness.

11.4. Conclusions

AUTO-COLLEAGUE was evaluated in real-time with real users in order to check the validity and effectiveness of our work.

The first experiment was conducted in the University of Piraeus among 80 postgraduate students. The aim of this experiment was to evaluate the educational effectiveness of our system after applying the automatic group formation versus a random group formation. The results were positive, as 30% of the trainees presented no difference, 65% of the trainees presented progress and 4% of the trainees presented reduction in their level of expertise comparing the two stages of the experiment (automatic and random group formation). In addition, 1.25% of the trainees presented no difference, 90% presented reduction and 8.75% presented increase in the number of errors comparing the two stages of the experiment. It must be noted that the version of the evaluated system did not included at that time the affective criteria. As a conclusion, we had evidence on the effective results of our automatic group formation towards the performance of the trainees in UML.

The second experiment was conducted in a high school among 70 students of the software engineering class of the last grade. The aim of the evaluation was to have evidence on the successfulness of our choice to choose the Hersey and Blanchard Situational Leadership Theory, the way of calculating the maturity of the trainees and the effectiveness of the intelligent recommendations provided by the system.

The difference between the first (use of AUTO-COLLEAGUE) and the second (traditional laboratory course) stage of the experiment in the average increase rate of ability was 29% and of willingness was 16%. These results indicate the effectiveness of the use of the Hersey and Blanchard Situational Leadership Theory on both the ability and willingness in comparison with the educational outcome of a traditional class. However, these results may suggest that we should reconsider the way of calculating the willingness values of the trainees or add additional personality-related stereotypes that affect the calculation of willingness.

12

CONCLUSIONS AND CONTRIBUTIONS OF THE RESEARCH

12.1. Contributions to Intelligent Computer Supported Collaborative Learning Environments

The contributions of the system presented in this thesis are related to:

- The personality-related characteristics included in the student models and, especially, the way they are automatically traced and evaluated,
- The affectivity implemented to recommend optimum groups of trainees and
- The use of a leadership theory, and specifically the Hersey and Blanchard Situational Leadership Theory, for adapting intelligent recommendations in a learning environment.

12.1.1. Personality-Related Characteristics and Affective Features

A novelty presented in this thesis concerning Intelligent Computer Supported Collaborative Learning environments is the personality-related characteristics it automatically traces and the way perceived emotions are used to infer optimum groups of learners. There is no other CSCL system to have used emotional affect and/or similar to ours personality characteristics that are automatically traced.

The student models built in our system describe the student in three aspects: the *level of expertise*, the *personality* and the *emotional state*. The level of expertise describes in detail the knowledge level of the trainee on UML. The personality related stereotypes used in the system are: self-confident, diligent, participative, willing to help, sceptical, hurried, unconcentrated and efficient. There are studies proving that embedding human personality characteristics into the computer interface would enhance the users' performance, as well as the outcomes of the human-computer interaction (Richter & Salvendy, 1995; Murray & Bevan, 1985; Rothrock et al., 2002). The emotional states represent whether the trainee is experiencing more positive or negative emotions. They are automatically predicted using the OCC cognitive theory of emotions (Ortony, Clore & Collins, 1988). The emotional states are used for drawing conclusions about the emotional influence that the trainees have to each other while collaborating. Then, these conclusions are used as criteria for the group formation tool in order to match the trainees depending on their emotional interaction.

This structure simulates the information collected by a human teacher either consciously or unconsciously. A teacher would certainly evaluate the performance of the students concerning the curriculum to be taught through questions, exercises and tests. The teacher would also attempt to recognize personality characteristics of the students aiming at adapting his/her behavior towards them. Usually, the teacher tries to understand the students' emotions while interacting with them in order to approach them accordingly. In some other cases where group work is involved, the teacher would additionally observe the emotional influence between the students, aiming at arranging groups in the most effective way.

Most of the existing CSCL systems base their inferences on the performance and the collaborative attitudes (e.g. participation). There are other systems that consider domain independent data, such as learning styles, but not similar to the personality characteristics used in our system. Most of these related systems do not evaluate automatically their domain independent data. Instead, they use relative questionnaires and psychometric instruments (Carver et al., 1999; Shang, Shi & Chen, 2001; Bajraktarevic, Hall & Fullick, 2003; Wolf, 2003; Papanikolaou et al., 2003; Brown & Brailsford, 2004) or explicitly receive them as input (de Bra & Calvi, 1998; Stash et al., 2006; Grigoriadou et al., 2001). However, it should be emphasized that the use of such psychometric instruments needs caution, as in some cases reliability can be low (Lawrence & Martin, 2001) and learning styles are likely to change over time (Kolb, 1984; Gonyeau et al., 2006). In AUTO-COLLEAGUE, the personality characteristics are inferred automatically during the collaborative learning activities.

Regarding affective intelligent learning systems, there has been a recent interest in recognizing the students' emotions. However, the recognized students' emotions have been used mainly for animated pedagogical agents (Gratch & Marsella, 2001; Jaques & Vicari, 2007; Lester et al., 1999; Craig et al., 2004; Jaques et al., 2004; Elliott et al., 1999; Nkambou, 2006) and affective system responses, support and adaptation (Katsionis & Virvou, 2005; Moridis & Economides, 2008b; Poel et al., 2004; Leontidis et al., 2009; Conati & Zhou, 2004). Especially about CSCL and affective computing, Dillenbourg notices that: "affective and motivational aspects that influence collaborative learning have been neglected by experimental CSCL researchers" (Dillenbourg et al., 2009). To our knowledge, there is no CSCL system yet that predicts or uses emotions.

12.1.2. Using the Hersey and Blanchard Situational Leadership Theory

An important contribution of this thesis to Intelligent Computer Supported Collaborative Learning environments is based on the fact that no other learning environment has ever used any leadership theory to adapt intelligent recommendations or suggest to the trainer the most effective leadership style.

A usually neglected aspect in education is teacher leadership. Teacher leadership is considered essential, however it is often neglected and somehow meets impediments (Gabriel, 2005; Barth, 2001; Wilmore, 2007; York-Barr & Duke, 2004; Suranna & Moss, 1999). Aiming at providing support to the trainers focusing on their leadership roles in the virtual classroom, we studied relative literature on leadership theories. We decided to use the Hersey-Blanchard Situational Leadership Theory (Hersey et al., 2007), because it has gained general acceptance and can be incorporated as a computational model due to its simple nature (Vasu et al., 1998; Baker, 2009). Additionally, there are studies that suggest the adaptation of this theory in education (Hersey et al., 1982; Donahoo & Hunter, 2007; Weber & Karman, 1991). According to the Hersey-Blanchard Situational Leadership Theory, leaders should continually adjust their leadership styles depending on the maturity or readiness of the followers. Maturity is a variable defined by the ability and the willingness of the followers. Ability is related to the knowledge, skills and experience of a follower to complete a given task. Willingness concerns the degree of readiness, motivation and self-confidence of a follower to accomplish a given task. Another crucial element of the theory is that the maturity is dependent on each task given to the follower, rather than a global variable. Hersey and Blanchard have defined four different levels of maturity and four leadership styles (one for each maturity level).

In the adaptation of the Hersey and Blanchard Situational Leadership Theory implemented in AUTO-COLLEAGUE, the followers are the trainees and the leaders are the trainer and the system itself as it serves pedagogical functions while interacting with the trainees. The appearance and frequency of the recommendation messages are adapted to the trainees according to their maturity levels and following the principles imposed by the respective leadership style. The system also suggests to the trainer the estimated appropriate leadership style to follow per trainee and per task according to the calculated trainee's maturity.

12.2. Contributions to Group Formation Tools

The contributions of our research in Group Formation Tools are found in the (a) criteria of matching the trainees, (b) the way of calculating these criteria and (c) the algorithm used.

An important but often neglected aspect in Computer-Supported Collaborative Learning is the formation of learning groups (Mühlenbrock, 2005). There are many studies that highlight the importance of group formation in collaborative learning tools (Daradoumis et al., 2002; Inaba et al., 2000). However, there are few experimental studies that provide automatic group formation. Most of them are stand-alone group formation tools (Christodoulopoulos & Papanikolaou, 2007; Graf & Bekele, 2006; Cavanaugh et al., 2004; Wang et al., 2007; Gogoulou et al., 2007a; Martin & Paredes, 2004; Ounnas et al., 2009; Khandaker & Soh, 2010; Paredes et al., 2009; Kyprianidou et al., 2009) and few of them are integrated tools in CSCL systems (Soh et al., 2006; Liu et al., 2008; Ikeda et al., 1997; de Faria et al., 2006; Kreijns et al., 2002).

In almost all of these group formation tools, the group formation method is homogeneous and/or heterogeneous according to a variety of characteristics, such as knowledge, skills, performance, learning styles and social skills. The group formation tool presented in this thesis uses a novel approach in the considered criteria, which are related to (a) the desired and undesired combinations of personality-related stereotypes in the same group, (b) the desired group structure concerning the levels of expertise and (c) the observed by the system emotional affect between the trainees. The desired/undesired combinations of stereotypes are the pairs of personality-related stereotypes that their coexistence in the same groups would have a positive/negative influence on the performance of the individual trainees and of the groups. The default combinations are the outcome of an empirical study. The desired group structure concerns the number and kinds of levels of expertise (basics, junior, senior and expert) that should constitute each group. The emotional affect between the trainees is related to the observed emotional state during the collaboration of a trainee with the members of the same group. AUTO-COLLEAGUE includes an emotion recognition agent that infers the overall emotional state of the trainees adapting the OCC Theory of emotions (Ortony, Clore & Collins, 1988).

The majority of the existing group formation tools do not evaluate in real-time the criteria values (student characteristics) of their group formation algorithm. They receive it as input by the instructor of the systems or evaluate them based on scientific instruments, such as psychometric tests (Christodoulopoulos & Papanikolaou, 2007; Graf & Bekele, 2006; Cavanaugh et al., 2004; Wang et al., 2007; Gogoulou et al., 2007a; Martin & Paredes, 2004; Ounnas et al., 2009; Paredes et al., 2009; Kyprianidou et al., 2009). On the contrary, in our system, all criteria values are evaluated automatically.

The existing group formation tools use a wide range of searching algorithms and techniques for grouping, such as the Fuzzy C-Means algorithm, Ant Colony Optimization, hill-climbing, semantic web technologies, randomized and genetics algorithms. In AUTO-COLLEAGUE, the grouping algorithm, used for the first time in related systems, is the Simulated Annealing algorithm (Kirkpatrick et al., 1983). It is a genetic algorithm that serves as a general optimization technique for solving combinatorial optimization problems. In the case of forming groups of students according to such a variety of characteristics (which means large search space), the use of the Simulated Annealing Algorithm seems to fit properly.

12.3. Evaluation Results

AUTO-COLLEAGUE was evaluated in real-time with real users in order to check the validity and effectiveness of our work.

The first experiment was conducted in the University of Piraeus among 80 postgraduate students. The aim of this experiment was to evaluate the educational effectiveness of our system after applying the automatic group formation versus a random group formation. The results were positive, as 30% of the trainees presented no difference, 65% of the trainees presented progress and 4% of the trainees presented reduction in their level of expertise comparing the two stages of the experiment (automatic and random group formation). In addition, 1.25% of the trainees presented no difference, 90% presented reduction and 8.75% presented increase in the number of errors comparing the two stages of the experiment. It must be noted that the version of the evaluated system did not included at that time the affective criteria. As a conclusion, we had evidence on the effective results of our automatic group formation towards the performance of the trainees in UML.

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The difference between the first (use of AUTO-COLLEAGUE) and the second (traditional laboratory course) stage of the experiment in the average increase rate of ability was 29% and of willingness was 16%. These results indicate the effectiveness of the use of the Hersey and Blanchard Situational Leadership Theory on both the ability and willingness in comparison with the educational outcome of a traditional class. However, these results may suggest that we should reconsider the way of calculating the willingness values of the trainees or add additional personality-related stereotypes that affect the calculation of willingness.

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