1. PLACING THE FRAMEWORK

The future of the Web will become more humanized and intelligent with the Web 3.0 (Liu, 2014; Paquette, 2014) by tagging online information and creating links between interconnected pieces that will be entirely understood by both humans and computers. However, the definitions of Web 3.0, also known as the Semantic Web, vary considerably. Moreover, the term “Semantic Web” is used inconsistently by academic researchers holding a landscape of different fields, technologies, concepts and applications. From one point of view, Semantic Web technology could play an important role in the particular context of online Learning Management Systems (LMSs), giving the possibility to organize information for easy retrieval, reuse, and exchange between different learning systems/tools. From another, synchronized with the concept of intelligent Learning Management System (iLMS), blended (b-)learning scenarios can offer a number of learning tools, in a wide range of interaction, collaboration and sophistication (Dias et al., 2014; Dias, 2014). Lukasiewicz and Straccia (2008), more pragmatically, have examined five of the most important challenges facing Semantic Web, namely: vastness, vagueness, uncertainty, inconsistency, and deceit. However, nowadays, the central challenge would be to provide adapted and personalized solutions/alternatives, where intelligent models could contribute involving artificial intelligence and incertitude modeling e.g., via Fuzzy Logic (FL). In fact, FL is an efficient technique that is suitable for dealing with vagueness. In addition, it is considered a form of continuous multi-valued logic allowing “computing with words” and
modeling complex systems characterized by imprecise and vague behaviors by means of a linguistic approach (Zadeh, 1965, 1968, 1971). In general, the whole point of Web 3.0 is to provide accessible information to people and computers at anytime from anywhere. Furthermore, with new technological innovations for applying intelligent agents (Web 4.0), cloud computing services has been coined as an umbrella term to describe a category of sophisticated on-demand computing services, initially offered by commercial providers (such as Amazon, Google, and Microsoft) (Voorsluys et al., 2011). By embedding the cloud computing within iLMS, access to large amount of data and different computational learning resources/environments becomes feasible.

Based on the aforementioned perspectives, this chapter examines the potentiality of the quality of collaboration (QoC) within an Internet-based computer-mediated collaboration environment (Hadjileontiadou et al., 2004) and quality of interaction (QoI) with a LMS (Dias & Diniz, 2013) both involving FL-based modeling, as vehicles to improve the personalization and intelligence of an online learning environment (OLE). Furthermore, the combined measures proposed here (i.e., QoC and QoI) can form the basis for a more pragmatic approach of OLEs via Web analytics and Web controlling/monitoring, within the concept of semantic Web and the associated Web 3.0 features, as they effectively capture the underlying behavior and attitudes of the core stakeholders involved in the context of Higher Education.

1.1. Collaborative Environment Modeling

As the Internet matures, it is increasingly apparent that it is not merely a vehicle for conveying vast information to the desktop, but it can also provide an effective platform for working with colleagues, irrespective of location. Its use for collaboration is currently the focus of considerable interest and development and many new tools appear (e.g., Skype, Google+ Hangout/Drive/Groups, MediaWiki, TextFlow, DimDim, MindMeister, Zoho, TeamViewer, DropBox, CMapTools), which make online collaborative projects a realistic option for distributed workgroups. While the multidisciplinary
character of the Internet allows its use in many activities, such as holding meetings and ongoing
discussions, the definition of peer-to-peer collaboration here is restricted to methods of peers
collaborating rather than simply communicating. Under this perspective, the Internet-based
collaboration environment needs to be powerful and easy to use with integrated supporting facilities
that could contribute to successful peer-to-peer collaboration.

Artificial intelligence technologies play an important role in network collaboration, with the
promise of advanced features, adaptive functionality and intuitive interfaces (Levy & Weld, 2000). It
contributes to proper support to the users by allowing adaptive modeling of their collaborative
interactions in order to successfully track their individual skills. The employed models can be used
to provide support and feedback to the collaborators regarding the efficiency of their collaboration,
and to further motivate them towards the adoption of even more productive activities. Such modeling
may be based on:

(1) *a priori* knowledge-based models (AKM), with knowledge provided by domain experts.
Different approaches of knowledge representation within AKM include the object-oriented,
the procedural, and the rule-based programming paradigms (Gonzalez et al., 1993; Hicks,
2000; Huntington, 2000), and

(2) empirical data-based models (EDM), which are mined from the large amount of data that are
logged by the system during the computer-mediated interactions and are *a priori* knowledge-
free. The EDM rely on the fact that the intrinsic features of the observed interactions and their
mutual interrelations can be learned from the data using a great number of simultaneously co-
operating simple processing units or operations. This approach allows the extraction of
information (knowledge) from these low-level data into other forms that might be more
abstract (Fayyad et al., 1996; Chen et al., 2011).

So far, the AKM have been used for the analysis of participation rates, by counting words or
messages (Ogata et al., 2000), conversation mapping onto a belief-based model (Tedesco & Self,
2000), interrelation of structured external representations on a structural dimension (Muehlenbrock & Hoppe, 1999), matching group interaction to patterns (Vizcaino et al., 2000), integration of task and social aspects of interaction (Ayala & Yano, 1998), for effective embedded educational assessment (Reese & Gobert, 2012), and understanding the dialogue between group members (Barros & Verdejo, 1999; Hadjileontiadou et al., 2003).

On the other hand, the EDM have been mainly used for revealing characteristics hidden in data. Works in this area include the analysis of the quality of peers’ interactions (Soller & Lesgold, 2000a), and the modeling of the sequence of productive interactions (Soller & Lesgold, 2000b).

When the interactions analysis employs inference abilities to provide predictive utterances, the supporting system becomes even more enhanced. An example is given in (Beck et al., 1997), where a two parameter regression model predicts how a student will perform in the future, based on a student model that is developed within a statistical framework. In addition, Bayesian networks (BN) (Derry & DuRussel, 1999) have been used to represent causal relations in peers’ behavior (Reye, 1996), modeling pedagogical decisions (Gerner et al., 1998), modeling the learner’s level of understanding in collaborative learning (Komedani et al., 2005), and determination of peer’s level of competence within a domain (Collins et al., 1996). Although BN have been shown to be highly effective in modeling the user’s behavior, they exhibit some difficulties in implementation, in determining how evidence propagates, and in estimating the edge probabilities (Beck & Stern, 1999).

System modeling based on conventional mathematical formulation, such as differential equations, is not well suited for dealing with uncertain systems, such as human behavior. In contrast, EDM that make use of a fuzzy inference system (FIS), utilizing fuzzy IF-THEN rules, combine numerical and linguistic data to model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analysis (Beck & Stern, 1999). For enhanced performance, FIS could be combined with adaptive networks. The latter are network structures consisting of nodes and directional links through which the nodes are connected. Part or all of the nodes are adaptive; hence,
each output of these nodes depends on the parameters pertaining to this node. The learning rule specifies how these parameters should be changed to minimize a prescribed error measure (Jang, 1992). By embedding the FIS into the framework of adaptive networks, we obtain the neurofuzzy-model structure that adaptively maximizes the performance index through Adaptive Network-based FIS (ANFIS) (Jang, 1993).

Motivated by the aforementioned concept, we propose in this chapter a novel, adaptive neurofuzzy EDM, namely Collaboration/Metacognition–ANFIS (C/M-ANFIS) model, to ground an adaptive distance-collaborator supporting system that promotes learning on how to collaborate. In particular, the C/M-ANFIS model combines ANFIS with sets of collaborative and metacognitive data, acquired with a suitable Internet-based collaboration tool (Hadjileontiadou et al., 2003), during peers’ computer-mediated collaboration. The collaborative and metacognitive data refer to peers’ collaborative activity and to their beliefs on the quality of their collaboration, respectively. When these data are utilized by neurofuzzy structures in the C/M-ANFIS model the following advantages emerge:

(1) both collaborative and metacognitive activities are considered,

(2) the feedback, which is presented to each peer, is adapted according to his/her collaborative skills,

(3) by extracting the common collaborative strategy adopted by each peer we can generalize his/her collaborative behavior,

(4) the peer’s collaboration activity in a forthcoming collaborative session can be potentially predicted, and

(5) it is possible to focus on the user’s behavior despite the particular task-content.

The above characteristics define a new approach in modeling peers’ collaborative activity. Based on this modeling, individual support could be provided to each peer that could contribute to improve
his/her collaboration management. A graphical representation of the proposed process is shown in Fig. X.1.

**FIGURE X.1 SHOULD APPEAR ABOUT HERE**

Evaluation of the C/M-ANFIS when applied in experimental data from the collaboration of distant pairs of students in environmental engineering education proves the potentiality of the model to provide a successful support to distance learners, enhancing their collaborative learning procedure.

1.2. OLE Interaction Modeling

From the variety of theoretical frameworks that coexist in the field of OLEs, the ones that have theoretical importance in the field, commonly used, and influence other online learning models are listed in Table X.1.

**TABLE X.1 SHOULD APPEAR ABOUT HERE**

The first OLE model of Table X.1 is the one proposed by Salmon (2000), which epitomizes the role of e-moderator (teacher, facilitator) during the process of construction of knowledge in OLEs. The skills development assumes the immersion of the tutor in the learning environment and, consequently, the importance of training in online context. In this case, the author proposes a comprehensive synthesis of the skills of the e-tutor, connecting two types of variables: a) the characteristics, i.e., understanding the online process, technical skills, online communication skills, mastery of contents and personal skills, and b) the qualities, i.e., confidence, constructive spirit, ability to stimulate the development, ability to share knowledge and creativity. Regarding the level of teacher’s intervention in OLEs, this model is structured in five steps, i.e., Access and Motivation (first contact with the learning environment), Online socialization (construction of learning community), Information exchange (exchange of information between the elements of the community), Knowledge construction (the beginning of interaction processes), and Development
(constructivist learning strategies). In short, this model clearly shows the multifaceted role of the e-moderator, requiring creative qualities to construct appropriate and varied e-activities in a gradual increase of the intensity of interaction. Also, is perceptible that students, at each step, need to develop technical skills to smoothly advance to the next one.

The second OLE model of Table X.1 is Anderson’s online pedagogical model (Anderson, 2004); it is based on three types of interactions presented by Moore (1989), i.e., student-student interaction, teacher-student interaction, and student-content interaction. Anderson’s OLE primarily focuses on independent and collaborative learning, highlighting the importance of the role of the interaction. It is also known as a model of e-learning, which allows structuring and organizing online learning through six particular types of interaction, i.e., teacher-content, content-student, student-student, student-teacher, student-content and content-content. Indeed, the two identified actors (teacher and student) interact with each other and with the contents. During this interaction a wide variety of activities (synchronous and asynchronous) can be used, based on the Internet (e.g., audio, video, conferencing, chats, and virtual worlds). These environments are particularly enriched, promoting the development of social skills, collaborative work, as well as at the level of interpersonal relationships between the participants (Anderson, 2004).

The Siemens learning model (Siemens, 2006) offers an ecological vision of learning, i.e., the Learning Ecology, with the premise that the search of knowledge is a constant across life, in other words: “we keep looking until we find people, tools, content, and processes that assist us in solving problems” (Siemens, 2006, p. 33). This author introduces the theory of connectivism, which is based on the understanding of the learning process as a process of networking. The latter describes how learning can be developed in the digital age, standing behind the idea that information flows at high velocity, difficulting its processing and interpretation (information overload). Indeed, the connectivity is understood as the integration of some principles that are explored by chaos, social networks, by the theories of complexity and self-organization. In the Knowing Knowledge book, the
author seeks to clarify the multifaceted and multidimensional atmosphere of learning, considering four specific domains, namely: *transmission, emergency, acquisition, and accretion* (Siemens, 2006, p. 34). From this scenario, the Internet can be seen as a learning ecology with different potentials, revealing itself a center of creative chaos, such as Siemens (2006) clarifies: “Connectivism is the integration of principles explored by chaos, network, complexity, and self-organization theories” (p. 30).

The fourth OLE presented in Table X.1 refers to the term Technological Pedagogical Content Knowledge (TPACK) – based on an extension of Shulman’s model (1986), which supports the assumptions that teaching is a mixture of art and science and, on the other hand, teacher’s knowledge represents a mixture between the content and pedagogy (Pedagogical Content Knowledge) – is presented as a theoretical model that describes the responsibilities of the teacher concerning the integration of ICT and the use of a LMS (Mishra & Koehler, 2006; Schmidt et al., 2009). This model (Mishra & Koehler, 2006) focuses on the interaction and the complexities of different kinds of knowledge: content, pedagogy and technology. In turn, the concept of TPACK as being the result of the intersection of knowledge from a teacher at three levels, namely: content (Curriculum Content Knowledge-CK), teaching methods (Pedagogical Knowledge-PK), and technological skills (Technological Knowledge-TK). Additionally, this model integrates three different components of knowledge: i) *Pedagogical Content Knowledge*; ii) *Technological Content Knowledge*, and iii) *Technological Pedagogical Knowledge*. Several researchers have used the TPACK model to analyze some cases of quality in training and further training in the teachers and in finding the ways to integrate technology in their teaching methodology (Niess, 2005; Lim et al., 2010).

Nowadays, social media tend to be increasingly associated with different mechanisms to meet and interact with people. However, *social media* can represent an important working tool to be socially and consciously constructed in an educational vision. In general, the Bosman-Zagenczyk online learning model presented here (Bosman & Zagenczyk, 2011) is based on the use of different social
media tools following the different levels of the taxonomy of Benjamin Bloom (1956). Indeed, Bloom’s taxonomy and adjacent hierarchical classification of learning objectives seem to be an important academic contribution, in particular to the faculty that appreciates social resources, in order to stimulate higher-order thinking of the students. From a SWOT-based analysis, this conceptual framework aims to integrate the different social media in the classroom (Bosman & Zagenczyk, 2011). Nevertheless, in order to facilitate the interpretation of this model, some authors point out different tools that can adapt to different levels of learning (Solomon & Schrum, 2007; Hayman, 2007; Bunzel, 2010; Prensky, 2010; Waycott et al., 2010). Considering the latter perspectives, Zagenczyk and Bosman (2011) defined six levels that should be included in the educational process, i.e., Level 1 - Remembering with Social Bookmarking (remember relevant knowledge of long-term memory through e.g., Delicious, Google, Diigo tools), Level 2 - Understanding With Social Blogging (realize the meaning of oral communication, written messages or graphics through e.g., Edublogs, Blogwordpress, Google Blogger), Level 3 - Applying with Social File Sharing (apply certain procedure in a specific situation using e.g., Moodle, Google Docs, Wikis), Level 4 - Analyzing with Social Collaboration (analyze how the parts relate to each other in a global structure through e.g., DimDim, Skype, David Button tools), Level 5 - Evaluating with Social Decision Making (evaluate on the basis of criteria or standards defined, using e.g., UserVoice, Doodle, Kluster); and Level 6 - Creating with Social Creativity Sharing (collect elements to create a whole or create a unique product using e.g., YouTube, Flickr, Scribd, Whiteboard).

In 2008, based on key vectors - technology, organization and pedagogy - Sangrà revealed the TOPs online learning model (Sangrà, 2008), as a triangle of factors that are closely related to each other in a symbiotic way. More specifically, between 2004 and 2005, from a SWOT-based analysis, five European case studies were examined, namely: University of Milan (UNIMI), University of A Corunã (UDC), University of Alicante (UA), University of Rovira i Virgili (URV) and Open University of Catalonia (UOC), enabling to observe how some universities have integrated ICT into
their activities. In general, the SWOT technique revealed a diagnosis of the situation of the internal and external reality of each institution. However, a step forward was done when Bates and Sangrà (2011), showed the results (mainly qualitative) from 11 individual case studies, focusing at the richness of interconnections between the various strategies, visions, policies, and institutional contexts of each institution. In summary, Bates and Sangrà’s online learning model clearly underlines the fact that successful technology integration requires equal attention to following three main components, i.e., *pedagogy* (teaching methods), *technology*, and *organization*. Also, they point out that it is vital to change the circumstances, giving special attention to organizational and cultural issues. Training for instructors/managers and institutional incentives/strategies are also considered essential requirements to create an online environment that encourages change and innovation in teaching and learning.

The Redecker et al.’s (2009) online learning model is the final model referenced in Table X.1; it introduces the concept of Learning 2.0 *iLANDS*, focusing particular in areas in which social computing applications support innovation in learning. From an in-depth analysis of existing practices, and considering the social computing concept for learning as a multidimensional and dynamic phenomenon (in a constant evolution), some distinct areas (that form the abbreviation of *iLANDS*) were distinguished by the authors (Redecker et al., 2009, p. 42), i.e., *Learning* (L) – the Web 2.0 tools (social computing) can be used as a support in the implementation of educational strategies that facilitate/improve the process of learning and the transformation of knowledge, customize the learning processes, and allow the progress of learning to respect the student’s individual pace, *Achieving* (A) – the social computing can contribute to learning outcomes and motivation of students (individually and adapted) vis-à-vis their own learning needs, contributing to the development of social and cognitive skills (e.g., reflection and metacognition), *Networking* (N) – the social computing can be seen as an instrument of communication between students and teachers and student-teacher dialectic, which supports the sharing of knowledge and resources in different
networks, facilitates community building and provides collaborative (multi-) platforms, *Embracing Diversity* (D) – the Web 2.0 can be seen as a means of integration of learning in a wider community, allowing the achievement of virtual knowledge of other age groups and professionals, with different cultures and experiences, sharing experiences, opening new channels to build knowledge and skills development, and *Opening up to Society* (S) – the Web 2.0 can be used to develop an institutional learning accessible and transparent to all members of society. Generally, moving from the core to the peripheral logic, these five areas seem to give new spaces for innovation (i) in learning (LANDS). Each dimension (area) specifies different approaches, strategies and objectives. This model aims, essentially, to show how social computing is used in formal educational contexts, and simultaneously, how social computing tools are used to support learning processes, distinguishing technological, organizational and pedagogical innovation as the main enablers of transformation.

In the aforementioned models, the concept of interaction is always implied as a common ground; to this end, similarly to the case of C/M-ANFIS model, a FIS-based model is also adopted here, namely FuzzyQoI (Dias & Diniz, 2013), to set a supporting system to the users that promotes learning on how to interact with the OLE. Based on this modeling, individual support could be provided to the user that could contribute to improve his/her OLE interaction management. A graphical representation of the proposed process is shown in Fig. X.2.

**FIGURE X.2 SHOULD APPEAR ABOUT HERE**

Evaluation of the FuzzyQoI, when applied to experimental data from the users’ interaction (professors and students from a HEI) with the LMS Moodle (http://moodle.org) within a b-learning context, proves the potentiality of the model to provide a successful support to teachers and learners, enhancing their interaction with OLEs.
2. QUALITY OF COLLABORATION-QUALITY OF INTERACTION

2.1. Quality of Collaboration (QoC)

The activity that takes place during the collaboration involves a variety of interactions that affect the QoC. Nevertheless, here, we focus on collaborative and metacognitive interactions. In general, collaboration is a situation where two or more people, sharing the same objective, are engaged in a common activity in order to transform the objective to an outcome (Nardi, 1996). For the achievement of this transformation the construction and maintenance of effective collaborative activities is fundamental (Dillenbourg et al., 1996). To do so, attention should be given to the analysis and modeling of interactions that occur during collaboration, leading to a more process-oriented approach (Dillenbourg et al., 1996; Lai, 2011). Such collaborative interactions include creative conflict, productive argumentation, knowledge sharing, and critique provision (Webb et al., 1995; Coleman, 1997). These interactions that occur during collaboration could be described by means of intermediate collaborative variables that can be empirically and theoretically related to the conditions of collaboration and to the particular outcome (Dillenbourg et al., 1996; Lai, 2011). In this way, a microgenetic approach is adopted, which calls for a closer look at how change in collaborative behavior occurs as individuals go through the collaborative experience. This knowledge of the collaborative process, rather than the outcome, is useful to set up an effective collaboration environment among peers.

Moreover, metacognition includes individual’s awareness of his/her own knowledge, actions, and emotional situation, along with the ability to monitor and consciously adjust them during a learning procedure (e.g., collaboration) (Hmelo-Silver et al., 2013). The use of metacognition may significantly improve the individual’s QoC; hence, adopting metacognitive strategies upon a collaborative procedure the individual is able to consciously monitor his/her collaborative interactions and adjust them in order to enhance the effectiveness of his/her collaborative activity (Hmelo-Silver et al., 2013). The metacognitive activity is conscious, therefore it is translatable.
through metacognitive interactions, and furthermore countable (Davidson et al., 1994). Such metacognitive interactions include explaining/self-explaining one’s own thinking and describing planned actions. Similarly to the collaborative interactions, *intermediate metacognitive variables*, which can be used in the quantitative interpretation of metacognitive interactions, could be defined.

In the case of computer-mediated collaboration the collaborative/metacognitive activity may be enhanced (Dillenbourg et al., 1996; Lai, 2011):

1. *methodologically*, as the system-designer is able to set rules and control some aspects of the collaborative/metacognitive activity (e.g., foresee rules for turn taking). Furthermore, s/he can monitor the activity and collect empirical data of the intermediate collaborative/metacognitive variables at different levels of interest for further elaboration, and

2. *pedagogically*, as the system-designer is able to establish a communication model to challenge certain types of cognitive/metacognitive interactions that are expected to promote a more effective collaborative activity. Moreover, s/he is able to develop and provide support towards an effective collaboration, elaborated upon pre-acquired empirical data.

From the above characteristics it is evident that the computer-mediated collaboration significantly contributes to the interpretation of the collaborative interactions. The empirical data from the intermediate variables can be used to better understanding the contribution of the interactions to the collaboration process itself. Consequently, objective and reliable support could be provided to peers through an automated user-support system.

The design of a computer-mediated collaboration environment involves several components that support peers and facilitate the collaborative activity (e.g., technological artifacts, pedagogical methodologies). Among these, the provision of feedback is of major pedagogical concern and the following issues must be considered during its design:
(1) **Timing.** Feedback may be given either as summative by the end of the collaborative activity (Barros & Verdejo, 1999) or as formative at the end of discrete, intermediate steps of the collaborative activity (Hadjileontiadou et al, 2003).

(2) **Content.** The content of the feedback to the user may include action reflection through display of raw data log files, visualizations of indicators (estimated-desired values) for self-diagnosis of interactions, recommendations and coaching advice for interaction improvement (Jermann et al., 2001).

(3) **Modularity.** The feedback component must be able to create product variants, that is, to adaptively provide feedback according to the user’s needs (Huang & Kusiak, 1998).

(4) **Interpretability.** The design of the support includes representational and delivery issues for the facilitation of ease interpretation of the content by the peers.

As it has been made clear from the analysis so far, the provision of feedback to the user is focused on his/her collaborative activity, rather than on his/her performance at the task level, using data derived from his/her collaboration monitoring. The latter could be derived from a variety of computer-supported collaborative environments, involving Web-based pages and/or micro/macro-scripts, with the latter often used in mobile (m-)learning (Dillenbourg & Crivelli, 2011). In our case, the Web-based Lin2k tool (Hadjileontiadou et al., 2003) was adopted, which supports the collaboration between two distant peers in an asynchronous written mode (Hadjileontiadou et al., 2003). The collaboration is developed in a step-by-step approach of a case study, and the peers communicate through the Internet using semi-structured interfaces. These interfaces facilitate the peers in performing collaborative and metacognitive interactions.

During the collaborative/metacognitive activity, intermediate collaborative and metacognitive variables are fired, shown in Table X.2.

**TABLE X.2 SHOULD APPEAR ABOUT HERE**
The intermediate variables are quantified by the system through monitoring the peer’s activities, such as selecting interactions category, submitted text during collaboration, and are archived in a peer’s activity database. In this way the collaboration is progressively developed, whereas the system gathers raw data on the collaborative/metacognitive interactions at each step. The acquired values of the intermediate collaborative variables are used for the estimation of the QoC. The term quality refers to the domain-expert’s knowledge of ‘proper’ collaboration (Hadjileontiadou et al., 2003). Similarly, the acquired values of the intermediate metacognitive variables are used for the estimation of the peer’s intention of improvement during the collaborative activity (Hadjileontiadou et al., 2003). The intention of improvement reflects the user’s metacognitive awareness of his/her collaborative-activity quality and beliefs for further improvement (Hadjileontiadou et al., 2003; Hmelo-Silver et al., 2013). The Lin2k employs FIS, i.e., Collaboration/Metacognition-FIS (C/M-FIS), to provide a quantitative estimation of the collaboration quality and the intention of improvement. Using appropriate IF-THEN fuzzy rules and membership functions based on expert’s knowledge (Hadjileontiadou et al., 2003), the Lin2k combines the acquired values of the intermediate variables to infer two crisp values at each step of the case study, i.e., $C_n^s(p)$ and $M_n^s(p)$, where $n = A, B$ denotes the student, $p = 1, \ldots, N$ the pair, and $s = 1, \ldots, L$ the step of the case study. The $C_n^s(p)$ and $M_n^s(p)$ values are used as measures of the collaboration quality and the intention of improvement, respectively. The working structure of the Lin2k for the $s$ step is depicted in Fig. X.3.

FIGURE X.3 SHOULD APPEAR ABOUT HERE

The values of $C_n^s(p)$ and $M_n^s(p)$ define the input signal of the proposed C/M-ANFIS model. The latter combines these empirical data with neurofuzzy structures to materialize an ‘external counselor’, who provides feedback in order to challenge readjustment of the peer’s collaboration interactions. The importance of this approach is profound, as it grounds a novel, automated, adaptive users’ support
during an Internet-based collaboration, which formatively refines the QoC and urges the users to further improve.

2.2. Quality of Interaction (QoI)

Quality of learning experience directly relates with the amount and the quality of interaction (QoI) and the sense of commitment to a community of inquiry and learning. Those could be achieved through the effective integration of technology, while at the same time exploiting the advantages of a traditional course that includes lectures and meetings (Garrison & Kanuka, 2004). Towards this blending, designing, developing and deploying programs that are well organized, using multimedia to engage the learner by employing various intelligences, capturing the experiences and knowledge of the learners, while incorporating and promoting interactivity and training instructors to facilitate online delivery, demand a strategic decision to be made and adequate resources be made available.

Determining learning behavior in electronic media, however, is a complex problem that requires the development of effective methods of determining and evaluating learner’s behavior in electronic environments (Hijón & Velázquez, 2010), a role that is undertaken by LMSs.

The user's interaction with a LMS (e.g., Moodle) is actually realized within OLEs, which are characterized by fastness and immediacy, i.e., the ability to quickly access a vast amount of information coupled with a plurality of Web 2.0 tools (Conole et al., 2008; Redecker et al., 2009). Apparently, the efficiency of the LMS depends on how effectively the users can access its multifaceted benefits when interacting with it. According to Wagner (1994), the interaction can be seen as the occurrence of reciprocal events that require the existence of at least two objects and two actions, and when they influence each other. Chatteur et al. (2008), also report that in OLEs is not uncommon for individuals to interact spontaneously, i.e., without being motivated and/or encouraged through interaction strategies and/or activities. In addition, Herrington et al. (2007) argue that the (un)successful learning is intrinsically dependent on the degree of interaction that takes place in a
specific educational context. Hence, interaction can be synthesized as an active process, which requires learners to do more than passively absorb information.

The QoI between learner with online content is one of the imperative factors in determining the efficacy of Web-based teaching-learning towards the creation and maintenance of sustainable learning communities (Anderson et al., 2001; Kidd, 2005; Lim & Lee, 2007; Grant & Thornton, 2007). Interaction with content is an internal dialogue of reflective thought that occurs between learner and the substance. Interaction is often triggered and supported by events in the learning environment—on how the learner interacts with what is to be learned. For example, in an analysis of student's use of a courseware website, Peled and Rashty (1999) found out that the most popular online activities were passive and involved getting information rather than contributing. Their conclusion is that the students were very goal-oriented in their use of the Web site.

Further information can be gained from knowing when students access resources (Sheard et al., 2005). This can help educators understand student’s preferred learning patterns. A study carried out by McIsaac et al. (1999) explored interactions of doctoral students with an online environment and they concluded that student interactions were goal-focused. For instance, in Hellwege et al. (1996), it was shown that students were accessing resources according to immediate need. In this way, another study (Hijón and Velázquez, 2006) of this characteristic showed that the average connections to the LMS was over thirty minutes. Analysis of learner’s interactions may also be used to compare learning behaviors of different groups of students. In some empiric studies made, it is highly remarkable the importance on time and dedication to the course habits (Nian-Shing & Kan-Min, 2002), the connection time (Kickul & Kickul, 2002) and the total number of accesses to the system (Ramos & Yudko, 2008).

The aforementioned suggest the approach of user’s LMS interactions from the perspective that reveals their quality, so the latter could be used to unfold the true nature of the users’ attitude when interacting with the LMS within a b-learning environment. So far, works focused on QoI usually
employ statistical analysis of LMS data, combined with transcripts of the discussions and exchanges of teacher and learners within the online forums, specifically investigating the dimension, depth and category of exchanges occurred (Ping et al., 2010).

The FuzzyQoI model adopted here (Dias & Diniz, 2013) takes into account the users’ (professors’ and students’) interactions, as expressed through the LMS usage within a b-learning environment, and, by translating the knowledge of the experts in the field to fuzzy constructs, estimates, in a quantitative way, a normalized index of the users’ QoI. The latter, then, can be used to identify users’ LMS interaction trends and provide personalized feedback to the users.

Both the C/M-ANFIS and the FuzzyQoI models are described in the succeeding sections.

3. THE C/M-ANFIS MODEL

Prediction of human behavior is of great importance on the basis of counseling and instruction (Tyler, 2013). Incorporating this approach in a collaboration environment, predictions of the quality of the peer’s collaborative activity in a forthcoming collaborative session, may ground the provision of advanced individualized feedback, towards self-improvement. Such prediction however, may be produced by the generalization ability of a model that realizes the correlation of the peer’s collaborative/metacognitive behavior at previous successive steps of collaboration; this is the backbone of the C/M-ANFIS model.

In particular, the C/M-ANFIS model constitutes a strong advisory student-supporting component, which estimates student’s collaborative activity of the next step \( \tilde{C}^{s+1}_n(p) \), prior to the concrete collaborative experience, when presented with current \( C^s_n(p) \) and \( M^s_n(p) \) values, as depicted in Fig. X.4.

**FIGURE X.4 SHOULD APPEAR ABOUT HERE**

To infer the \( \tilde{C}^{s+1}_n(p) \) value, the C/M-ANFIS model is trained to evaluate the relation between the forthcoming collaborative activity with the current collaborative and metacognitive activity.
However, this initially unknown relation is hidden within the empirical data that are obtained from the Lin2k. Therefore, C/M-ANFIS training is an equivalent procedure to learning from empirical data. This coincides with ANFIS structure (Jang, 1992) and motivates us for its use in the present study. In fact, C/M-ANFIS is based on an ANFIS five-layer feed-forward network structure. During training, at each level, the parameterized nodes perform specific functions of the incoming signal, as follows.

For simplicity we suppose that the C/M-ANFIS rule-base contains two rules of Sugeno type (Jang, 1993):

R1: IF $C^*_n(p)$ is $A_1$ AND $M^*_n(p)$ is $B_1$ THEN $f_1 = p_1 C^*_n(p) + q_1 M^*_n(p) + r_1$ ELSE,

R2: IF $C^*_n(p)$ is $A_2$ OR $M^*_n(p)$ is $B_2$ THEN $f_2 = p_2 C^*_n(p) + q_2 M^*_n(p) + r_2$,

where $A_i, B_i$ and $p_i, q_i, r_i$, with $i = 1, 2$, are linguistic variables and constants, respectively (Jang, 1993). The $ith$ node function of the first layer performs fuzzification of the incoming signal as follows:

$$O^1_{C_i} = \mu_{A_i}(C^*_n(p)), O^1_{M_i} = \mu_{B_i}(M^*_n(p)), i = 1, 2,$$

(1)

where $\mu_{A_i}, \mu_{B_i}$ denote the membership functions that specify the degree to which $C^*_n(p)$ and $M^*_n(p)$ belong to the corresponding linguistic variables $A_i$ and $B_i$, respectively. $O^1_{C_i}$ and $O^1_{M_i}$ describe the collaborative and metacognitive activity, respectively, using fuzzy values (i.e., low or good collaboration; low or satisfactory metacognition). The shape of the continuous and piecewise differentiable membership functions is described by parameters. These are the premise parameters and are adjusted by using the learning algorithm. Each node of the second layer $O^2_i$ presents the firing strength of a rule, estimated by multiplying the incoming membership values of the previous layer:

$$O^2_i = w_i = O^1_{C_i} \cdot O^1_{M_i}, i = 1, 2.$$

(2)

The $ith$ node of the third layer $O^3_i$ normalizes the firing strength of the rules:
\[ O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \] (3)

The node function at the fourth level is of the form:
\[ O_i^4 = \bar{w}_i f_i = \bar{w}_i (p, C_n^i(p) + q, M_n^i(p) + r), \quad i = 1, 2, \] (4)
where \( \{p, q, r\} \) are the consequent parameters. A single node constitutes the fifth layer, which computes the overall crisp output:
\[ O_i^5 = \tilde{C}_n^{i+1}(p) = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \] (5)

The C/M-ANFIS model structure is depicted in Fig. X.5.

**FIGURE X.5 SHOULD APPEAR ABOUT HERE**

The training of the C/M-ANFIS model is achieved through the following process. Let the following vectors:
\[ Z^{1L}_C(p) = [C_A^1(p), C_A^2(p) \ldots, C_A^L(p), C_B^1(p), C_B^2(p) \ldots, C_B^L(p)]^T, \] (6)
\[ Z^{1L}_M(p) = [M_A^1(p), M_A^2(p) \ldots, M_A^L(p), M_B^1(p), M_B^2(p) \ldots, M_B^L(p)]^T. \] (7)

The input-output pairs
\[ y = \begin{bmatrix} Z^{1L-1}_C(1) & Z^{1L-1}_M(1) \\ Z^{1L-1}_C(2) & Z^{1L-1}_M(2) \\ \vdots & \vdots \\ Z^{1L-1}_C(N) & Z^{1L-1}_M(N) \end{bmatrix}, \] (8)
\[ w = [Z^{2L}_C(1), Z^{2L}_C(2) \ldots, Z^{2L}_C(N)]^T, \] (9)
respectively, are all presented to the system during the C/M-ANFIS model training. Learning is implemented in epochs in order to define the values of the premise and consequent parameters by minimizing, with a predefined accuracy, the Root Mean-Squared Error (RMSE),

20
\[
RMSE = \sqrt{\frac{(w - \hat{w})^T (w - \hat{w})}{2(L-1)N-1}},
\]

where \( \hat{w} \) denotes the estimate of \( w \). Each epoch foresees two passes: a forward pass of the signal, where the premise parameters are kept fixed and the consequent parameters are calculated by the least squares method, and a backward pass, where the consequent parameters are kept fixed and the premise parameters are updated by the gradient descent method (Jang, 1992, 1993).

4. THE FUZZYQOI MODEL

Evaluation of the user’s QoI with LMS requires for intelligent systems that could provide a model of the domain expert’s evaluating system, with the promise of advanced features and adaptive functionality (Levy & Weld, 2000). Based on the latter, a Mamdani-type (Tsoukalas & Uhrig, 1996) fuzzy logic-based QoI modelling, namely FuzzyQoI scheme, was recently proposed by Dias and Diniz (2013). Similarly to C/M-ANFIS, the FuzzyQoI model constitutes a FIS structure that is able to produce evaluative inferences upon input data. In particular, the latter correspond to the key-parameters and variables (metrics) of LMS Moodle involved within a b-learning environment concerning the user’s interaction with the system, whereas the outputted inference forms a quantitative measure of the user’s overall QoI (Dias & Diniz, 2013) (see Fig. X.2).

The FuzzyQoI model incorporates 110 LMS Moodle metrics (Dias & Diniz, 2013), which correspond to 12 categories that serve as inputs to the FIS structure. These 12 input variables are further handled by a nested sequence of five FISs forming the FuzzyQoI scheme, illustrated in Fig. X.6, along with the intermediate variables produced by each nested FIS.

FIGURE X.6 SHOULD APPEAR ABOUT HERE

For the construction of the knowledge base of the FuzzyQoI scheme, an expert in the field of analyzing LMS Moodle data within the context of b-learning is used, for defining the structure of the
membership functions used for each FS and the corresponding IF/THEN fuzzy rules. In particular, a three-level of trapezoid membership functions corresponding to Low (L), Medium (M) and High (H) values, respectively, are used for the FIS1-FIS4, whereas a five-level of trapezoid membership functions corresponding to Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH) values are adopted for the final FIS5, increasing, this way, the resolution in the segmentation of the universe of discourse of the AC, TP and ET inputs and QoI output in the final FIS5 (Dias & Diniz, 2013).

The bridging of theoretical concepts (i.e., C/M-ANFIS and FuzzyQoI models) with practical implementations is eminent from the evaluation paradigms that follow.

5. EVALUATION PARADIGMS

5.1. The C/M-ANFIS Model Evaluation Case Study

The implementation and validation issues of the C/M-ANFIS model, when embedded in the Lin2k computer-mediated collaboration environment and applied into two case studies related to environmental engineering education, are presented here. The first case study is used for training and testing the C/M-ANFIS model, whilst the second one for validation of the supporting role of its best-trained version.

The training data set was obtained from the distant collaboration of 44 pairs of civil engineering students (7th semester) at the Department of Civil Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece. They were randomly selected, and since they had never used a computer-mediated collaboration environment before, they received an introductory seminar to get acquainted with the Lin2k interface (Hadjileontiadou et al., 2003). A case study was set in the course of environmental technology concerning everyday problems. The aim of the peers’ collaboration was to produce a written technical report on those problems. At the task level, the case study approach had been structured in six steps, as presented in Table X.3, producing, at the collaborative/metacognitive
activity level, a series of six successive sessions. Hence, the two-input one-output training vectors that were obtained were the ones described by (8) and (9), respectively, with \( L = 6 \) and \( N = 44 \). The overall empirical data were 88 input-output vectors. In order not only to train but also to test the training of the C/M-ANFIS model, 75% of the empirical data was used for the training procedure while the rest 25% for model testing.

**TABLE X.3 SHOULD APPEAR ABOUT HERE**

During the C/M-ANFIS training, the analytical forms of prod and probor operators (Tsoukalas & Uhrig, 1996), were used for the connectors AND and OR, respectively, the min for the IF-THEN implication and the max for the ELSE aggregation (see linguistic terms in the aforementioned rules R1 and R2), and the defuzzification method wtaver produced the crisp output (Tsoukalas & Uhrig, 1996). The whole procedure was implemented in Matlab 2012b (Mathworks Inc., Natick, MA).

The C/M-ANFIS model training aimed at selecting the premise and consequent parameters by minimizing, with an accuracy of 0.01, the \( \text{RMSE} \). Different set ups were tested during the training procedure, resulting in the \( \text{RMSEs} \) presented in Table X.4. From the latter, it is clear that the set up in the last raw (bold values) results in the minimum \( \text{RMSE} \), both in training and in testing procedures, and consequently it was considered as the best-trained version of the C/M-ANFIS model. The quite high number of rules (100) in the best-trained version of the C/M-ANFIS model is due to its effort to model the unknown relation between \( C_n^s(p) \) and \( M_n^s(p) \) data.

**TABLE X.4 SHOULD APPEAR ABOUT HERE**

To validate the performance of the trained C/M-ANFIS model as a supporting component under ‘real’ conditions, a second case study was carried out. After the completion of the C/M-ANFIS model-training phase, we embedded the model to Lin2k (see Fig. X.4), and conducted an experiment to
validate its performance as a supporting component. We used the best-trained version of the C/M-ANFIS model to all steps of the case study under investigation. The participants in this experiment were ten pairs of civil engineering students (from the same semester, yet different than the ones involved within the training phase). They collaborated on a six-step case study with a similar structure as the one depicted in Table X.3, and a content that this time had been assigned in the course of economical and environmental policy in the European Union. Half of the pairs constituted the experimental team whereas the rest of them the control team. The first team received the enhanced Lin2k feedback including the predicted by the C/M-ANFIS model \( \tilde{C}_{n+1}^{\text{Lin2k}}(p) \) value, whereas the second team received the Lin2k normal feedback information. The whole procedure was again implemented in Matlab 2012b (Mathworks Inc., Natick, MA).

Figure X.7 presents two examples of the QoC as it is expressed by the \( C_{n}^{15} (l) \) values (ranging from 0 to 100%) during the collaboration between two pairs from control (Fig. X.7(a)) and experimental (Fig. X.7(b)) teams, respectively. Solid and dashed lines in Fig. X.7 correspond to \( n = A \) and \( n = B \), respectively, while asterisks and squares in Fig. X.7(b) denote the estimated by the C/M-ANFIS model \( \tilde{C}_{n}^{26} (l) \) values for \( n = A \) and \( n = B \), respectively. For the evaluation procedure, the \( C_{n}^{16} (l) = 50\% \) value was set as the desideratum percentage that corresponds to a balanced collaboration between the peers, seeing them as complementary members of a team. Values of \( C_{n}^{16} (l) \) lower or higher than 50% correspond to a rather unbalanced collaboration, i.e., the collaborative activity of the one collaborator suppresses the collaborative activity of the other, and vice versa.

**FIGURE X.7 SHOULD APPEAR ABOUT HERE**

From Fig. X.7(a) it is clear that the pair from the control team exhibited slow convergence (after step four) to balanced collaboration, whereas the experimental team converged rather faster (after step two), as it is shown in Fig. X.7(b). It is noteworthy that the presentation of the predicted
\( \tilde{C}_A^2(l) = 60.3\% \) value prior to step two to the A collaborator warned him to correct his collaborative activity at the forthcoming step and collaborate in a more balanced mode. His reaction to this warning resulted in a more balanced collaboration at the following steps. This shows that the support of the C/M-ANFIS model could serve as a kind of prognosis that keeps the peer to a more balanced collaboration track.

The qualitative validation of the C/M-ANFIS model as a supporting component was conducted through the following procedures:

1. Comparison of the quality of the case studies technical reports, through the marks given by two external evaluators. The fact that the average of the experimental team results was higher than the control team results is indicative of the enhanced Lin2k performance due to the C/M-ANFIS model integration.

2. Elaboration of the questionnaires that were addressed to the experimental team revealed that the feedback of the C/M-ANFIS model was very well accepted. Nine students out of ten stated that they considered the feedback information that was given prior to their next step collaborative activity, whereas all of them found this information useful and innovative.

From the above results it is evident that the best-trained version of the C/M-ANFIS model truly contributes to the enhancement of the support provided to the distant peers, since, due to its predictive functionality, it provides a reliable estimation of the forthcoming collaborative performance of the peers, guiding them to more efficient and balanced QoC.

5.2. The FuzzyQoI Model Evaluation Case Study

The LMS Moodle data for the validation of the FuzzyQoI model (Dias & Diniz, 2013) were drawn from a b-learning environment related to five undergraduate courses (Sport Sciences, Ergonomics, Dance, Sport Management and Psychomotor Rehabilitation) offered by a public HEI (i.e., Faculty of Human Kinetics (FKH), University of Lisbon, Portugal). The users of the LMS Moodle were both
professors (68 in total) and students (1421 in total) all started to use LMS Moodle in the 2009/2010 academic year. The data used in this case study correspond to a 51-week LMS Moodle usage time-period (academic year 2010/11), including 990734 interactions in total (88066 from professors and 902668 from students). For each LMS Moodle metric included in the category ‘Action’ (alone or combined with the category ‘Module’) logged by a user, a number from 1 to 12 was assigned, according to the correspondence of LMS Moodle metrics with the 12 input variables of FIS1-FIS3 (see Fig. X.6). In order to accommodate any possible absence of users’ interactions with the LMS Moodle for one day (or perhaps a couple of days) per week, the number of the daily data loggings belonging to the same category per user was summed across the duration of one week; hence, setting the latter as the analysis time-unit. In accordance to this, the input variable TP of FIS5 (see Fig. X.6) was corresponded to a sequence of numbers from 1 to 51, whereas the values of the input variable ET of FIS5 (see Fig. X.6) were kept in seconds, as they were initially formatted by the LMS Moodle archiving engine. Since the universe of discourse of all (input/output) variables of the FuzzyQoI scheme ranges from 0 to 1, all derived input variable values per week were normalized to the corresponding maximum value across the analyzed total time-period, i.e., 51 weeks, for each user. Furthermore, some distinct dates across the whole examined time-period were taken under consideration to segment the latter. These were used in order to identify any possible changes in the users’ interaction behavior correlated with a specific time-period section. To this end a time-period segmentation was adopted, resulting in time-period sections (e.g., semesters (S1: 2-16, S2: 23-38 weeks), exam periods (1st: 18-23, 2nd: 38-46 weeks), and interruptions (16-18, 24-25; 30-31 weeks)) that served as landmarks in 51-week total examined period.

The contour plot of Fig. X.8 (top) depicts the estimated output QoI from the FIS5 (see Fig. X.6) of the FuzzyQoI model for the case of professors (sorted in an ascending order according to the date of their first access to the LMS Moodle) across the examined period (51 weeks). The estimated QoI values lie within the range of [0.0957, 0.9112]. Note that in the contour plot, each point corresponds
to the pair (x-axis: week#, y-axis: professor#), whereas the greyscale intensity expresses the value of the specific fuzzy output within the range of [0, 1] for the specific pair. Moreover, the lines in parallel to y-axis are drawn at the specific weeks that define the time-period segmentation, so to facilitate visual grouping of the results at the specific time-period sections.

Figure X.8 (middle) shows the mean value (solid middle line)±std (gray area) of the estimated QoI, averaged across the professors, whereas Fig. X.8 (bottom) illustrates the similar graph as in Fig. X.8 (middle) but for the case where the estimated QoI from Fig. X.8 (top) surpasses the level of 0.1 (just above zero). In this way, the group-like tendency of their interaction with the LMS Moodle across the examined time-period, from all professors (both with QoI=0 and QoI≠0 per week) and from those that at least exhibited a level of QoI>0.1 per week can be monitored.

**FIGURE X.8 SHOULD APPEAR ABOUT HERE**

The derived QoI domain of Fig. X.8 (top) can serve as monitoring space of the quality of interaction for each single professor across the whole examined time-period, providing a means for setting an evaluation process that could activate possible metacognitive procedures towards more efficient incorporation of LMS Moodle in their activities as educators.

From the inspection of Fig. X.8 (middle) it is clear that, as a group, all professors show a low-towards-moderate interaction (in all estimated parameters the mean value lies within [0.1, 0.3]), which dependents on the time-period segmentation. Nevertheless, when considering those that at least exhibit QoI>0.1 (Fig. X.8 (bottom)) a more sustained attitude is seen, as the mean QoI is sustained around 0.5 for almost the whole academic year, exhibiting a decline to 0.4 after the 2nd exam period (>46 week). Note that in week 24 (carnival interruption) the professors’ QoI values sustained quite low (<0.1), producing the zero value in Fig. X.8 (bottom).
Monitoring of the alterations of the mean QoI and the corresponding std across the whole time-period can assist the acquisition of the dynamic underlying attitude of the professors as a group, regarding their effective interaction with the LMS Moodle. This, then, could be used as an informative parameter that could evoke initiatives towards rethinking of the value and efficiency of the LMS-based b-learning environment, both by the educators, the LMS designers and education policy makers.

Similarly to the professors’ case, the contour plot of Fig. X.9 (top) depicts students’ estimated output QoI from the FIS5 (see Fig. X.6), lying within the range of [0.0916, 0.9112]. As it is seen from Fig. X.9 (top), there are many cases where the QoI value is sustained significant for more than one week across students (see for example the QoI values that correspond to the students’ number lying within 800-1000).

Similarly to the case of professors, the derived QoI domain of Fig. X.9 (top) can also serve as monitoring space of the quality of interaction for each single student across the whole examined time-period, initiating evaluation processes that, in turn, could promote possible metacognitive procedures towards more efficient incorporation of the LMS Moodle in their activities as learners.

The group-like tendency of students’ interaction with the LMS Moodle across the examined time-period is illustrated in Fig. X.9 (middle), which shows the mean value (solid middle line)±std (gray area) of the estimated QoI, averaged across the students. Moreover, Fig. X.9 (bottom) depicts the same information as the one in Fig. X.9 (middle), yet involving only those students that exhibit QoI>0.1 per week. From Figs. X.9 (middle and bottom) it is clear that, as a group, students show a low-towards-moderate interaction (in all estimated parameters the mean value lies within [0.1, 0.3]), which dependents on the time-period segmentation. Nevertheless, the students that show QoI>0.1 per week sustain this attitude for the whole academic year, presenting a decay almost at its end (week 48). Note that the low mean values of Fig. X.9 (middle) are mainly due to students’ time-delayed and merely discontinued interaction seen in Fig. X.9 (top), so in the averaging across students, frequently,
the lower values dominate to the higher ones. Note that at week 24, only one student exhibits QoI value greater than 0.1 (QoI=0.488); hence, the mean QoI is sustained around 0.5.

**FIGURE X.9 SHOULD APPEAR ABOUT HERE**

From a global approach of the estimated QoI values exhibited by the LMS Moodle users (both professors and students), the distribution users (percentages of the total number of professors and students, respectively) along the QoI range from 0 to 1 (step 0.1) was estimated; the latter is depicted in Fig. X.10. As it can be seen from Fig. X.10, two distinct ranges could be identified as the most dominant ones, i.e., the QoI∈[0.1-0.2] and QoI∈[0.4-0.5], both in professors’ and students’ cases, yet with a reversed relation in the corresponding percentages. In general, there is a similar behavior between the professors and the students, exhibiting a statistically significant correlation coefficient of $r = 0.9832$ (probability of false alarm $p = 3.43 \times 10^{-7} \ll 0.01$). This, potentially, express an influence and interconnection between the professors’ and students’ attitude with the LMS use.

**FIGURE X.10 SHOULD APPEAR ABOUT HERE**

In Figs. X.8 (top) and X.9 (top), ups and downs in the QoI of interaction (both from professors and students, respectively) could be associated with the time-period segmentation, revealing the influence of the structure of the academic year, in terms of formal teaching, interrupting and examining time periods, to the users’ interaction attitude with LMS. To further elaborate this finding, the distribution of the users’ number that exhibited $QoI > 0.1$ for the two semesters of the academic year of 2010/11 and for the two users’ types, i.e., professors and students, was estimated and illustrated in Fig. X.11, along with the corresponding time-period segmentation (vertical lines). As it apparent from Fig. X.11, the number of users that exhibit QoI>0.1 reduces during all interruption periods, except of the Easter’s one (weeks 30-31). Moreover, there is a reduction in the professors’ number with QoI>0.1 during the two exam periods (weeks 18-22; weeks 38-46), a pattern that is not
followed by the students, whose corresponding number is sustained high, especially as the exam period evolves. In general, a bell-shaped schema could be identified in all graphs of Fig. X.11, showing the gradual evolution of the interaction with the LMS Moodle to reach a maximum in the number of users involved during each semester, followed by a gradual reduction (especially in the case of professors). Interestingly, both professors and students continue to keep themselves involved with the LMS, even after the end of the 2nd exam period (weeks >46), probably, as a follow-up attitude to their LMS-based activities during the previous time-periods.

**FIGURE X.11 SHOULD APPEAR ABOUT HERE**

The two case studies presented so far, exemplify the potential of the QoC and QoI to serve as important metrics that could contribute to a personalized feedback to the user, enhancing his/her interaction with the OLE. This concept is elaborated further in the succeeding section.

### 6. TOWARDS HYBRID MODELING WITHIN SEMANTIC WEB 3.0

Our starting point was the thesis that personalized support to OLE users is further enhanced if it is based on efficient modeling of their collaborative/metacognitive interactions and their interaction with the OLE itself. By using computer-mediated collaborative tools and neurofuzzy modeling, along with nested FISs, we have been able to generalize from empirical data and reveal the rules that govern the outcome of peers’ collaborative and metacognitive activities along with their interaction attitude with LMS. Based on this knowledge, efficient and individual support could be provided to each user; this is justified by the following discrete contributions per model that could further be combined in a hybrid approach and placed within the semantic Web 3.0.
6.1. The C/M-ANFIS Model Contribution-QoC

The C/M-ANFIS model support aims at increasing the effectiveness of collaboration between the peers by providing advice strictly on collaboration issues, such as equality of participation, reaching a common understanding (Edwards & Mercer, 2013), and not on task-oriented ones, such as understanding and application of key domain concepts.

The C/M-ANFIS model support combines two approaches: i) to provide indicators to the peers, and ii) to advise them. For the first approach, it uses the collaborative and metacognitive data provided by the Lin2k tool in order to aggregate them into three high-level indicators, i.e., $C_n^s(p), M_n^s(p), \tilde{C}_n^{s+1}(p)$, and graphically display them to the collaborators along with a set of desired values (as the QoC in Fig. X.7). At this stage, the collaborators are expected to manage the interaction themselves, having been given the appropriate information to do so. Since the displayed indicators express an abstraction of the complex variables of the employed model of interaction their interpretation and action upon the indicator values by the peers is facilitated. In addition, the peers easily comprehend the displayed indicators without any special analysis that would increase the peer’s cognitive load and might lead to misinterpretation of the indicators. The adaptive character of the C/M-ANFIS model further enhances the support to the peers, since their individual collaborative and metacognitive activity has been taken into account by the model. Moreover, the display of the two indicators, $M_n^s(p), C_n^s(p)$, at the $s$ step, next to the predicted one for $s+1$ step, $\tilde{C}_n^{s+1}(p)$, provides the peer with the information regarding: i) how the system has judged his/her collaboration, ii) how s/he has thought about her/his collaboration, and iii) how the system predicts his/her collaboration for the next step. In that way, a positive impact on peers’ metacognitive activities is achieved, supporting the construction and gradual optimization of a shared mental model of interaction. The latter, may encourage peers to regulate their interaction explicitly, leading to a better coordination of the joint effort to reach a solution (Jermann et al., 2001).
For the advisory support, the C/M-ANFIS model mimics the role of a human advisor in a collaborative learning environment. Actually, the advisor, based on collaborative data, i.e., close observance of group interaction, trial and error, and experience (Jermann et al., 2001), advises the peer both on his/her current status of collaboration and on the future actions s/he must take for further improvement. Similarly, the C/M-ANFIS model, by inferring on collaborative and metacognitive data, foresees the status of collaboration in the next step and offers the peers with tips to improve their interaction and achieve or maintain equilibrium (ideal collaboration). Actually, these tips propose some simple remedial actions, such as “As far as I can tell from your collaboration activity so far and my prediction for the next step, you have to dramatically increase your participation from now on”. The tips are drawn from a message-database, which includes messages for achieving, maintaining, and warning, according to the combined values of the three indicators $C_n(p), M_n(p), C_{n+1}(p)$. In particular, big differences between the indicators and the desired value of 50% provoke achieving messages, whereas small ones provoke maintaining messages. In addition, conflicts between the values of the indicators provoke warning messages.

The employment of both indicators and advice in the support provided to peers by the C/M-ANFIS model motivates self-diagnose and sustains coaching, forming an efficient support scheme that leads distant collaborators to improve in different ways.

From an overview of the C/M-ANFIS model performance the following characteristics emerge:

1. The C/M-ANFIS model can provide real-time support in an asynchronous mode of collaboration, without imposing any time constrains in the flow of the collaborative procedure.

2. The C/M-ANFIS model proves to be a supporting system, which may be integrated in computer-mediated collaboration environments, independently from the task content.

3. The integration of the C/M-ANFIS model within a collaboration environment i.e., Lin2k, extends the dynamic of the latter, tooling it up with the ability to provide individualized
support to the users with adaptive characteristics. Moreover, this automated support, can be practically addressed to an unlimited number of users without human intervention, which many times encompasses errors or bias.

(4) The C/M-ANFIS contributes to modeling the correlation of the peer’s cognitive and metacognitive activity or otherwise the peer’s skills and beliefs during a collaborative activity, in a novel but yet meaningful way, which is very well accepted by the users.

A noteworthy characteristic of the C/M-ANFIS model is its microgenetic design (Fazio & Siegler, 2013), which calls for a closer look at how change in behavior occurs as individuals go through a learning experience (Lavelli et al., 2005). In particular, the C/M-ANFIS model elaborates on the following key actions (Lavelli et al., 2005):

(1) It regards the individual as the unit of analysis and observes the changes in his/her collaborative behavior through a period of time, i.e., duration of the case study. The observations take place during the period in which the change occurs.

(2) It takes into account the elevated density of the observations within the transition period (Fogel, 2011). That is, observations take place in time intervals i.e., weeks for the steps of the case study, shorter than the period in which the change is expected to take place i.e., months for the completion of the case study.

(3) The observed behaviors are intensively analyzed (Fazio & Siegler, 2013), through the neurofuzzy methodology with the goal of identifying the processes that give rise to the change.

The C/M-ANFIS model, through the aforementioned microgenetic design, elicits from empirical observations and makes explicit the behavioral patterns of change of the peer’s cognitive and metacognitive activity, during incremented sessions of collaboration. However, the approach to observe and realize behavioral change calls for not only a meticulous observation of how the change occurs, but also the possibility of an impetus for change, as Kuhn suggests (Kuhn, 1995; Elad-
The impetus may come from the settings and cultural artifacts in the mediated collaboration environment, e.g., a planned function, or a regulative force that evaluates, monitors, and selects the strategies that will be used (Das, 2000). Hence, there is a need to further investigate the way in which a planned change at the micro-level of interactions may give rise to new patterns of the collaborative behavior at the macro-level (Lavelli et al., 2005), i.e., to provoke overall collaborative skills improvement. In order for this change to occur, new meaningful information needs to be presented at the micro-level (Oyama, 2000). The C/M-ANFIS model contributes to the occurrence and acceleration of this change through its generalization capability. Presenting to the individual, at successive intervals of the micro-level (end of each step of the case study), the estimated value of the forthcoming collaborative activity \( \tilde{C}_{n+1}(p) \), it highly increases the possibilities to cause the desired change, as it was justified by the experiments (see Fig. X.7). Consequently, the C/M-ANFIS contributes to a formatively improvement of the peer’s collaborative behavior, which is the core of the provided support.

From a rough comparison between the C/M-ANFIS model and other related works the following can be noted:

1. Unlike AKM (Collins et al., 1996; Gerner et al., 1998) and some of the EDM approaches (Beck et al., 1997; Soller & Lesgold, 2000b), the C/M-ANFIS model combines both collaborative and metacognitive data and makes explicit the relation of cognitive and metacognitive interactions during collaboration. Thus, it introduces another level of abstraction for the realization and interpretation of hidden and complex relations in human interactions. This knowledge enhances the quality and efficiency of the provided support.

2. Unlike most of the systems that support collaborative learning, thoroughly reviewed by Jermann et al. (2001), the support provided by the C/M-ANFIS model has a predictive character derived from its neurofuzzy generalization capabilities. This prediction can influence the peer’s collaborative interactions at a micro- and/or macro-level, causing
convergence towards a desired change. A model where the peer’s future performance is predicted is given in (Beck et al., 1997). However, unlike our model, these predictions refer to the task performance and not to the collaboration activity.

(3) Finally, unlike the AKM, and like all EDM, the C/M-ANFIS needs sufficient amount of data in order to enhance its performance, i.e., to increase its generalization ability with simultaneous minimization of its training error. Nevertheless, its low computational complexity, its modular character, and its task-content independence, enables it to be easily integrated into other collaboration environments, similar to Lin2k, applied in a variety of collaborative case studies. As Lin2k is a Web-based tool, it could easily be transferred to mobile devices, such as smartphones and tablets, enabling, further, the use of C/M-ANFIS in the m-learning context.

6.2. The FuzzyQoI Model Contribution-QoI

As described in the previous section, the proposed FuzzyQoI model was validated on data drawn from LMS Moodle. The latter provides many communication tools, facilitates the creation and administration of learning objects, allows management of user data, fosters usability, and exhibits adaptation capabilities (Graf, 2007). At the current stage, LMS provides the same course for each learner. Learners then have the possibility to use the provided learning material in different ways. According to Felder and Silverman (1988), learners might have difficulties in learning if their learning style is not supported by the teaching environment. As a remedy to this, they recommended to provide courses with many different features which support different learning styles rather than providing courses that suit only one learning style. This is also supported by the b-learning environment. Although there are conflicting results about the effectiveness of incorporating learning styles in traditional and online education and the impact on performance and/or behavior (Jonassen & Grabowski, 1993; Coffield et al., 2004), adaptation of the LMS courses to the individual learning
styles of learners can be useful (Graf, 2007). In addition, by enhancing LMSs with adaptivity, teachers can continue holding their courses in LMSs and therefore, taking all advantages of LMSs. Extending this perspective here, the intermediate estimated fuzzy outputs and the final QoI output of the FuzzyQoI model can be used as indicators twofold, so they that can:

(1) serve as the basis for the generation process of adaptation features for the LMS (system’s response) and

(2) evoke metacognitive procedures within the users (like those from the QoC), so they could improve their QoI with the LMS (user’s response).

Turning into the design of the FuzzyQoI model, it should be noted that a unified approach across professors and students was adopted. The nature of the fuzzy logic itself, however, allows for the independent firing (or not) of a fuzzy rule, according to the current value presented to the model input(s); hence, any differentiation in the interaction attitude between the two user groups is easily reflected on the activation (or not) of the proper fuzzy rule(s). This design makes the application of the FuzzyQoI model easier in practice, for example to be embedded as a module within the LMS structure, and reduces the computational burden by avoiding redundant repetition in its structural components.

The potentiality of the FuzzyQoI model to efficiently explore behavioral aspects of professors and students as they interact with the LMS Moodle within a b-learning context is further described in the recent work of Dias and Diniz (2013). In the latter, specific aspects and more detailed analysis of the individual behaviors or the group trends identified via the estimated QoI, both for professors and students, are provided. The following potentialities of the FuzzyQoI model, however, could be appreciated, i.e.:

(1) encouragement of LMS managers/pedagogical designers to include the measure of QoI in OLEs;
(2) reflection upon issues, such as system-quality, system-use and user-satisfaction into evaluation techniques of LMS-based b-learning systems efficiency;

(3) provision of a fast and early feedback to the HEIs to enhance their understanding of the level of online learning systems efficiency;

(4) undertaking corrective actions (if necessary) for improvement in a more administrative level; and

(5) applying the FuzzyQoI to similar data from consequent academic years, in order to reveal possible macro-/meso-/microscopic causal dependencies, converged/dispersed interaction trends, periodicities/specific patterns dominance in the interaction attitude.

6.3. The Hybrid Model-QoC/QoI in Semantic Web 3.0

The past decade has seen enormous growth in the use of LMSs in HEIs, providing the potential for rich learning environments built on social constructivist theories under the concept of b-learning. An essential factor, however, in determining the efficacy of online teaching/learning towards the creation and preservation of sustainable learning communities is the users’ QoI with LMSs; yet, in many cases, QoI has not been properly acquired, mainly, due to its inherent qualitative character. To remedy the latter, the FuzzyQoI model described in this chapter has shown significant potential to:

(1) handle a multitude of variables and inference upon them, furnishing us with a quantitative approach to evaluate the quality of interaction, both in professors’ and students’ case; and

(2) function as a means for better understanding and explaining the nature of underlying aspects, which influence the construction of users’ interaction behavior under the LMS-based b-learning approach.

In addition, the examined C/M-ANFIS model contributes to the quantitative evaluation of the QoC, taking into account both the personal (metacognitive) and the social (collaborative) contexts. The exploratory trajectory followed through the case studies, revealed noticeable aspects within the OLE, which all are influenced by the human behavior characteristics. OLE usability, profiles and
interaction issues holistically relate with the human factor. Combined with the boosting of the Internet metamorphosis to an increasingly social tool, the need for online education that efficiently incorporates users’ characteristics, evolving social needs and expectations becomes apparent. This, really, could transform the perception of the LMS to a more intelligent tool that functions in a more “personalized” way.

Talking about personalization, the problem becomes crucial when authors want to provide materials, which should support different users in there different phases of the learning process. The task, thus, is to find a (technological and procedural) solution in order to support the learners effectively. The knowledge society demands competencies and skills that require innovative educational practices based on open sharing and the evaluation of ideas, fostering creativity and teamwork (collaboration) among the learners. The vast number of tools supporting collaboration on the Web is an indicator that social software tools are not only a flash in the pan, but lead to a new notion of learning and a measure for sustainable competence development. Towards such endeavor, ideas such as *semantic analysis* of learning activities, tagging opportunities with a focus on appropriateness for learning, visualization of communities and people with similar (learning) interests, new approaches to content and network analysis, and a technical integration of different LMS, should be considered. These ideas clearly comply with the emerging concept of semantic Web 3.0 (Lukasiewicz & Straccia, 2008). The latter is about connecting data, all data, everywhere and putting them in massive graph databases that can be read and conceptually understood by computers. Currently, most Web pages are designed to be read by people, not machines. Nevertheless, because linked, graph-based data are machine-readable, hence, computers could be able to answer increasingly sophisticated questions for the user-to interpret data, understand context, infer meaning and do reasoning. In other words, semantic databases, which sprang out of Artificial Intelligence, allow computers first to “think”, to understand big, conceptual queries, and then find and combine exactly the information humans need to make ever-smarter decisions.
In this context, teaching-learning process should be seen as a complex and constantly dynamic reality (Peters, 2001; Garrison & Kanuka, 2004; Bates, 2005) that could be supported by ICT-based techno-pedagogical models that include representations, visions, skills, resources, attitudes and practices of their social actors, all placed under the concept of the semantic Web 3.0. In fact, the combination of traditional F2F and online learning, within the context of b-learning, offers different delivery methodologies/modes that have the potential to optimize the learning development, deployment costs and time (Oliver & Trigwell, 2005). In parallel, education paradigms shifted to incorporate online collaborative learning environments (Johnson et al., 2013). Actually, collaborative learning can assist students to feel more interactive and also exerts a positive influence in terms of motivation, behavior and self-determination, as well as engagement in learning activities (Reeve & Tseng, 2011; Wijnia et al., 2011).

Taking the aforementioned perspectives together, an enhanced LMS-based intelligent teaching/learning modelling approach could be formed, by suggesting the incorporation of the hybrid and innovative processing techniques from the fields of neurofuzzy modelling and fuzzy set theory, as presented in the previous sections. In this fashion, a novel research framework could be established, by exploring the ways effective teaching could be accomplished when bridging the fields of blended- and collaborative-learning into a hybrid, LMS-based, enhanced teaching-learning environment. In this way, a holistic approach of the fundamental channels from which the educational process is conveyed could be adopted, combining cognitive and social information of the peers’ behavior and interactions. Consequently, the following objectives could be set:

(1) development of an educational and innovative framework around the online instructional environments, by exploring the potentialities of b/c-learning/teaching in the context of higher education and semantic Web 3.0;

(2) contribution to educational improvement on teaching practice supported in the LMS Moodle, providing new tools more suited to users’ QoC and QoI;
(3) development, application and validation across a vast number of users (students/professors) of efficient hybrid modelling approaches of LMS Moodle data, based on fundamentals of fuzzy inference systems;

(4) introduction of extended means, new tools and pathways for shifting from the typical form of LMS to the iLMS (Dias et al., 2014), incorporating issues such as personalization and technological adaptiveness;

(5) course effect analysis using the FuzzyQoI model, to examine how the course content affects the users’ QoI with LMS Moodle across the years;

(6) identification of possible macroscopic causal dependencies, converged or dispersed interaction trends, periodicities, specific patterns dominance in the LMS Moodle interaction/collaborative/metacognitive attitude, all reflected at the C/M-ANFIS and FuzzyQoI models response;

(7) comparative analysis across the forthcoming hybrid modelling approaches, blending the benefits of each one and identifying their pros and cons; and

(8) construction of new guidelines/recommendations about the enhancement of OLE-based teaching/learning processes, contributing to the enrichment of the HEI services and reformulation of educational policies/practices.

Adding to the above, ontologies could be used to link the quantitative metrics of QoC and QoI to information coding, so it could easier been processed by software agents, opening the door for a slew of new semantic Web 3.0-based applications. In fact, according to Gruber (1993), an ontology is a formal, explicit specification of a shared conceptualization. Pragmatically, a common ontology defines the vocabulary with which queries and assertions are exchanged among software entities. An ontology has concepts that identify the data entities of interest and these concepts are organized in a hierarchy called a taxonomy; concepts might have attributes and relationships, whereas a data item that has been marked up with a label corresponding to a concept is called a data instance. Through
this organization, ontologies could contribute to a shared and common understanding of QoC and QoI that can be communicated among the educational stakeholders and LMSs/OLEs. As the latter involve Web-based educational material, ontologies can be used to describe relationships between pages and other data (like QoC and QoI metrics), so to contribute to a personalized supporting system that could maximize the QoC and QoI, hence enhancing user’s teaching/learning experience. They can, therefore, be used to recommend learning resources of potential interest to the learner that potentially increase his/her QoI; even to recommend a ‘study-buddy’, with whom the learner shares common abilities and interests and can maximize his/her QoC when collaborates with him/her. From a technical point of view, this could be achieved by employing, for example, the DARPA Agent Markup Language/Ontology Inference Layer (DAML+OIL) ontology language (McGuinness et al., 2002), which describes structure of the domain, combined with the Resource Description Framework (RDF), which is used, in the same time, to describe specific instances, and Ontology Web Language and Information Retrieval (OWLIR) that handles the Event Ontologies (Connolly et al., 2001).

In one step further, using Cloud computing platforms (e.g., Microsoft Azure) and technologies in conjunction with semantic Web 3.0 technology and metadata, a shift from the traditional LMS to Cloud Learning Environments (CLEs) could be achieved, by facilitating the autonomous or collaborative study of user-chosen blends of content and courses from heterogeneous sources (Mikroyannidis, 2012). In CLE, semantic knowledge base serves as the core of the OLE, facilitating

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**There are no sources in the current document.** learners in finding educational services and collaborate on the Cloud, evoking collaborative ontology management techniques. In this concept, the proposed hybrid model could combine both LMS and CLE in the learning process, placing the user at the center and capturing his/her interaction with both contexts. This could, actually, assist HEIs to enrich their educational framework, facilitating, at the same time, the professors’/learners’ interaction (both autonomous and collaborative) with the OLEs. A schematic presentation of the
proposed architectural structure of the hybrid model is depicted in Fig. X.12, as an extension of Figs. X.1 and X.2.

FIGURE X.12 SHOULD APPEAR ABOUT HERE

Apparently, the online communication channels considered in Fig. X.12 should not be seen as static, yet with fluidity, directed to provide flow opportunities of communication in human–computer interaction in an OLE. From a common perspective, learners should be behaviorally, intellectually, and emotionally involved in online learning tasks. Nevertheless, the role of educational technology is to improve academic literacies in students, to create engaging communities of practice, and to improve learner’s motivation and self-empowered learners (Wankel & Blessinger, 2013). Generally, it is our hope that the ideas discussed in the present chapter will provide an intelligent framework, for possible reforms and alterations to the b- and c-learning modeling, and, hence, to effective process of online teaching/learning environment at HEIs.

7. CONCLUSION

New approaches in modeling collaborative/metacognitive and LMS interaction data in order to provide personalized support to OLE users have been presented in this chapter. From one hand, the examined C/M-ANFIS model adopts a neurofuzzy structure to adaptively infer on the users’ relation between collaborative and metacognitive activities. When embedded in an Internet-based computer-mediated collaboration environment, it combines cognitive and metacognitive empirical data to generalize on their relation. In that way, a system that adaptively supports OLE collaborator towards improving his/her collaborative skills is grounded.

The user’s support includes indicators (QoC and intension of improvement), and advices (achieving, maintaining, warning messages), combining self-motivation and coaching, respectively.
The ability of the C/M-ANFIS model to estimate future values of these indicators provokes creative changes in the micro- and macro-level of peers’ collaborative activity, guiding them to achieve or maintain equilibrium (ideal collaboration). Training, testing and validation results from the application of the C/M-ANFIS model on two case studies from environmental education at a Greek HEI prove its fast convergence to minimum error, its ability to accurately generalize from data, and its predictive performance. The FuzzyQoI model, on the other hand, provided an estimation of the QoI of professors and students in LMS Moodle, through the use of fuzzy logic that can handle the complexity and multi-variability of b-learning environments. In this way, development of a comprehensive and panoramic vision, which considers the human factor and the complex nature of b-learning, resulting in a quantitative explanation translated by the QoI index was achieved. The latter can represent a distinct path on approaching OLEs, since, on the one hand, it incorporates human subjectivity and, on the other hand, extends the experiences of monitoring of refined inter-action processes based on efficient LMS under b-learning mode. The efficiency of the presented FuzzyQoI scheme, validated via its application on experimental LMS Moodle data drawn from a Portuguese HEI, justifies the adoption of fuzzy logic in the field of education, while at the same time, motivates and prepares the way for an alternative approaches of the OLE modeling for b-learning modalities.

This is further explored with the proposal of a hybrid model that combines QoC and QoI within the context of semantic Web 3.0 and CLEs in a holistic perspective of the online learning educational context, shedding light upon the requirements for offering personalized feedback to learners, supporting them throughout their learning journey, and enriched recommendation services to HEI policy/service quality managers.

We are currently working on the implementation of the hybrid model that will employ the new concepts discussed in this chapter. We plan to pilot this prototype with the Open University (Greece) and the Faculty of Human Kinetics (Portugal) professors and students, in order to study and analyze the evolution of QoC and QoI within academic years. The outcomes of these pilots will allow us to
further validate our methodology and expand our database and implementation of the hybrid model on case studies from diverse areas, for its further generalization refinement. It is our hope that this effort could significantly add to the appreciation of the potentialities of the newly available technological means and networking concepts, such as semantic Web 3.0, in the field of Higher Education.

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Chapter Highlights

New modeling approaches within the Online Learning Environment (OLE) are presented in this chapter, particularly referring to the application of Neurofuzzy Networks in collaborative and metacognitive interactions modeling, along with to nested Fuzzy Inference Systems (FISs) that model the users’ interaction with Learning Management System (LMS). Both approaches provide personalized feedback and support to users (professors/students) within the collaborative- and blended-learning context, respectively. The first examined model, namely Collaboration/Metacognition–Adaptive Network-based Fuzzy Inference System (C/M-ANFIS), utilizes empirical data derived from a collaborative Web-based tool, namely Lin2k, to generalize on the relationship between collaborative and metacognitive activities, independently of the task-content. Based on the estimated relationship obtained and after training, the model predicts forthcoming values of a feedback indicator (quality of collaboration-QoC). Current and future values of the latter, current value of a metacognitive indicator (intension of improvement), and coaching advices (achieving, maintaining, warning messages) are presented to the users during successive steps of their collaboration. This kind of support provokes creative changes in peers’ collaborative activity, guiding them towards balanced collaboration. The second examined model, namely FuzzyQoI, models the 110 LMS Moodle activity metrics and via a series of five nested FIS infers for the users’ quality of interaction (QoI). Experimental training, testing and validation results of the C/M-ANFIS and FuzzyQoI models, when applied to collaborative and LMS interaction data from two Higher Education Institutions (HEIs), respectively, justify their accurate generalization from data and prediction abilities. As an extension of the two examined models, an alternative approach of the OLE modeling for b-learning modalities is further explored, with the proposal of a hybrid model, which combines QoC and QoI within the context of semantic Web 3.0 and Cloud Learning Environments, fostering user’s personalized support and offering a holistic perspective of the online learning context at HEIs.

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