A Situation-aware Learning System based on Fuzzy Cognitive Maps to increase Learner Motivation and Engagement

Giuseppe D'Aniello
Dip. Ingegneria dell'Informazione ed Elettrica e Matematica Applicata
University of Salerno
Fisciano, SA, Italy
gidaniello@unisa.it

Massimo De Falco
DISA-MIS
University of Salerno
and *CORISA*
Fisciano, SA, Italy
mdefalco@unisa.it

Matteo Gaeta
Dip. Ingegneria dell'Informazione ed Elettrica e Matematica Applicata
University of Salerno
Fisciano, SA, Italy
mgaeta@unisa.it

Mario Lepore
Consorzio di Ricerca Sistemi ad Agenti
CORISA
Fisciano, SA, Italy
marlep@corisa.it

***Abstract*— The lack of motivation and engagement is recognized as one of the main causes of learners dropping out of e-learning systems. In this paper, an Adaptive Learning System, based on the principles of situation awareness, is proposed to tackle such an issue. The work proposes a situation model based on motivation and engagement. A technique based on Fuzzy Cognitive Map (FCM) has been defined to identify the current situation by tracking the behavior and the interactions of the learner with the system. The FCM drives the process of feedback generation to improve the situation awareness of the learner, and therefore their motivation and engagement. The system has been evaluated using the Situation Awareness Global Assessment Technique, involving students and teachers. The experimental results demonstrate that the system is able to significantly improve the situation awareness of both learners and teachers, reducing the risk of learner dropout.**

Keywords*— *Fuzzy Cognitive Map; Situation Awareness; e-Learning;

I. Introduction

The experience of a learner in an e-learning environment is not only influenced by the learning contents delivered by the platform, but it is also strongly influenced by extrinsic factors (like the overall learning process, the interactions with the platform, the interface) and by intrinsic factors like the emotional state of the learner and the social aspects. If we analyze many e-learning platforms, it is not rare to find many students who leave the learning course, also shortly after the beginning. Such a phenomenon, called "dropout", is always more frequent among the students who are not sufficiently engaged and motivated with the learning experience [1].

The root causes of students dropping out are the lack of motivation and engagement [2], [3]. The motivation takes into account the level of interest in the course while the engagement represents the level of involvement in the learning experience with the platform. For these reasons, a modern learning platform cannot be limited to the simple learning content delivery task, but it should support the learners in their whole learning experience, leading them to successfully reach their learning objectives. To do so, a learning platform should be adaptive, in the sense that it should provide each learner with the contents, feedback, suggestions, and experience which are tailored to her current learning state [4] [5].

This work proposes an adaptive e-learning system based on the use of a Fuzzy Cognitive Map (FCM) for the identification of the current situation of the student. The situation, for our purposes, represents the current state of the learner, primarily in terms of engagement and motivation. The situation is identified by analyzing the behavior and the interactions of the learner with the system. The objective of the system is to maintain a high level of engagement and motivation for all the students. This is achieved by means of a feedback generation technique, which sends personalized feedback to each learner according to the specific current situation. The main novel contributions of the paper are: a conceptual architecture of the learning system; a conceptual definition of the situation in the context of e-learning system; a semantic model of the learner's situation; a technique, based on FCM, for the identification of the situation; a feedback generation process. The system has been evaluated with an experiment involving students and teachers by applying the Situation Awareness Global Assessment Technique (SAGAT) [6] to measure the improvement in the level of Situation Awareness of the participants.

II. Background Knowledge

A. Motivation and Engagement in e-Learning

Many scholars have dealt with the issue of student dropout, trying to find the main reasons of this phenomenon. Jun [7] focused on the main causes of dropout and proposed a survey of the main works in this field, classified in: individual background, motivation, academic integration, social integration, technological support. Other relevant works [8][9][10][11] discuss the role of motivation and engagement in the learning process and demonstrate that they are strongly related to the dropout. What emerges from the literature is that the motivation of a learner can be classified into three categories [9]: intrinsic, extrinsic, and social. Intrinsic motivation means that the learner undertakes a new course just for the pleasure in making it, because it is considered rewarding and motivating in itself. The extrinsic motivation means that the learning activity

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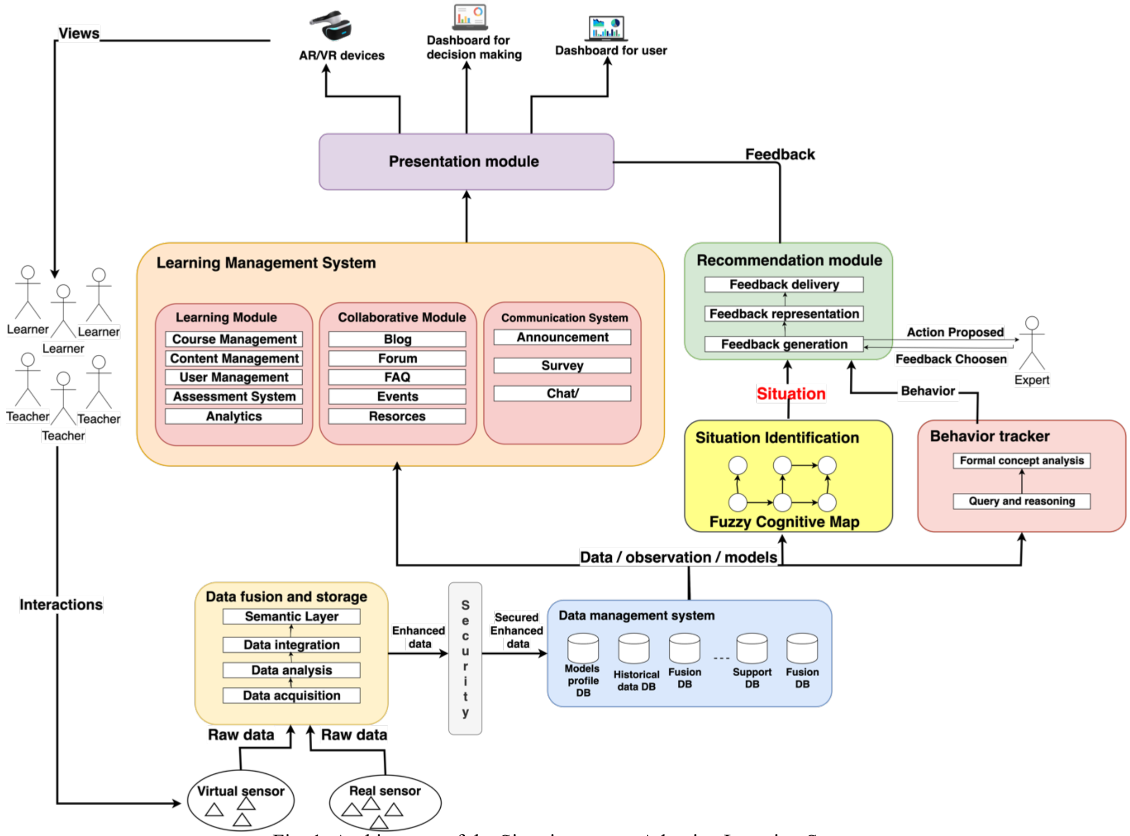

Fig. 1. Architecture of the Situation-aware Adaptive Learning System.

is carried on due to reasons that are external, for instance, to receive an acknowledgment, a certificate, a good vote or to avoid a bad situation like a rebuke. Social motivation leads the learner to take part in activities only to meet new people with similar interests or to make activities together with a friend, even if there is no interest in the activity per se.

The engagement, instead, represents the availability of the learner to participate in routine activities like following lessons, completing the assignment, following the teacher. However, recently the term is used also to describe the involvement of the learner in the whole learning environment. This means involvement in all the tools of a platform, like lessons, quiz, assignment, social tools, messaging, forum, etc. The engagement can be active (learner actively participates in the learning environment by publishing posts in the forum, asking questions, etc.); passive (the learner only answers or vote the posts of other users; she follows the lessons but without asking questions, etc.); disengagement, when the learner has poor participation and interest in the course [12]. The motivation is strictly related to engagement [9]. The motivation can predict the engagement of the learner, while the engagement can predict the retention of the learner in the course.

B. *Situation Awareness*

The Situation Awareness (SA), as defined by Endsley in [13], is the capability of perceiving what is happening around us, comprehend the meaning of the perceived information according to our goal, and to predict how it can be used in the next future to make a decision or take an action. Endsley's model of SA consists of three levels. Level 1 (Perception) concerns the capability of perceiving the information from the environment through our senses. Level 2 (Comprehension) is the capability of understanding the meaning of the perceived information concerning a given goal. Level 3 (Projection) is the capability of the user to predict, according to what has been understood, the possible future evolution of the environment. To support the SA of the system's operators, a proper design of the system should be realized, paying particular attention to the user interface. A set of design principles to define software systems for supporting SA has been proposed in [6].

III. ADAPTIVE LEARNING SYSTEM

This section describes the main characteristics of the Adaptive Learning System. We have collaborated to the design and development of this system during the Research & Development Project "MOLIERE". One of the objectives of this project is the adoption of a motivational approach to support learning by creating an engaging experience, with the aim of reducing the student dropout. The conceptual architecture of the Adaptive Learning System is sketched in Fig. 1. The architecture has been developed following the design principles of situation awareness [6]. The architecture was organized into tiered subsystems: i) Data fusion and storage; ii) Data management system; iii) Learning Management system; iv) Situation Identification Module v) Behavior tracker; vi) Recommendation module; vii) Presentation module. Real and virtual sensors are needed to record the interactions of the students with the system and to monitor her facial expressions during the use of the system, useful for identifying the situation. The Data fusion and storage level deals with acquiring the raw data provided by the sensors, analyzing and integrating them. Such elaborated data are transferred, after been semantically enriched and secured (Security Layer), to the Data management system. Such subsystem includes relational databases and triple stores capable of storing the data and models that are used by the Learning Management System (LMS), Situation Identification Module, and the Behavior tracker. The LMS includes the modules necessary for the classic services of an e-learning system such as Course Management, User Management, Blog, Forum, Chat, etc. The Situation Identification Module contains the Fuzzy Cognitive Map (FCM) used to identify the current situation in terms of motivation and engagement. The Behavior Tracker subsystem acquires data, observations and models which are examined and processed in order to produce useful knowledge to derive user behavior on the platform, through Formal Concept Analysis (FCA) processes and reasoning on semantic models. Specifically, it is useful for extracting some behavioral patterns to identify dropout risks. The Recommendation module aims at producing and forwarding adaptive and personalized feedback useful for maintaining adequate levels of engagement and motivation in order to limit the phenomenon of learner dropout on the platform. The modules of this subsystem are: Feedback generation, Feedback representation and Feedback delivery. The Feedback generation module generates feedback based on the current learner situation identified by the Situation Identification Module with the FCM. The Feedback representation module has the task of visually constructing the feedback based on the target device, for example by appropriately choosing icons, colors, and text to enhance its meaning and to facilitate the understanding. The third module, Feedback delivery, has the function of transferring the feedback generated to the Presentation module, towards the device of the user (e.g., a mobile device, an augmented reality device, or a classic PC). The generation of feedback in batches, at a pre-established frequency, for instance, weekly, involves the use of data from the Situation Identification and Behavior tracker modules. Feedback can be generated automatically or through the teacher's supervision. For the generation of real-time feedback, the data are provided in a continuous stream to the Recommendation module for an on-the-fly analysis; however, these data are also stored in the system for subsequent long-term analysis. The Presentation module is the subsystem that deals with the display of information to users according to the models and principles of Situation Awareness and Goal-Directed Task Analysis [6].

The prototype platform has been designed and implemented from scratch and it is based on a series of open-source solutions. The web infrastructure is developed using the Model-View-Controller (MVC) pattern implemented using Play 2.7 (www.playframework.com), Akka (https://akka.io) and Java. The analysis process for the generation of the student's situation through FCMs has been implemented using the JFCM library (https://jfcm.megadix.it), based on Java. The Data fusion and storage and the Data management system modules have been implemented using well-known semantic-based techniques like the ones proposed in [14][15][16].

IV. A SITUATION-AWARE APPROACH TO IMPROVE ENGAGEMENT AND MOTIVATION OF LEARNERS

The proposed Learning System is adaptive concerning the learner situation. This means that the system can change its behavior, primarily in terms of feedback sent to the learners, according to the situation in which the learner is at a given moment. In this section, we describe the situation model and how it is represented. Lastly, we propose a situation identification method that uses a Fuzzy Cognitive Map to identify the situation.

A. *Situation Model: Engagement and Motivation of Learners*

In the context of the Adaptive Learning System, a situation can be intended as the current state of the learner concerning her experience with the system. A learner who have a good situation awareness is a learner that is perfectly aware of her current learning progresses, learning objectives, difficulties, tasks to complete, and so on. The system needs an operational representation of the situation which is targeted to the main objective of the learning system, which is to send adequate feedback to reduce student dropout. Student dropout is, most of all, related to the lack of motivation and low engagement of the learner with the learning system and the course. Therefore, the situation model considers the following two main elements:

- **Motivation**: how much the learner is motivated in going on and concluding her learning program/course.
- **Engagement**: how much the learner is involved in the learning process and with the learning system.

Note that these two elements are not alone sufficient to describe the complete state regarding a learner interacting with the adaptive learning system. However, we limit our analysis to these two main concepts since they are the two elements that mostly influence student retention in a learning platform [9]. The level of motivation and engagement depends on many factors, both intrinsic (related to the personality, objectives, characteristics of the learner) and extrinsic (related to the learning environment, the system, the teacher, etc.). Many studies, as [9], suggest that a good way to evaluate the learner motivation and engagement, in the case of e-learning system, is to consider the interaction patterns of the learner with the platform, especially those regarding the social activities (e.g., forum, instant messaging, etc.). To this aim, in the proposed situation model, the Engagement concept depends on:

- Interactions: the interactions the learner has with the activities of the course;
- Assignments: the interactions the learner has with the tests, practice activities, assignments delivery;
- Social (forum) activities: the activities (post publishing, comments, etc.) the learner performs using the social tools (forum).

Table 1 describes all the variables (i.e., data gathered by the learning system) which allows computing, for each learner, the value of each of the aforementioned concepts composing the level of engagement.

The motivation is given by two main concepts, one related to the social activities, and the other one related to the kind of motivation that led the learner to follow the course:

- Social (forum) Interactions: the interactions the learner has with the social tools (i.e., the forum).

- Type of Motivation (Intrinsic, Extrinsic, Social): it represents the reason that motivated the learner in following the course.

TABLE I. VARIABLES USED TO COMPUTE THE LEVEL OF ENGAGEMENT CATEGORIZED ACCORDING TO THE THREE CONCEPTS OF THE ENGAGEMENT

	Variable	Description
Interaction	Num_LessonsViewed	number of lessons the learner has followed
	Num_FollowedCourses	number of courses followed by the learner
	LastLesson	date of the last lesson followed by the learner
	TotalDaySpentTime	total time spent on the learning platform in a day
	AVG_SpentTime	average time spent on the platform
	AVG_Session	average duration of a session
	AVG_ActPace	average number of actions in a session
	Num_VideosViewed	number of videos watched
	Num_VideosWatched	number of videos watched entirely
Assignments	Avg_SubmissionLead Time	average time between quiz submission and deadline of the assignment
	AVG_Scores	average score
	Num_Submissions	number of submitted assignment
	ChangeInWeekly Average	difference between the scores of this and precedent week
	Num_PartecipatedQuiz	number of completed quizzes
	Num_PassedQuizzes	number of passed quizzes
	Num_AttemptQuizzes	number of trials for the quizzes
	LastQuiz	date of the last quiz
	TimeOnTask	rate between the current task session time and the overall time spent on assignments
Forum activities and interactions	AvgPostSentiment	average of the reactions related to posts
	PostActivity	number of learner posts respect to the average
	NumPostsMade	number of the published posts
	NumThreadsRead	number of discussions read by the learner
	NumPostsVoted	number of posts voted by the learner
	LastView	date of the last visit on the forum
	LastVote	date of the last vote made by the learner

Table 2 describes the variables that allow to identify the type of motivation of the learner: intrinsic, extrinsic and social. Considering that it is very difficult to identify the type of motivation that leads a learner to follow a course by just analyzing her interactions with the learning system, this kind of information is identified by submitting a survey to the learner, as suggested in [9]. For what concerns the Social (forum) Interactions concept, it is identified by using the same variable of Social (forum) activities, reported in Table 1, although they have a different impact on the motivation, as modeled in the FCM (Section IV.C).

TABLE II. VARIABLES TO IDENTIFY THE MOTIVATION. THE VALUES ARE IDENTIFIED USING A QUESTIONNAIRE SUBMITTED TO THE LEARNERS.

Intrinsic Motivation	Curiosity	Degree of curiosity of the learner
	Enjoyment	Degree of enjoyment
	GeneralInterest	Degree of general interest in the course
Extrinsic Motivation	Certificate	Interest in obtaining a certification
	Credential	Interest in obtaining credits
	Academic	The course is related with the academic objectives
	Job	The course is related with the job position
Social Motiv.	Connection	The learner is interested in a social contact with someone sharing similar interests
	Friendship	The learner is interests in the course because a friend follows it.

B. *Semantic representation of the situation model*

The Data Fusion and Storage module of the architecture in Fig. 1 contains a Semantic Layer which represents the data gathered by the sensors, as well as the data produced by the different tools of the system, with semantic technologies (using the standard technologies of the W3C Semantic Web Stack http://www.w3.org/standards/semanticweb/). The choice of using a semantic model to represent the critical information of the system is for supporting the interoperability between the different systems and tools integrated into the learning system, providing them with greater flexibility in the data management, thanks to a unique, shared, formal data model. Moreover, the semantic model is useful to support novel learning analytics techniques (e.g., Formal Concept Analysis [17]) that need a formal representation of the data. Such a formal representation sustains reasoning and inference which can support the decision-making processes of teachers and analysts.

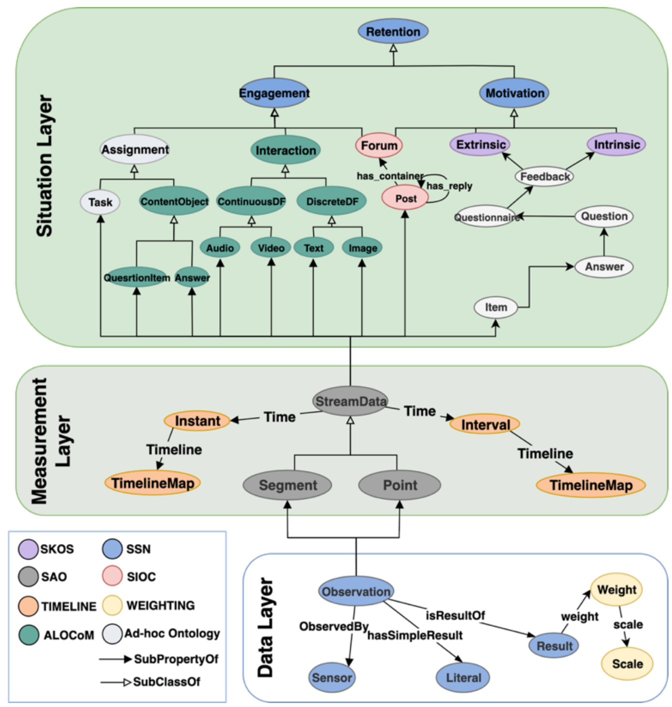

Fig. 2. Semantic Representation of the situation model of the learner.

Fig. 2 depicts the semantic model of the learning system. The model represents both the situation model described in the previous section and the information regarding the sensors and measurements. The lower level of the model, namely Data Layer, integrates the Semantic Sensor Network Ontology (SSN) [18] to represent the sensors, their properties and the gathered observations. The Measurement Layer is the bridge between the representation of the low-level information (sensors and raw data) of the Data Layer and the high-level information representing the situation. This layer integrates the Stream Annotation Ontology (SAO) [19] which describes the data streams coming from the sensors. It uses the class Segment to represent continuous measurements and the class Point to represent discrete measurements. Such information can be enriched with temporal information using the Timeline Ontology. The upper layer is the Situation layer, which is built by integrating SIOC (http://rdfs.org/sioc/spec/), SSNO, ALOCoM [20] and SKOS [21] ontologies. Specifically, using such models, it is possible to represent the main elements of the situation model: engagement, motivation, assignment, interactions, etc, represented using the SKOS ontology. The ALOCoM ontology represents quizzes and tests. The SIOC ontology allows representing the social activities of the learner.

C. Fuzzy Cognitive Map for situation identification

This section describes the situation identification technique, based on a Fuzzy Cognitive Map (FCM) [22], we defined and implemented in the learning system. The objective of the FCM is to consider all the effects that the variables identified in the Situation Model (Table 1 and 2) have on the engagement and motivation of the learner, which are the two high-level concepts representing the current situation of the learner. With respect to other fuzzy approaches that could be used to represent the situation model (like, for instance, Fuzzy Inference Systems with if-then rules) the use of FCM provides us with these advantages: i) FCMs are based on causal cognitive mapping, which provides an efficient way to elicit and capture knowledge of the experts of the domain and provide an intuitive way to represent such a knowledge which can be easily managed and updated by such experts [23]; ii) maps can be based on interviews, text analysis or group discussions and can be easily modified or extended by adding new concepts and/or relations or changing the weights assigned to causal links [22][23]; iii) FCMs have been extensively used as a way to support situation identification and decision making, helping decision-makers in gaining a better understanding of the domain, of the situation and improving their mental models [24]; iv) traditional FIS could require a high number of rules to represent complex relations, especially when a high number of inputs needs to be considered [25].

The FCM has been defined by a team of five experts of the Research Project "MOLIERE". Each expert, starting from the situation model we have defined, and considering the data available in the semantic model, has proposed his FCM to identify the causal relationships and the weights existing between the available concepts. The weights are represented by seven linguistic terms: *no impact*=0.00, *very low*=0.165, *low*=0.335, *medium*=0.50, *almost high*=0.665, *high*=0.835, *very high*=1.00. Then, we aggregate the different maps proposed by the experts to obtain one FCM. When some differences arise between the relationships and weights proposed by the experts, we asked them to discuss these differences and try to find an agreement, until they achieve a sufficient degree of consensus. This allowed us to obtain the FCM of Fig. 3.

The FCM can be considered as organized in three layers (input layer, middle layer, final layer), following the work of Kokar and Endsley [24]. The input layer contains the concepts of the FCM representing the variables of Table 1 and Table 2. The activation levels of these concepts represent the value of each variable. When a value of these variables changes (due to the actions performed by the learner), the other concepts of the FCM are influenced according to the causal relationships between them. The middle layer contains the concepts composing the engagement and motivation, as described in Section IV.A: Interaction, Assignment and Forum Activities. The final layer contains the concepts Engagement and Motivation, representing the current learner situation. These concepts are influenced by the concepts of the middle layer according to the situation model described in Section IV.A.

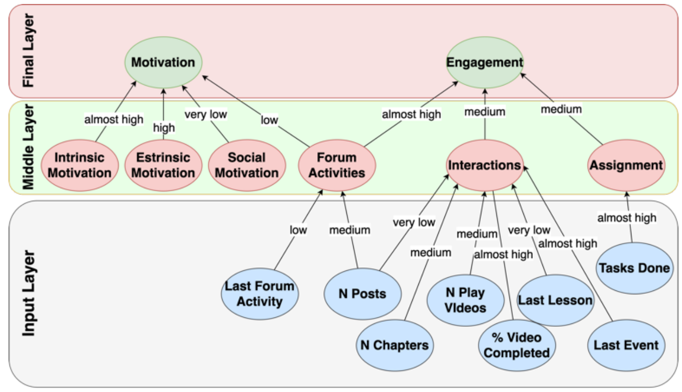

Fig. 3. Fuzzy Cognitive Map for situation identification.

The activation values of the concepts of the middle and final layers are computed, starting by the activation levels of the input layer, using the inference process of the FCM. Specifically, the activation level A_i of the concept C_i can be iteratively calculated:

$$A_i^{k+1} = f\left(A_i^k + \sum_{j=1, j\neq i}^{n} A_j^k w_{ji}\right) \quad \text{(Eq. 1)}$$

where A_i^{k+1} is the activation value of concept C_i at time $k+1$, A_j^k is the activation level of the conceot C_j at time k, w_{ji} is the weight between concept C_j and C_i, $f(\cdot)$ is a transformation function. In this work, we used a linear function for $f(\cdot)$:

$$A_i^{k+1} = \alpha\left(A_i^k + \sum_{j=1, j\neq i}^{n} A_j^k w_{ji}\right) \quad \text{(Eq. 2)}$$

where α is a real number.

D. Situation-driven feedback generation

The situation identified by the Fuzzy Cognitive Map drives the generation of feedback to the learner. Based on the current level of engagement and motivation, the system adapts the contents of the interface to present the users with specific kinds of action (e.g., suggest studying new learning contents, asking to complete another exercise, etc.). Specifically, the activation levels of engagement and motivation are discretized in three ranges: Low [0.0, 0.33]; Medium [0.34, 0.75]; High [0.76;1.00]. For each of the nine pairs, a different set of feedback can be submitted to the learner. The sets of feedback to be used in each situation has been identified by combining and harmonizing the results of the works of Jung and Lee [26], Abeera and Miria [27], El-Seoud et al. [28]. As an example, according to these works, when both motivation and engagement have a low value, correcting actions and learning support actions should be taken to improve the learner's situation. When the values are in the medium range, instead, it is better to send hints and praises to the learner. Note that for each pair of values, a set of different feedback can be sent to the learner. The specific feedback that will be sent could be decided by the system itself or by the teacher.

V. Evaluation

The evaluation aims at verifying if the proposed situation identification technique is useful to increase the level of situation awareness (SA) of the learner. A learner with a high level of SA is more conscious of the current signs of progress, difficulties, objectives, and can make better decisions regarding the learning process. In this way, we could understand if the level of motivation and engagement are two good indexes for understanding the level of situation awareness of the learner, and therefore if they represent a good learner situation model.

A. Method

The SAGAT methodology [6] is adopted to assess how the proposed feedback system impacts the student's awareness of the situation, exploring possible relationships with the learner’s motivation and engagement levels. SAGAT relies on the knowledge of domain experts to develop a questionnaire to assess the level of awareness of users’ situation. The user is involved in simulations of one or more realistic scenarios with the implemented system. At a certain point, the simulation freezes, according to the SAGAT guidelines, and a series of questions are asked to the user to probe the SA. The questions proposed to the user are chosen to evaluate which is the degree of awareness achieved in the three levels of: perception, comprehension, and projection. Two scenarios were identified based on requirements from the MOLIERE project. These scenarios have been simulated with the adaptive learning system. The participants of the experiments are both students and teachers. Although students and teachers will execute the same two scenarios, they will have a different goal. The students should understand which should be the next activity for improving their learning processes and achieve the learning objectives. The teachers, instead, should understand the difficulties in the class and decide which kind of action should perform to increase the motivation and engagement of the class.

The first scenario is related to the course “Algorithm” of a bachelor’s degree in Computer Science. In this scenario, the students of the Algorithms course have a medium-low level of engagement and motivation; over the weeks, thanks to the teacher’s corrective actions, the overall level of engagement and motivation has improved, becoming medium-high, also favored by facing a subject known to students. Let us consider the situation of two students of this course: the first student (student A) has a small number of tasks completed compared to the average of the class but her results are sufficient. The second student (student B) has an overall level of engagement and motivation which is positive and the obtained results are good. In the second scenario, we consider the “Mathematical Analysis II” course of the same degree. This course had a medium-high level of engagement and motivation, that dropped down in two weeks. The average results of the assignments are little more than sufficient. This is because the difficulty of the course is high for a subject not known to students. Let us focus on two students. The first (student C) took a long time to learn the topics in the course and had just enough results. The other (student D) has insufficient results.

The participants to the experimentation (students and teachers) will use the system that simulates the aforementioned scenarios, and then they are asked to answer a questionnaire. In the two scenarios, the questions asked to assess perception (level 1 SA) are linked to the identification of specific elements or parameters. For example, the teacher should identify the engagement and motivation values of a course, while the student should identify the percentage of completion of the activities in the course. To test level 2 SA, questions were asked about the status of a course or the student status to be evaluated through the activities done and the results achieved. Finally, for level 3 SA (projection), questions ask what actions should be taken: the student should choose the next activity, while the teacher should decide which actions are needed to increase the level of engagement within the course. The participants used the proposed system which simulates the described scenarios. Each scenario is executed twice for testing two modalities of the system. In the first modality, the system does not provide the feedback; in the second one, it provides students and teachers with the feedback using the proposed approach. Specifically, in the first modality, those who used the system without feedback did not have the notification section and the widget with the list of received feedbacks. In this way, by comparing the difference in the percentage of correct answers given by the participants, it is possible to understand if the proposed feedback generation technique is useful to increase the situation awareness.

The scenarios are executed in a random order. Figure 4 shows a screenshot of the dashboard used by the student participants. Figure 5 shows a screenshot of the dashboard used by the teacher participants. Users who participated in the evaluation were chosen arbitrarily; the sample was taken from the University of Salerno (Italy) with all the participants external to the MOLIERE project.

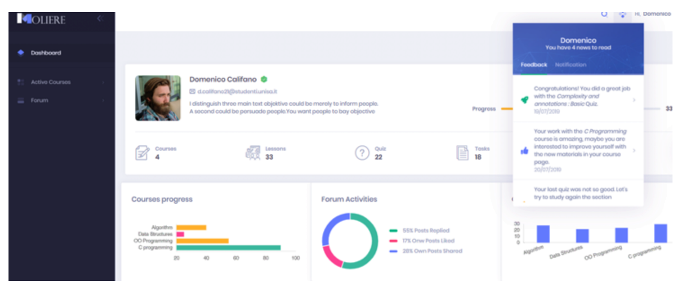

Fig. 4. Screenshot of the dashboard for the student.

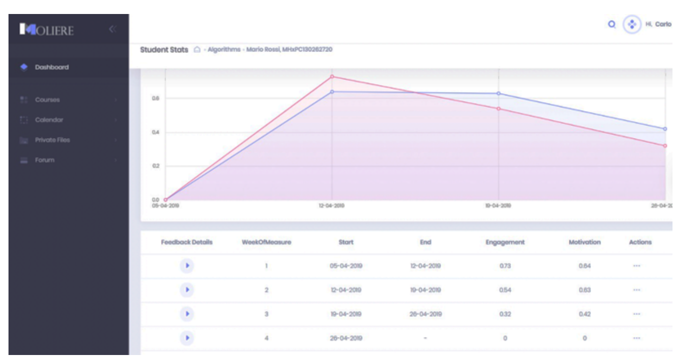

Fig. 5. Screenshot of the dashboard of the teacher.

The Cochran formula [29] was used to calculate the sample size:

$$n_0 = \frac{Z^2pq}{e^2} \qquad \text{(Eq. 3)}$$

Where:

- e is the desired level of precision (i.e. the margin of error);
- p is the (estimated) proportion of the population which has the attribute in question;
- q is $1 - p$;
- The z-value is found in a Z table. It is the abscissa of the normal curve that cuts off an area α at the tails (1 - α equals the desired confidence level, e.g., 95%);
- n_0 is the sample size

In our experimentation, the chosen parameters were: {Z = 1.96; p = 0.77; e = 0.13}. From the application of the formula with these parameters, a sample size of 40 participants emerged, which were equally divided into a group of 20 students and a group of 20 teachers.

B. *Results and Discussion*

Fig. 6 shows the results of the evaluation. The figure shows the percentage of correct answers given by the participants. Specifically, each graph shows the average rate of correct answers given by a group of participants. On each graph:

- S1 is the group of students who participated in the Scenario 1;
- S2 is the group of students who participated in the Scenario 2;
- T1 is the group of teachers who participated in the Scenario 1;
- T2 is the group of teachers who participated in the Scenario 2;
- Student is the group of all students. The percentage of correct answers are given by aggregating S1 and S2;
- Teacher is the group of all the teachers. The percentage of correct answers is given by aggregating T1 and T2;
- All: is the group containing all the 40 participants (both students and teachers).

Each graph depicts the results related to one level of SA. The last graph shows the results of the overall SA, obtained as an average of the three levels. To verify if the obtained results are statistically significant, we performed an ANOVA test, comparing two groups: Group A is the group of participants who used the system without feedback (first modality); Group B is the group of participants who used the system with feedback (second modality). We obtained the following results for the F-test statistics, considering a significance level $\alpha = 0.05$:

- Considering all the teachers and students together, F(1, 38) = 20.89, with a F-critic = 4.09 and p-value=0.00005.
- Considering only the students, F(1,18) = 7.62, with F-critic = 4.41 and p-value = 0.01.
- Considering only the teachers, F(1,18) = 12.89, with F-critic = 4.41 and p-value = 0.002.

Consequently, the tests demonstrate that the results can be considered statistically significant.

Let us analyze the results of Fig. 6. We can observe that there is not a significant improvement related to Level 1 of SA (perception). This is because the learners already have a very high level 1 SA, which means that the interface is good enough to show the most important, low-level information. Regarding Level 2, we observe a significant improvement in all the scenarios, both for students (an improvement of 25%) and teachers (+15%), which means an improvement of 20% when considering all the participants. This demonstrates that the feedback is particularly important to support students in the comprehension of their current learning process, and for the teacher to understand the state of the whole class. But where we can observe the greatest improvement is in Level 3 SA (+30% for students, and +50% for teachers). This is an important result because level 3 of SA is related to the capability to project the current situation to make a decision. This means that the provided feedback helps both student and teacher in their decision-making processes. In such a way, the student can

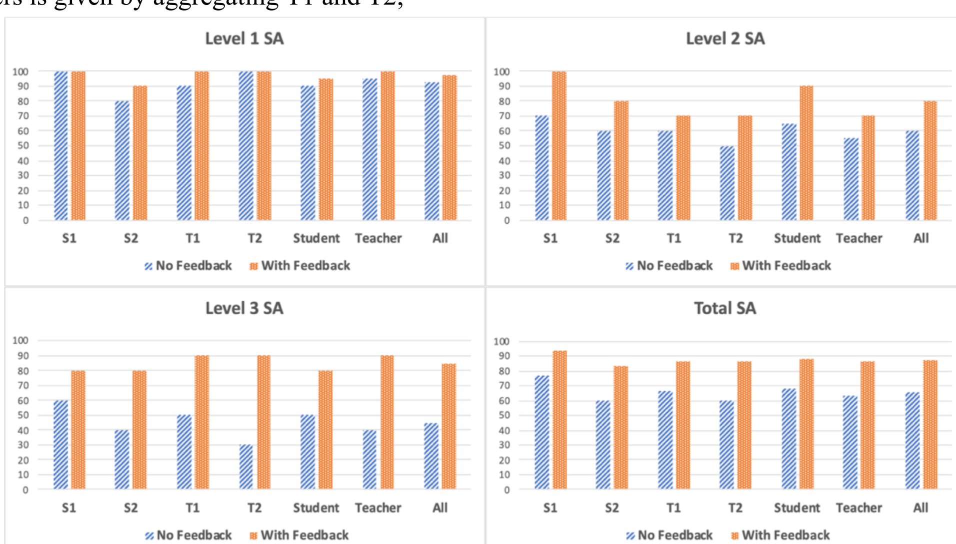

Fig. 6. Results of the evaluation. Percentage of the average number of corrected answers for the three levels of SA and for the total SA. In each graph, the figure compares the percentage of corrected answer for the system without feedback and the one with feedback.

become more autonomous regarding how to follow the course with success (e.g., which can be the next learning activity to perform, etc.) and the teacher can make better decisions regarding the class or regarding the students with an high risk of dropping out.

VI. Conclusion

An adaptive e-learning system based on situation awareness has been proposed in this paper. The system has been designed and developed according to the design principles of SA. The feedback selection process is driven by a Fuzzy Cognitive Map, implemented to identify the learner situation by analyzing the activities on the platform. The system has been evaluated in a set of scenarios of the MOLIERE project involving real stakeholders (students and teachers). The results show that the situation identification technique and the situation model are capable of increasing the level of situation awareness of the users. Considering that the situation is represented in terms of motivation and engagement, the results suggest a possible relation between the improvement of the situation awareness and the levels of motivation and engagement, but such a relation needs further investigation. Future work is planned for evaluating such a possible correlation between SA increase and motivation and engagement involving students in the experimentations. Lastly, further experimentations will be conducted to compare the proposed feedback generation mechanism based on FCM with state-of-the-art fuzzy and non-fuzzy techniques for feedback generation.

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