Fuzzy Cognitive Mapping of LMS Users’ Quality of Interaction within Higher Education Blended-Learning Environment

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Abstract Learning Management Systems (LMSs) under blended (b-) learning modality can efficiently support online learning environments (OLEs) at Higher Education Institutions (HEIs). Mining of LMS users’ data, involving artificial intelligence and incertitude modeling, e.g., via fuzzy logic, is a fundamental challenge. This study addresses the hypothesis that the structural characteristics of a Fuzzy Cognitive Map (FCM) can efficiently model the way LMS users interact with it, by estimating their Quality of Interaction (QoI) within a b-learning context. This study introduces the FCM-QoI model (combined with a model visualizer) consisting of 14 input-one output concepts, dependences and trends, considering one academic year of the LMS use from 75 professors and 1037 students at a HEI. The experimental findings have shown that the proposed FCM-QoI model can provide concepts interconnection and causal dependencies representation of Moodle LMS users’ QoI, helping pedagogical instructors of HEIs to holistically visualize, understand and assess stakeholders’ needs.

Keywords Blended learning; Moodle learning management system; Fuzzy cognitive maps (FCMs); Quality of interaction (QoI); FCM-Viewer application.
1 Introduction

Education can be seen as a set of processes designed to transmit knowledge, skills and values to develop individual and collective abilities. At the same time, Learning Management Systems (LMSs), such as Modular Object-Oriented Dynamic Learning Environment (Moodle), within an Online Learning Environment (OLE), can provide educators an environment to place their online course materials and for students to receive that education while interacting with other students/teachers; however, students’ interactions, attention and communications are seen as relatively low in the LMSs (Musbahtiti & Muhammad, 2013). Nevertheless, it seems fair to say that higher education institutions (HEIs) are facing the need of constant monitoring of users’ interaction with LMS, in order to identify key areas for potential improvement. This could be expressed in terms of quality of interaction (QoI) through the LMS use within a blended (b-)learning environment (Woltering, Herrler, Spitzer, & Spreckelsen, 2009; Miyazoe & Anderson, 2010; López-Pérez, Pérez-López, & Rodríguez-Ariz, 2011; Oliver & Stallings, 2014).

In fact, the lack of interaction is considered an important obstacle to online learning (Parker, 1999); however, several improvements in Information and Communication Technologies (ICTs) over the last years have enhanced the QoI in online environments. In this vein, there are different types of interactions that educators can consider into the curriculum, more specifically: learner to instructor, learner to learner, learner to content, learner to tools, and learner to environment (Bastedo & Vargas, 2014).

Considering the aforementioned perspectives, QoI can be extended from individuals to groups/networks, from closed to open learning environments, and from small groups to massive opportunities. The QoI is usually estimated by employing 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, Cheng, & Manoharan, 2010). An alternative approach has been proposed by Dias and Diniz (2013), who introduced for the first time a fuzzy logic (FL)-based model, namely FuzzyQoI, to estimate the QoI, taking into account the users’ (professors’ and students’) interactions, as expressed through the LMS usage within a b-learning environment. Note that for a state-of-the-art review upon the use of FL in education the reader could refer the work of Dias and Diniz (2013) and Dias, Diniz, and Hadjileontiadis (2014). In the FuzzyQoI model, the knowledge of the experts in the field was translated into fuzzy constructs, and, through five nested fuzzy inference systems (FISs), an estimation, in a quantitative way, of a normalized index of the users’ QoI was achieved (Dias & Diniz, 2013).

In the FuzzyQoI model, the input (users’ LMS metrics)–output (normalized index of users’ QoI) mapping was integrated into a system as a quantitative map, yet, internally it can be considered as a set of qualitative linguistic rules that could be used to model the type of vague or ill-defined systems that are difficult to handle using conventional binary valued (crisp) logic (Tsoukalas & Uhrig, 1996).

Stemming from the FL concept proposed in FuzzyQoI model (Dias & Diniz, 2013), an alternative approach, yet within the field of FL, is proposed here, based on the concept of Fuzzy Cognitive Map (FCM) (Kosko, 1986). In general, FCMs can model causal relationships in complex systems that evolve with time. From this line, several studies have shown how FCMs can provide an understanding of problematic domains or systems and/or knowledge for strategic purposes in terms of maximization of benefits, minimization of risks and management issues (e.g., Sharif & Irani, 2006; Rodriguez-Repiso, Setchi, & Salmeron, 2007; Glykas, 2013; Jetter & Sperry, 2013). The adoption of the FCM approach is motivated by the fact that they are: i) easy to use, create, visualize and parameterize, ii) flexible in representation/visualization, iii) understandable for nontechnical experts and for different stakeholders groups, iv) able to handle with complex and dynamic issues, and v) capable of
providing an efficient feedback mechanism that combines information drawn from distinct resources to create an enrich body of knowledge.

In line to the above, the use of FCMs in modeling the QoI of the LMS users within b-learning environment aims at providing a “strategic mapping” to better understand the particular domain of HE in an interconnected way of thinking. In fact, the theory of FCM is mainly concerned with modeling factors and their interrelationships within complex domains/systems. Knowing that the adoption of LMSs in HEIs represents a complex domain with multiple influencing aspects, FCMs seem quite suitable to model this particular domain; simultaneously, considering that FCMs have the ability to model dynamic systems (Kosko, 1992), they are promising tools to capture the (internal/external) dynamic aspect of the LMSs. Furthermore, the FCM-based model could present a predictive power for estimating the QoI, involving concepts, dependences and trends, considering the time period of the LMS use. From this perspective, experimental validation using real LMS Moodle data drawn from a large database from a HEI, could reveal the efficiency of the proposed FCM-based model under the LMS-based b-learning approach.

To accomplish the aforementioned goals, this study addresses the hypothesis that the structural characteristics of a FCM can efficiently model the way LMS users’ interact with it and, further, evaluate it by estimating their QoI within a b-learning context.

2 Literature Review

The literature review is divided into two major sections. The first section reviews research done on the use of FCM in the educational context, while the second one focuses on literature review dealing with improvements in the FCM functionality.
2.1 FCM within the Educational Context

Originated from the theories of FL, neural networks, soft computing and computational intelligence techniques, FCMs can be understood as a modeling methodology based on exploiting knowledge and experience (Kosko, 1986, 1992; Papageorgiou & Stylios, 2008). Nowadays, FCMs have played an important role in different scientific fields, such as behavioural sciences (e.g., Carvalho, 2013), medicine (e.g., Bourgani, Stylios, Manis, & Georgopoulos, 2014), engineering (e.g., Vaščák & Reyes, 2014), management and business (e.g., Campaña, Medina, & Vila, 2014; Glykas, 2013), environment (e.g., Wildenberg, Bachhofer, Isak, & Skov, 2014), and information systems (e.g., Irani, Sharif, Kamal, & Love, 2014). Regarding to the FCMs use for educational scenarios/issues, examples of research studies (adopting an intentional trajectory from 2008 to 2014) follow.

Hossain and Brooks (2008) have applied FCM to model educational software at UK secondary schools, modeling the stakeholders’ perceptions about that kind of software. Based on findings from the semi-structured interviews, they considered three different stages, namely: i) the building of individual FCMs based on the empirical data from the fully structured interviews with each participant; ii) the aggregation of the individual FCMs to get an augmented FCM model; and iii) the improvements to the augmented FCM. They concluded that by using a mixed-methods approach, this holistic model can provide insight into the context of educational software adoption in schools, which can be adopted to guide both educational decision-makers and software developers in terms of more appropriate software development efforts.

Georgiou and Botsios (2008) applied FCM to learning style recognition, proposing a three-layer FCM schema to allow experienced educators or cognitive psychology to tune up the system parameters to adjust the accuracy of the learning style recognition. In this way,
they considered that the FCM emerged as a useful tool for learning style recognition, since it can handle the uncertainty and fuzziness of a learning style diagnosis in an efficient way.

Salmeron (2009) proposed to build an augmented FCM to model critical success factors (CSFs) in LMS, helping decision makers to extract from the multidimensional learning process the main activities that are essential for success. From this perspective, using FCMs for modeling CSFs can provide support to the online learning community, by allowing prediction comparisons to be made between numerous tools measured by multiple factors and its relations. In addition, ten LMS CSFs categories (i.e., Asynchronous communication tools, Synchronous communication tools, Usability, Content structure, Standards compliancy, LMS cost, Easy maintenance, Students attitude, Assignments, and Multimedia) were adopted by an expert panel. The results revealed that these categories can help decision makers to efficiently/effectively select e-learning technologies.

Luo, Wei, and Zhang (2009) designed a game-based learning system based on FCMs. Since FCM cannot get new knowledge from existing data, the Hebbian learning rule (Hebb, 1949) was used here to solve the problem and the concept of unbalance degree was used to improve the game-based learning ability. In this way, based on the improved FCM, a novel game-based learning model was proposed, including a teacher sub-model, a learner sub-model and a set of learning mechanisms. In addition, an automobile driving learning system was developed to demonstrate the effectiveness of the suggested model.

Cai, Miao, Tan, Shen, and Li (2010) developed the Evolutionary Fuzzy Cognitive Map (E-FCM), as an extension of the FCMs. Basically, the E-FCM approach was used to model dynamic concepts and their causal relationships in the virtual world, including modeling characters and contexts. In this way, the virtual world can become more dynamic, with plausible characters/contexts, enhancing player’s experience in the interactions with the environment. Compared with the FCM, the E-FCM presented three main improvements, in
particular: i) it allowed a different update time schedule for each variable; ii) it enabled self-mutation of the context variables, showing the dynamics of the world variables as evolving behavior; and iii) it involved the probabilistic causality among the variables, reflecting realistic relationships among the concepts and adding more dynamics to the character.

van Vliet, Kok, and Veldkamp (2010) used FCM as a communication and learning tool for linking stakeholders and modellers in scenario studies. Their work demonstrated the potential use of a highly participatory scenario framework that involved a blend of qualitative, semi-quantitative, and quantitative methods.

Chunying, Lu, Dong, and Ruitao (2011) proposed the Rough Cognitive Maps (RCM) as an FCM extension to model the whole set of relations between two concepts in real world, in order to improve the simulation capabilities of the FCM. In general, they concluded that RCM is more flexible and robust than FCM, simulating the real world in a better way.

Altay and Kayakutlu (2011) applied FCM to factor reduction in a decision-making environment. To be more precise, FCM-based factor prioritization was applied to large companies and the findings were compared with the choices of small- and medium-size enterprises. As a result, the initial 48 criteria were reduced to 24, by using FCMs, in order to provide a sufficient number of criteria with an acceptable loss of information.

Nownaisin, Chomsuwan, and Hongkrailert (2012) proposed the FCM technique to identify the causalities of the education management of the Thailand science-based technology school. Generally, they concluded that this approach was easy to use and easy to understand by linked graph representation.

Yesil, Ozturk, Dodurka, and Sahin (2013) adopted the FCMs in order to model the control engineering educational CSFs. More specifically, the concepts of the FCM model were developed by the support of the academics and aggregated to construct the final FCM to model the control engineering educational CSFs. In addition, the model was coded to
investigate some scenarios via different simulations, revealing the effectiveness of FCMs to better understand the success factors of educational organizations.

Chrysafiadi and Virvou (2013) proposed a knowledge representation approach of an adaptive and/or personalized tutoring system. According to their opinion, the domain knowledge should be represented in a more realistic way, in order to allow the adaptive and/or personalized tutoring system to dynamically deliver the learning material to each individual learner, taking into account his/her learning needs and his/her different learning pace. In this way, the FCMs were implemented in an e-learning adaptive system for teaching computer programming and also used by the students of a postgraduate program in the field of Informatics.

Barón, Crespo, Espada, and Martínez (2014) presented a learning assessment system that uses multivariate analysis based on structural equation modeling and FCMs as a tool. Mainly, the aim of the proposed system was to facilitate the assessment of learning on interactive environments. In this way, a sequence of scenarios to stimulate cognitive function of planning in a child population was applied. The results have shown that most practical tasks obtain better results, confirming the Hebb rule on learning and cellular neurophysiological relationship (Hebb, 1949).

Peña-Ayala and Sossa-Azuela (2014), based on FL fundamentals, proposed an extension of the traditional FCMs called Rules-Based Fuzzy Cognitive Maps (RBFCM). Actually, the RBFCM can offer decision-making services to the sequencing module of an intelligent and adaptive web-based educational system (IAWBES), provoking learners’ traits to adapt lectures to enhance their apprenticeship. In addition, they suggested that this approach can model the teaching-learning environment and simulating the bias exerted by authored lectures on the student’s learning.
2.2 Improving FCM Performance

In general, FCM has the ability to analyze and depict human perception of a given system. This is due to the inherent production of a conceptual model, which is not limited by exact values and measurements, and thus, is well suited to represent relatively unstructured knowledge and causalities expressed in imprecise forms (Glykas, 2010; Papageorgiou, 2014). Usually, there is a manual construction of FCMs, and, thus, they cannot be applied when dealing with large number of variables. In such cases, their development could be significantly affected by the limited knowledge and skills of the knowledge holder; thus, it is vital to use learning algorithms to accomplish this task (Papageorgiou, 2014).

In order to improve the performance of FCMs, several methodologies have been explored; for instance, Peña, Sossa, and Gutierrez (2007) proposed a model for the design and development of ontology agents to manage rule-based FCMs (i.e., RB-FCM), taking into account the ontology agents and the FCMs represented by fuzzy rule bases. Based on a theoretic analysis, Pedrycz (2010) presented the synergy of granular computing and evolutionary optimization to design efficiently FCMs. On the other hand, Song, Miao, Roel, Shen, and Catthoor (2010) proposed a fuzzy neural network to improve the learning ability of FCMs, incorporating the inference mechanism of conventional FCMs with the determination of membership functions and the quantification of causalities. Papageorgiou (2011) proposed a methodology to design augmented FCMs combining knowledge from experts and from different data sources in the form of fuzzy rules generated from rule-based knowledge discovery methods. In another study (Acampora, Loia, & Vitiello, 2011), a FCM-based emotional agent in an Ambient Intelligence (AmI) environment was developed, in order to provide advanced services and to enhance the quality of life. In general, this approach tried to maximize the system’s usability in terms of efficiency, accuracy and emotional response. Finally, more recently, Štula, Stipaničev, and Šerić (2012) investigated the possibility of
multi-agent systems (MAS) application in distributed computation by using FCM technique. For a thorough description of the literature review upon the FCM and its use the reader could refer to (Papageorgiou, 2012, 2014; Papageorgiou & Salmeron, 2013). The way FCM is used here it is explained in the methodology section that follows.

3 Methodology

3.1 FCM Functional Structure

A FCM is depicted as a fuzzy causal graph, where nodes represent concepts, whereas directed edges between the concepts denote causal relationships present between them (Kosko, 1986). Under the FCM approach, a given system is defined as a collection of concepts (e.g., events, actions, values, goals, etc.) that possess influential interconnections, expressing cause-effect relationships, which are quantified through a weighting correspondence, usually normalized to the [-1, 1] interval. In the latter, positive values of weights describe promoting effect, whereas negative ones describe inhibiting effect; other values correspond to different intermediate levels of the causal effect. A generic representation of the FCM model is presented in Figure 1, consisting of four concepts, i.e., C1, ..., C4, interconnected with the following 4x4 weight matrix W:

$$W = \begin{bmatrix}
0 & -1 & 0 & 1 \\
0 & 0 & 0 & -1 \\
0.5 & -0.1 & 0 & -0.3 \\
1 & 0 & 0.2 & 0 \\
\end{bmatrix}.$$  

(Fig. 1 about here)
In general, a FCM is defined using a 4-tuple \( \{C, W, A, f\} \), where \( C = \{C_1, C_2, ..., C_N\} \) denotes the set of \( N \) concepts of the graph, \( W: (C_i, C_j) \rightarrow w_{ij} \) is a function that associates a causal value \( w_{ij} \in [-1,1] \) to each pair of nodes of the connection matrix, denoting the weight of the directed edge from \( C_i \) to \( C_j \), representing the causality degree between the interconnected concepts; hence, the weight matrix \( W_{N \times N} \) gathers the system causality, usually determined by knowledge experts. Every label \( A_i \in C \) (in the example of (1) \( i = 1, ..., 4 \) is mapped to its activation value \( A_i \in [0,1] \), i.e., \( A: (C_i) \rightarrow A_i \), with 0 and 1 corresponding to no and full activation, respectively. In fact, \( A \) is a function that associates the activation degree \( A_i \in \mathbb{R} \) to each concept \( C_i \) at the iteration \( k (k = 1,2, ..., K) \). Finally, a transformation (or threshold) function \( f: \mathbb{R} \rightarrow [0,1] \) is employed to keep the activation value of concept within the interval \([0,1]\). The most frequently used threshold functions include the bivalent function, the trivalent function and the sigmoid variants (Bueno & Salmeron, 2009). The labels from \( C \) can be interpreted as linguistic terms that point to fuzzy sets (Kosko, 1986; Glykas, 2010), meaning that each \( A_i \) is interpreted as the value of fuzzy membership function that measures the degree in which an observed value belongs to the fuzzy set pointed by the related term. Moreover, the \( C_i \) labels (in the example of (1) \( i = 1, ..., 4 \)) denote the real valued variables, with their domains assumed to be normalized into the \([0,1]\) interval (Papageorgiou, 2014).

For the manual construction of the FCM, the number and kind of concepts (e.g., input or output) are determined by a group of knowledge experts and each interconnection is described by either with an IF-THEN rule that infers a fuzzy linguistic variable from a determined set or with a direct fuzzy linguistic weight, which associates the relationship between the two concepts and determines the grade of causality between the two concepts. Then, all the linguistic variables suggested by the knowledge experts are aggregated using the SUM method (Kosko, 1986) and an overall linguistic weight is produced, which is then
transformed into a numerical weight $w_{ij}$, belonging to the interval $[-1,1]$, by using a defuzzification method (e.g., the center of gravity (Kosko, 1986)), and, finally, a numerical weight for $w_{ij}$ is calculated. In this way, all the weights of the FCM model are inferred.

As it was mentioned above, an automated estimation of the $W$ can be achieved, overcoming the dubious effort and potential subjectivity of the knowledge expert in his/her involvement in its definition process, by adopting learning algorithms. Towards such endeavor, adaptive Hebbian-based learning algorithms, the evolutionary-based (e.g., genetic algorithms) and the hybrid approaches (composed of Hebbian type and genetic algorithm) (Papageorgiou, Stylios, & Groumpos, 2003; Stach, Kurgan, Pedrycz, & Reformat, 2005; Glykas, 2010; Papageorgiou, 2012, 2014), have been proposed and widely used as the most efficient methods for training FCMs.

Once the FCM is constructed, it can receive data from its input concepts, perform reasoning and infer decisions as values of its output concepts. During reasoning, the FCM iteratively updates its state by multiplying the causal weight matrix by the current state vector until convergence is reached or a stopping condition is met (e.g., the $K$ number of iterations has been reached). Note that, in the case of the involvement of a learning algorithm within the construction of the FCM, apart from the $A_i$, the $W$ matrix is also updated at each iteration.

3.2 The Proposed FCM-QoI Modeling Approach

A schematic representation of the proposed FCM-based model, namely FCM-QoI model, is depicted in Figure 2. As it is clear from the Figure 2(a), the user interacts with the LMS Moodle and 110 metrics are acquired, exactly the same as the ones used in the FuzzyQoI model (Dias & Diniz, 2013-Table 1). These metrics are then categorized into 14 categories, denoted as $C_1, C_2, ..., C_{14}$, corresponding to the 14 categories used in the FuzzyQoI model (Dias & Diniz, 2013), i.e., $C_1$: {Journal/Wiki/Blog/Form (J/W/B/F)}, $C_2$:
{Forum/Discussion/Chat (F/D/C)}, C3: {Submission/Report/Quiz/Feedback (S/R/Q/F)}, C4: {Course Page (CP)}, C5: {Module (M)}, C6: {Post/Activity (P/A)}, C7: {Resource/Assignment (R/A)}, C8: {Label (L)}, C9: {Upload (UP)}, C10: {Update (U)}, C11: {Assign (A)}, C12: {Edit/Delete (E/D)}, C13: {Time Period (TP)}, and C14: {Engagement Time (ET)}. These 14 concepts are considered the inputs of the FCM within the FCM-QoI model and the additional FCM-QoI concept is considered its output (see Figure 2(b)). The FuzzyQoI model (Figure 2(a)) outputs the $QoI^{FIS}$, which is used in the training phase of the FCM within the FCM-QoI model (Figure 2(b)). In the proposed FCM-QoI model, the Nonlinear Hebbian Rule (NHB)-based learning algorithm (Papageorgiou et al., 2003) is adopted. For the sake of completeness, a mathematical description of the adopted FCM updating process (both of $A_i$ and $W$) is presented in Appendix A. During the iterative learning process ($k = 1, 2, ..., K$ maximum iterations), the weights $w_{ji}^{(k)}$, along with the corresponding labels $A_i^{(k+1)}$, are updated, using Eqs. (A.3) and (A.5), respectively, towards the satisfaction of Eq. (A.6) (see Appendix A). When the latter is met, the FCM is considered trained and the updated weights ($w_{ji}^{UP}$) are used in the testing phase of the FCM-QoI model using Eq. (A.8), considering the satisfaction of Eq. (A.7) (see Appendix A). The fulfilment of the latter denotes the final estimation of the $QoI^{FCM}$ output of the FCM-QoI model.

----------------- (Fig. 2 about here) -----------------

As it is clear from the aforementioned description of the FCM-QoI model, the involved FCM plays the role of a system representation, dismantling the 14 inputs-1 output relations, as represented by the estimated $W^{UP}$ matrix. This actually reflects the expert’s knowledge representation hidden in the IF/THEN fuzzy rules of the FuzzyQoI model, yet in a more quantitative way, i.e., in the form of the interconnection weight values.
The efficiency of the proposed FCM-QoI model has been evaluated through its application to the same data used in the FuzzyQoI model (Dias & Diniz, 2013), drawn from a real-life LMS Moodle use case from higher education (HE), involving both professors and students, as thoroughly described in the succeeding section.

4 Experimental Validation of the FCM-QoI Model

4.1 Data Characteristics

The LMS Moodle data for the validation of the proposed FCM-QoI model were drawn from a b-learning environment related to five undergraduate courses (Sport Sciences, Ergonomics, Dance, Sport Management and Psychomotor Rehabilitation) offered by the first Author’s affiliated HEI. As it was mentioned before, the data were identical to the ones used for the validation of the FuzzyQoI model (Dias & Diniz, 2013) for comparison reasons. LMS Moodle data from both professors [75 in total, 49% male, aged from 24 to 54 yrs (mean±std = 47.19±8.8 yrs)] and students [1037 in total, 45% male, aged from 18 to 48 yrs (mean±std = 25.05±5.9 yrs)] were used. All of them started to use LMS Moodle in the 2009/2010 academic year. The time-period involved spanned 51 weeks (August 26, 2009-August 18, 2010), including 610775 LMS users’ interactions in total (94288 from professors and 516487 from students). The number of the daily data loggings belonging to the same category per user was summed across the duration of one week (the analysis time-unit), and 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; this segmentation is depicted in Figure 3, involving Lectures, Interruptions and Exams time-period sections for the first (soft-stems) and the second (heavy-stems) semesters.
4.2 Training and Testing Dataset Configuration

The whole dataset of the 14 input-1 output data from the FuzzyQoI model was randomly split into 75% as a training dataset and 25% as a testing dataset for the FCM-QoI model. The latter was kept separate from the former one, in order to test the generalization power of the FCM model. Two training/testing scenarios were conducted, i.e., time-dependent and time-independent.

In particular, in the time-dependent training scenario, the time unit of analysis of one week is taken into account, in order to obtain the best estimation of \( QoI^{FCM} \) per week. To this end, 1000 randomized selections of the 75% of the training set were considered and, for each random selection, the mean value across the users per input/output per week was estimated, setting, in this way, the initial values of the \( A^{(1)}_i, i = 1,2, ..., 15 \), per week in the updating equation of Eq. (A.5) (see Appendix A). The initial values of the \( W \) matrix (\( w_{ji}^{(0)}, j \neq i \) in Eq. A.3) per week were randomly selected from the range of \([-1,1]\) (apparently \( diagonal(W) = 0 \)). Consequently, the training process in the time-dependent scenario outputted a \( W^{up} \) per week (\( W^{up,w} \)).

In the time-independent training scenario, the same process as in the case of the time-dependent scenario was followed, yet here, for each random selection of the 1000 randomized selections of the 75% of the training set, the mean value across the users per input/output and across the weeks was estimated. In this way, the training process in the time-independent scenario outputted a \( W^{up} \) per academic year (\( W^{up,y} \)).

In the time-dependent and time-independent testing scenarios, the estimated \( W^{up,w} \) and \( W^{up,y} \) were used in the Eq. (A.8), respectively, conducted upon the initially selected testing
set (25% of the initial data) to infer the $\text{QoI}^{\text{FCM}}$ per week and per academic year, respectively.

In all cases, the evaluation of the performance of the FCM-QoI model was realized via the estimation of the Root Mean Squared Error (RMSE) and the correlation coefficient between the estimated $\text{QoI}^{\text{FCM}}$ and the $\text{QoI}^{\text{FIS}}$ derived from the FuzzyQoI model.

4.3 Implementation and Visualization Issues

The implementation of the whole analysis of the FCM-QoI model was carried out in Matlab 2014a (The Mathworks, Inc., Natick, USA), using custom-made programming code. The archived data in the LMS Moodle repository were exported from .xml to .xlsm (Microsoft Excel format) and imported to the Matlab environment and archived as .mat files. The values used for the updating process of the FCM were selected as the optimum ones that minimize the number of iterations for meeting the termination criteria of Eqs. (A.6) and (A.7) (see Appendix A). In particular, $K = 20000, \eta_k = 0.01, \forall k$ (see Eq. (A.3)), $\{\lambda = 2.0, \mu_{\text{training}} = 1, \mu_{\text{testing}} = 0.5\}$ (see Eq. (A.4)), $\{\nu = 1, \sigma_{\text{training}} = 0, \sigma_{\text{testing}} = 0.5\}$ (see Eq. (A.5)), $\varepsilon = 0.001$ (see Eqs. (A.6) and (A.7)).

The visualization of the estimated FCM graphs was carried out via an especially programmed Matlab application, namely FCM-Viewer (see Appendix B). It should be noted that FCM-Viewer is freely available from the authors upon request.

The results from the analysis of the aforementioned LMS Moodle data with the proposed FCM-QoI model scheme are described and discussed in the succeeding subsections.

5 Results and Discussion

5.1 Professors’ QoI

5.1.1 Time-dependent scenario: Training phase
The mean RMSE between the estimated $P - QoI^{FCM}$ and the $P - QoI^{FIS}$ across 1000 iterations during the time-dependent training phase of the FCM-QoI model for the professors’ case (denoted by the prefix of $P$) was found equal to 0.0201, spanning between 0.015 and 0.024, and showing a similar behavior across the 1000 iterations. This denotes a consistency in the behavior of the FCM-QoI model during the time-dependent training phase, sustaining the RMSE in low values. The latter is reflected in Figure 4, where the estimated $P - QoI^{FCM}_{\text{minRMSE}}$ (dense black line), which corresponds to the iteration (291) that exhibits the minimum RMSE, is illustrated in Figure 4(a), whereas the estimated $P - QoI^{FCM}_{\text{maxRMSE}}$ (dense black line), which corresponds to the iteration (415) that exhibits the maximum RMSE, is shown in Figure 4(b). In both subplots, the corresponding $P - QoI^{FIS}$ (light grey line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-dependent training phase of the FCM-QoI model is superimposed to facilitate the comparison. Moreover, the vertical lines illustrate the time-period segmentation according to Figure 3. As it can be seen from Figure 4, the estimated $P - QoI^{FCM}_{\text{minRMSE}}$ and $P - QoI^{FCM}_{\text{maxRMSE}}$ exhibit a very good phase synchronization with the $P - QoI^{FIS}$, denoting a successful training outcome (even in the case of the maximum RMSE, Figure 4(b)). This is justified by the corresponding correlation coefficients, i.e., $r_{(P - QoI^{FCM}_{\text{minRMSE}}, P - QoI^{FIS})} = 0.9311 (p \ll 0.01)$ and $r_{(P - QoI^{FCM}_{\text{maxRMSE}}, P - QoI^{FIS})} = 0.9608 (p \ll 0.01)$.

----------------- (Fig. 4 about here) ---------------

The higher correlation seen in the case of maximum RMSE, compared to the case of minimum RMSE, is justified by Figure 4, where the $P - QoI^{FCM}_{\text{maxRMSE}}$ (Figure 4(b)) follows more uniformly, compared to the $P - QoI^{FCM}_{\text{minRMSE}}$ (Figure 4(a)), the phase alterations of $P - QoI^{FIS}$, yet exhibiting an underestimation of the true values of $P - QoI^{FIS}$; this is
reduced in the case of $P - QoI_{F_{minRMSE}}^{FCM}$, justifying the corresponding minimum RMSE value. As it can be seen from Figure 4(a), the $P - QoI_{F_{minRMSE}}^{FCM}$ shows its main phase mismatch with the $P - QoI_{F^{FIS}}$ at weeks 17 and 20 of the first semester, whereas in the second semester it clearly follows the changes of $P - QoI_{F^{FIS}}$.

The corresponding $P - W_{up,w}^{w}$ matrix exhibits a degree of sparseness with sufficient balance between the negative and positive weight values, showing an increase in the latter ones around week 32 (just after the Carnival interruption at week 31). Obviously, the complexity of the 4D-matrix of $P - W_{up,w}^{w}$ does not allow for easy visualization of the corresponding FCM per week across the academic year. Nevertheless, specific weeks in distinct time-periods are isolated and the corresponding FCMs are visualized in the forthcoming Time-Period Dependences subsection.

5.1.2 Time-dependent scenario: Testing phase

Figure 5 illustrates the results from the testing phase of the time-dependent scenario of the FCM-QoI model. As it was noted before, the data used in the testing phase were totally independent from the ones involved in training phase of the time-dependent scenario. Apparently, the $P - W_{up,w}^{w}$ was used in the construction of the FCMs per week for the estimation of the $P - QoI_{(P,W_{up,w,testing})}^{FCM}$(thick grey line), as it corresponds to the minimum RSME form the training phase of the time-dependent scenario. For comparison reasons, the $P - QoI_{testing}^{FIS}$ (light black line), which corresponds to the $QoI$ estimated from the FuzzyQoI model across the same professors that are incorporated in the construction of the testing data of FCM under the time-dependent scenario, is superimposed. The RMSE and the correlation coefficient between the $P - QoI_{(P,W_{up,w,testing})}^{FCM}$ and $P - QoI_{testing}^{FIS}$ are equal to 0.0368 and 0.4045 ($p = 0.0032$), respectively. Clearly, the derived RMSE is quite low, showing an
efficient generalization of the FCM-QoI model in predicting the QoI after a training procedure based on historical data.

The estimated correlation coefficient shows a good phase synchronization of the \( P - QoI_{FCM}^{(P-W_{up,w,testing})} \) with \( P - QoI_{FIS}^{testing} \), yet not in all weeks across the academic year. From Figure 5 it can be seen that the estimated \( P - QoI_{FCM}^{(P-W_{up,w,testing})} \) matches better the phase alterations of \( P - QoI_{FIS}^{testing} \) after week 26, i.e., in the second semester, in comparison to the ones in the first semester, with the exception of the underestimation of the \( P - QoI_{FIS}^{testing} \) peak at week 25. In general, however, the \( P - QoI_{FCM}^{(P-W_{up,w,testing})} \) is in good agreement with the \( P - QoI_{FIS}^{testing} \), showing a satisfactory performance of the FCM-QoI model to the QoI estimation for the case of professors.

5.1.3 Time-independent scenario: Training phase

The mean RMSE between the estimated \( P - QoI_{FCM} \) and the \( P - QoI_{FIS} \) across 1000 iterations during the time-independent training phase of the FCM-QoI model for the professors’ case was found equal to 0.024, spanning between \( 10^{-5} \) and 0.0316, and showing a similar behavior across the 1000 iterations mostly between 0.005 and 0.0316 RMSE values. Unlike the case of the time-dependent scenario, where the week is the time-analysis unit, in the case of time-independent scenario the academic year serves as the analysis unit; hence, the results of the training phase under this scenario are depicted across the 1000 iterations. This is illustrated in Figure 6, where the estimated \( P - QoI_{FCM} \) (diamonds) along with the \( P - QoI_{FIS} \) (dots), corresponding to the double averaged (across the professors of the training phase and across the 51 weeks of the academic year) \( P - QoI_{FIS} \) values estimated from the
FuzzyQoI model (Dias & Diniz, 2013), are depicted for the 1000 iterations of the training phase of the time-independent scenario.

Moreover, the $\text{mean}[P - QoI^{FCM}] = 0.1529$ and $\text{mean}[P - QoI^{FIS}] = 0.1768$ are also shown as horizontal solid lines, respectively. As it can be seen from Figure 6 and deduced from the corresponding mean values, the FCM-QoI model exhibits a kind of underestimation of the $QoI$ values per academic year derived from the FuzzyQoI model (training set).

Table 1 presents the estimated interconnection weight matrix $P - W^{up,y}$ between the 15 concepts (14 input concepts and $P - QoI$ as the output concept) of the time-independent training phase of the FCM-QoI model, which corresponds to the iteration (597) that exhibits the minimum RMSE ($10^{-5}$). As it is shown in Table 1, the estimated interconnection weights lie within the range of $[-0.29,0.24]$ and $P - W^{up,y}$ exhibits about 73% of sparseness. This is reflected into the FCM that corresponds to $P - W^{up,y}$ depicted in Figure 7. In the latter, the way the 14 input concepts and the output concept (within the red border) $P - QoI$ of the FCM-QoI model are interconnected is visualized via the $FCM$-Viewer (see Appendix B).

Note that $Ci, i = 1,4,5,6,7,12,14$, enclosed by thick border, are those concepts that are directly connected to the output $P - QoI$ concept.

5.1.4 Time-independent scenario: Testing phase

Since this scenario involves the double averaged values of the $P - QoI$, i.e., $P - QoI^{FIS}$, of the professors participating in the testing data, the output of the FCM-QoI model, i.e.,
\( P - QoI^{FCM} \), is a single value. In this vein, for the specific testing data it was found that 
\( P - QoI^{FCM} = 0.1622 \), close enough to the \( P - QoI^{FIS} = 0.1607 \). Moreover, although the time-independent scenario does not involve week-based analysis in the training phase, an effort to test the generalization power across the academic year (i.e., per week analysis) was attempted, by predicting the \( P - QoI^{FCM} \) per week, yet based on the \( P - W^{up,y} \) matrix, rather than on a \( P - W^{up,w} \) one. The results from this approach are shown in Figure 8, which illustrates the estimated professors’ \( P - QoI^{FCM}_{(P-W^{up,y},testing)} \) (thick grey line) during the testing phase of the time-independent scenario, along with the corresponding \( P - QoI^{FIS}_{testing} \) (light black line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-independent testing phase of the FCM-QoI model; the vertical lines illustrate the time-period segmentation of Figure 3.

\[ \text{----------------- (Fig. 8 about here) -----------------} \]

The \( P - W^{up,y} \) matrix of Table 1 was used here, derived from the training phase of the time-independent scenario. The RMSE and the correlation coefficient between the \( P - QoI^{FCM}_{(P-W^{up,y},testing)} \) and \( P - QoI^{FIS}_{testing} \) are equal to 0.0346 and 0.84 \((p < 0.01)\), respectively. The derived RMSE supports the generalization efficiency of the FCM-QoI model in predicting the QoI after a training procedure based on historical data. Moreover, the estimated correlation coefficient shows a good phase synchronization of the \( P - QoI^{FCM}_{(P-W^{up,y},testing)} \) with \( P - QoI^{FIS}_{testing} \), yet without providing a good estimation of the amplitude of the \( P - QoI^{FIS}_{testing} \) in all weeks across the academic year. Consequently, from Figure 8 it can be seen that the estimated \( P - QoI^{FCM}_{(P-W^{up,y},testing)} \) identifies better the morphology of the \( P - QoI^{FIS}_{testing} \) per week and provides, mainly, the trend of the latter, rather than an absolute matching of the \( P - QoI^{FIS}_{testing} \) values.
5.2 Students’ QoI

5.2.1 Time-dependent scenario: Training phase

The same analysis trajectory as in the case of professors was followed for the case of students. The mean RMSE between the estimated $S - QoI^{FCM}$ and the $S - QoI^{FIS}$ across 1000 iterations during the time-dependent training phase of the FCM-QoI model for the students’ case (denoted by the prefix of $S$) was found equal to 0.013. Similarly to the case of professors, the estimated RMSE exhibits a similar behavior across the 1000 iterations, covering a range between 0.0085 and 0.0175. This denotes a consistency in the behavior of the FCM-QoI model during the time-dependent training phase, sustaining the RMSE in low values. A justification of the latter is achieved via the estimated $S - QoI^{FCM}_{minRMSE}$ depicted in Figure 9(a) as dense black line, which corresponds to the iteration (87) that exhibits the minimum RMSE along with the estimated $S - QoI^{FCM}_{maxRMSE}$ shown in Figure 9(b) as dense black line, which corresponds to the iteration (554) that exhibits the maximum RMSE. In both subplots, the corresponding $S - QoI^{FIS}$ (light grey line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-dependent training phase of the FCM-QoI model is superimposed to facilitate the comparison. As usually, the vertical lines illustrate the time-period segmentation according to Figure 3. As it can be seen from Figure 9, the estimated $S - QoI^{FCM}_{minRMSE}$ and $S - QoI^{FCM}_{maxRMSE}$ exhibit an efficient phase synchronization with the $S - QoI^{FIS}$, denoting a successful training outcome (even in the case of the maximum RMSE, Figure 9(b)). This is justified by the corresponding correlation coefficients, i.e., $r(S - QoI^{FCM}_{minRMSE}, S - QoI^{FIS}) = 0.8496 \ (p \ll 0.01)$ and $r(S - QoI^{FCM}_{maxRMSE}, S - QoI^{FIS}) = 0.8405 \ (p \ll 0.01)$. As it can be seen from Figure 9(a), the $S - QoI^{FCM}_{minRMSE}$ shows its main phase mismatch with the $S - QoI^{FIS}$ between weeks 2 and 16 of the first semester, whereas in the second semester it clearly follows the changes of $S - QoI^{FIS}$. 
The corresponding $S - W^{up,w}$ matrix exhibits a degree of sparseness with sufficient balance between the negative and positive weight values, showing an increase in the latter ones around weeks 18-22 and 38-44, coinciding within the exam periods of the first and second semester, respectively. The alteration of the corresponding FCMs across specific time periods is further examined in the forthcoming Time-Period Dependences subsection.

5.2.2 Time-dependent scenario: Testing phase

Figure 10 depicts the results from the testing phase of the time-dependent scenario of the FCM-QoI model for the students’ case. Similarly to the professors’ case, the data used in the testing phase were totally independent from the ones involved in training phase of the time-dependent scenario. The $S - W^{up,w}$ was used in the construction of the FCMs per week for the estimation of the $S - \text{QoI}_{(S-W^{up,w,testing})}^{FCM}$ (thick black line), as it corresponds to the minimum RSME form the training phase of the time-dependent scenario. For comparison reasons, the $S - \text{QoI}_{testing}^{FIS}$ (light grey line), which corresponds to the QoI estimated from the FuzzyQoI model across the same students that are incorporated in the construction of the testing data of FCM under the time-dependent scenario, is superimposed. The RMSE and the correlation coefficient between the $S - \text{QoI}_{(S-W^{up,w,testing})}^{FCM}$ and $S - \text{QoI}_{testing}^{FIS}$ are equal to 0.0264 and 0.5363 ($p \ll 0.01$), respectively. Clearly, the derived RMSE is quite low (even lower compared to the corresponding one in the professors’ case), showing an efficient generalization of the FCM-QoI model in predicting the QoI after a training procedure based on archived data. The estimated correlation coefficient (higher compared to the corresponding one in the professors’ case), shows a good phase synchronization of the $S - \text{QoI}_{(S-W^{up,w,testing})}^{FCM}$ with $S - \text{QoI}_{testing}^{FIS}$, yet not in all weeks across the academic year.
From Figure 10 it can be seen that the estimated $S - QoI_{FIS}^{FCM_{(S-W^{up, w, testing})}}$ mismatches the phase alterations of $S - QoI_{testing}^{FIS}$ mainly at the beginning (weeks 1-4) and the end (weeks 44-51) of the academic year. Nevertheless, the $S - QoI_{FIS}^{FCM_{(S-W^{up, w, testing})}}$ is in good agreement with the $S - QoI_{testing}^{FIS}$, showing a satisfactory performance of the FCM-QoI model to the QoI estimation, even higher than that seen in the case of professors.

------------ (Fig. 10 about here) --------------

5.2.3 Time-independent scenario: Training phase

The mean RMSE between the estimated $S - QoI_{testing}^{FCM}$ and the $S - QoI_{testing}^{FIS}$ across 1000 iterations during the time-independent training phase of the FCM-QoI model for the students’ case was found equal to 0.017. The estimated RMSE spans between $8 \cdot 10^{-6}$ and 0.0316, showing a similar behaviour across the 1000 iterations mostly between 0.0022 and 0.0316 RMSE values. Similarly to the corresponding results in the professors’ case, the results of the training phase under the time-independent scenario for the whole academic year are depicted across the 1000 iterations in Figure 11. There, the estimated $S - QoI_{testing}^{FCM}$ (diamonds) along with the $S - QoI_{testing}^{FIS}$ (dots), corresponding to the double averaged (across the students of the training phase and across the 51 weeks of the academic year) $S - QoI_{testing}^{FIS}$ values estimated from the FuzzyQoI model (Dias & Diniz, 2013), are depicted for the 1000 iterations of the training phase of the time-independent scenario. Moreover, the $mean[S - QoI_{testing}^{FCM}] = 0.131$ and $mean[S - QoI_{testing}^{FIS}] = 0.148$ are also shown as horizontal solid lines, respectively. As it can be seen from Figure 11, the FCM-QoI model underestimates the QoI values per academic year derived from the FuzzyQoI model (training set), yet less when compared to the corresponding case of the professors (Figure 6). This is also reflected in the estimated
\[ \text{mean}[S - QoI_{FCM}] \] and \[ \text{mean}[\overline{S - QoI_{FIS}}] \] values, since their distance is less than that between the \[ \text{mean}[P - QoI_{FCM}] \] and \[ \text{mean}[\overline{P - QoI_{FIS}}] \] values.

----------------- (Fig. 11 about here) ------------ -----

Table 2 presents the estimated interconnection weight matrix \( S - W^{up,y} \) between the 15 concepts (14 input concepts and \( S - QoI \) as the output concept) of the time-independent training phase of the FCM-QoI model, which corresponds to the iteration (954) that exhibits the minimum RMSE (8 \( \cdot 10^{-6} \)).

------------ (Table 2 about here) ------------

As it is shown in Table 2, the estimated interconnection weights lie within the range of \([-0.25,0.26]\) and \( S - W^{up,y} \) exhibits about 71.5\% of sparseness. The corresponding FCM that incorporates the \( S - W^{up,y} \) is depicted in Figure 12, visualizing (via the FCM-Viewer, see Appendix B) the way the 14 input concepts and the output concept (within the red border) \( S - QoI \) of the FCM-QoI model are interconnected. From this figure it can be seen that from the 14 input concepts only the \( Ci,i = 2,3,5,7,14 \), enclosed by thick border, are directly connected to the output \( S - QoI \) concept. Compared to the case of professors, the \( Ci,i = 5,6,14 \) concepts are common to the both user’s type, with regard to their direct connection with the corresponding output concept (i.e., \( P,S - QoI \)).

------------ (Fig. 12 about here) ------------

5.2.4 Time-independent scenario: Testing phase

As in the case of professors, for the specific testing data a single valued output was estimated, i.e., \( S - QoI_{FCM} = 0.1551 \), comparable to the \( S - QoI_{FIS} = 0.1480 \). Moreover, the generalization power of the FCM-QoI model across the academic year (i.e., per week analysis) was also attempted for the case of students, by predicting the \( S - QoI_{FCM} \) per week,
yet based on the $S - W^{up,y}$ matrix rather than on a $S - W^{up,w}$ one. The results from this approach are shown in Figure 13, which illustrates the estimated students’ $S - QoI_{(S-W^{up,y,testing})}^{FCM}$ (dense black line) during the testing phase of the time-independent scenario, along with the corresponding $S - QoI_{testing}^{FIS}$ (light grey line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-independent testing phase of the FCM-QoI model; as before, the vertical lines illustrate the time-period segmentation of Figure 3. The $S - W^{up,y}$ matrix of Table 2 was used here, derived during the training phase of the time-independent scenario.

The RMSE and the correlation coefficient between the $S - QoI_{(S-W^{up,y,testing})}^{FCM}$ and $S - QoI_{testing}^{FIS}$ are equal to 0.0274 and 0.8047 ($p \ll 0.01$), respectively. As in the case of professors, the estimated RMSE supports the generalization efficiency of the FCM-QoI model in predicting the QoI after a training procedure based on historical data also for the case of students. Moreover, the estimated correlation coefficient shows a good phase synchronization between the $S - QoI_{(S-W^{up,y,testing})}^{FCM}$ and $S - QoI_{testing}^{FIS}$, yet, similarly to the professors’ case, without providing an efficient amplitude estimation of the $S - QoI_{testing}^{FIS}$ in all weeks across the academic year. Consequently, from Figures 11 and 13 it can be deduced that the estimated $P, S - QoI_{(P,S-W^{up,y,testing})}^{FCM}$ identify better the morphology of the corresponding $P, S - QoI_{testing}^{FIS}$ per week rather than their actual amplitude, mainly providing an estimation of their trends across the whole academic year.

### 5.3 Time-period Dependences

As it was shown in the previous two subsections, the structure of the FCM-QoI model supports the monitoring of the dynamics in the change of the QoI per week across the academic year, both for professors and students. This provides the opportunity to focus upon
some specific time-periods (see Figure 3) and compare the changes in the FCMs of the FCM-QoI model when shifting from one specific time-period to another. Apparently, all discontinuities in Figure 3 could be considered as points of interest for time-period dependences; yet, due to space limitations, the most profound ones that involve the main distinct periods of Figure 3 are analyzed here. Obviously, the same approach could be easily expanded to the rest of the transitional time-periods. In particular, the week-pairs of \( PR_1 = \{15,16\} \), \( PR_2 = \{17,18\} \), \( PR_3 = \{22,23\} \) and \( PR_4 = \{37,38\} \) were selected, as they represent the transition from Lecture \((1^{st} \text{ semester})\) to Interruption (Christmas), Interruption (Christmas) to Exam \((1^{st} \text{ semester})\), Exam \((1^{st} \text{ semester})\) to Lecture \((2^{nd} \text{ semester})\) and Lecture \((2^{nd} \text{ semester})\) to Exam \((2^{nd} \text{ semester})\), respectively. Figure 20 summarizes the corresponding FCMs (derived from the training phase of the time-dependent scenario) to the aforementioned week-pairs for the case of professors (Figure 14(a), P-PR1, P-PR2, P-PR3, P-PR4) and students (Figure 14(b), S-PR1, S-PR2, S-PR3, S-PR4), using the FCM-Viewer (see Appendix B). In all FCMs of Figure 14, the concept interconnection weights have been omitted for better visualization of the changes in the FCMs structure across the week-pairs (note that all numerical material corresponding to the FCM-QoI model parameters are freely available upon request from the authors). Moreover, the concepts of each FCM that are directly connected to the corresponding output (i.e., \( P,S \rightarrow QoI \)) are visualised as circles with thicker border than the rest ones.

As it can be seen from Figure 14(a) (professors’ case), the number of concepts that are directly connected to \( P \rightarrow QoI \) is decreased from six to three within the P-PR1 and increased from three to eight within the P-PR2; moreover, it is increased from four to six within P-PR3 and from two to 10 within P-PR4. In this context, the concepts \( C_5 \) (\{Module (M)\}), \( C_{11} \) (\{Assign (A)\}) and \( C_{12} \) (\{Edit/Delete (E/D)\}) appear in five out of eight weeks of the P-PR1:PR4 week-pairs, leaving behind the rest ones that appear in one up to three weeks of the
week-pairs. In an analogy, from Figure 14(b) (students’ case), it is deduced that the number of concepts that are directly connected to $S - QoI$ is decreased from eight to three within the S-PR1 and increased from seven to 10 within the S-PR2; furthermore, it is increased from six to eight within S-PR3 and decreased from nine to six within S-PR4. Moreover, the concept $C3$ ({$Submission/Report/Quiz/Feedback (S/R/Q/F)$}) appears in seven out of eight weeks of the S-PR1:PR4 week-pairs, concepts $C1$ ({$Journal/Wiki/Blog/Form (J/W/B/F)$}) and $C5$ ({$Module (M)$}) appear in six out of eight weeks, concepts $C8$ ({$Label (L)$}) and $C14$ ({$Engagement Time (ET)$}) appear in five out of eight weeks, while the rest ones appear in one up to four weeks of the week-pairs. These characteristics, reflected in Figure 14, show that time-period dependency alters the number and the type of concepts of FCM-QoI model that directly affect the $P, S - QoI$. More specifically, in the case of professors, it seems that entrance to Lecture or Exam time-periods increases the number of concepts that directly influence $P - QoI$. This is also observed, in general, in the case of students, with the exception of S-PR4, where the transition from Lecture (2$^{\text{nd}}$ semester) to Exam time-period decreases the number of concepts that directly influence $S - QoI$.

----------------- (Fig. 14 about here) ------------------

Moreover, it seems that the nature of the aforementioned concepts with high appearance frequency, that have a direct impact on the estimation of $P, S - QoI$ within the examined week-pairs, comply with the corresponding role of the user’s type; that is, concepts $C5$, $C11$ and $C12$ refer to main activities of professors in the area of information addition and alteration (Dias & Diniz, 2013), reflecting the teaching role, whereas concepts $C3$, $C1$, $C5$, $C8$ and $C14$ (sorted from high to low appearance frequency) express students’ LMS interactions in the area of information view, addition and engagement (Dias & Diniz, 2013), potentially reflecting main activities of the learning process.
Apparently, the structure of the proposed FCM-QoI model allows for zooming into specific time-dependent characteristics of the users’ interaction with the LMS Moodle, capturing the internal changes that appear in the dynamics of the interconnected concepts that directly influence the final $P,S - QoI$ across the academic year.

5.4 Overall Perspective

5.4.1 Hypothesis justification

The proposed FCM-QoI model, when placed within the panorama of the works that combine FCMs with the educational context (see Literature Review section), fills a gap that relates to the way the users interact with LMS within a b-learning context. In this perspective, it justifies the hypothesis adopted (see Introduction section), by providing an estimation of the LMS users’ QoI, complying with the findings of Hossain and Brooks (2008) and further contributing to shed light into the way LMS is used in OLEs; hence, providing valuable information to both educational decision-makers and software developers towards more appropriate software development efforts. Moreover, the FCM-QoI model counterparts the CSFs of Salmeron (2009) and Yesil et al. (2013), providing quantitative measure (i.e., the QoI) for the LMS users’ interaction attitude, assisting to more effective categorization of the main activities that are essential towards optimization of the OLEs functionality. Similarly to the work of Nownaisin et al. (2012), the FCM-QoI model identifies the causalities within the different types of users’ interactions with the LMS that influence their QoI, presented in an easy to use and easy to understand interlinked graph representation. In accordance to the aims of Chrysafiadi and Virvou (2013), the FCM-QoI model allows dynamic monitoring of LMS users’ QoI across the academic year; hence, contributing to the perspective of OLEs from a dynamic rather static view, taking into account the alterations in the QoI of the LMS users with time. Furthermore, since the FCM-QoI model identifies the different LMS interaction
attitude between professors and students, in terms of their QoI, could be combined with the findings of Peña-Ayala and Sossa-Azuela (2014), for more holistically approaching their modeling of the teaching-learning processes within OLEs.

5.4.2 Comparison with the FuzzyQoI Model

Apparently, the FCM-QoI model stems from the FuzzyQoI one (Dias & Diniz, 2013), since its training phase is based on the $QoIFIS$ data provided by the FuzzyQoI model. Nevertheless, when looking from an overall perspective at these two models, the following could be identified:

- The knowledge representation in FuzzyQoI model was realized through 600 IF/THEN rules provided by an expert in the field (Dias & Diniz, 2013). In the case of FCM-QoI model, however, this knowledge is reflected in the $W_{[15 \times 15 \times 51]}^{up,ww}$ or $W_{[15 \times 15]}^{up,y}$ matrices, automatically derived after the training process.

- In the FuzzyQoI model, the way the estimated QoI output is interconnected with all 14 categorized LMS input metrics is not explicitly tangible, as it is implied through the 600 expert’s defined IF/THEN fuzzy rules (Dias & Diniz, 2013). On the contrary, in the FCM-QoI model, there is a direct and explicit representation of the way each one of the 14 categorized LMS input metrics is interconnected with the others and the estimated QoI output, visualized with an easy and comprehensible way via the FCM.

- Unlike the FuzzyQoI model, the FCM-QoI one incorporates a training process, since it draws its inference upon QoI after learning from historical data.

- Dissimilarly to the FuzzyQoI model that remains the same for both professors and students, the FCM-QoI one exhibits a different structure, in terms of the concept interconnection weight values, for the professors and the students. This provides a
higher degree of adaptation to the FCM-QoI model compared to the FuzzyQoI one, according to the characteristics of each user’s type.

- Both FCM-QoI and FuzzyQoI models share the same 14 inputs - 1 output scheme, handling the LMS users’ interaction data via the same metrics categorization. This makes both models comparable in terms of data handling, offering alternative ways of approaching and analyzing the same LMS data.

5.4.3 FCM-QoI model limitations

Considering the structure and the functionality of the proposed FCM-QoI model, some limitations could be identified. In particular, the need for historical data to achieve its training phase reduces its flexibility to adapt to other educational scenarios where there is a lack of available data. In these cases, however, the interconnection weight matrix could be manually formed, based on the fusion of the experts’ opinions (e.g., by forming a FL-based fusion schema). Moreover, according to the presented results, the use of the $W^{up,w}$ provides more efficient estimation of the QoI compared to use of the $W^{up,y}$. This, however, increases the complexity of the FCM-QoI model, as the former case incorporates a $[15 \times 15 \times 51]$ matrix rather than the latter case, which incorporates just a $[15 \times 15]$ matrix. Finally, the FCM-QoI model was trained using the mean values of $QoI^{FIS}$ across users provided by the FuzzyQoI model; this, however, merges the specific characteristics of each user to an average behavior. Apparently, following the course of each user across the academic years (or semesters), a “personalized” set of FCMs per user could be formed, using as training $QoI^{FIS}$ data the ones from the first academic year (or semester) and estimating the $QoI^{FCM}$ at the next academic years (or semesters).

5.4.4 FCM-QoI model implications
As mentioned before, recent research has demonstrated that the users’ interactions are relatively low in the LMSs. Considering the impact and benefits/opportunities of LMSs that have been created in the last decade, it is essential to ensure their successful implementation/adoption and development. From this perspective, the proposed FCM-QoI model arising from this study, based on QoI of the LMS users, clearly constitutes a practical implication to the domain of FCM research in the HE context. In the latter, managerial implications could be traced; actually, based on the concepts and the causal dependencies, the proposed FCM-QoI model can help pedagogical planners/instructors to holistically visualize, capture, understand, and assess stakeholders’ needs and their interdependencies. In other words, the FCM-QoI approach, here, can be used as ideal mechanism/feedback to support different stakeholder groups (including department heads, teachers, administrators, technical support staff, and learners) in the domain of HE, combining knowledge by mathematically aggregating individual/collective FCM models. Moreover, the causal relationships within the model are weighted in the sense that the strength of the influence of a causal factor on an effect factor can be assigned. Objectively, the assigned strength values to causal relationships in the proposed FCM-QoI model can reveal which factors are believed to have a greater effect on the adoption of online tools in the LMS Moodle, in a kind of simplified and global visualization for all combinations of inputs and output. Generally speaking, each concept can be examined, not only on its own values but also on the associated ones interconnected to it through the causal fuzzy weights. In this way, the analysis of a particular model can allow the expert to view the holistic picture, as the identified factors evolve, allowing the incorporation of an eclectic (strategic) perspective. Under this line, the fuzzy weights express the magnitude of change that a variable may undertake due its causal relationship with other variables.
Seen as a holistic and dynamic model, the FCM-QoI approach has the potential to explore possibilities and scenarios from different perspectives; for instance, pedagogical planners and decision makers can (re)adjust online tools, towards maximum use of the LMS Moodle within the teaching and learning practices.

In addition, a large real-life database was used to illustrate the power and applicability of the method adopted; in fact, very few organizations/HEIs are far along the maturity curve in dealing with the process of discovering useful patterns and trends in large data sets (i.e., big data); however the ability to address big data is going to be the most important infrastructure change for information technology in the next decade, with major implications for knowledge management (Larose & Larose, 2014). Furthermore, a relatively good visualization of the LMS use in the form of FCM can be obtained in a short time, giving a clear “mental landscape” of the system and revealing some of the assumption of the “mental modeling” behind the stakeholders’ perspectives.

6 Conclusions and Future Work

An original approach to the estimation of the QoI of both professors and students when interacting with the LMS Moodle within a b-learning context has been proposed in the present work, introducing the FCM-QoI modeling approach. The FCM-based structure of the FCM-QoI model provided an easy way to represent LMS Moodle academic community understanding, in a form of scaled up mental modeling, as a kind of internal representation of external reality. The efficient performance of the FCM-QoI model was validated on real data, incorporating adequate number of users and LMS data logs from a HEI. Combined with the FuzzyQoI model (Dias & Diniz, 2013), the FCM-QoI one extends further the potentiality of the FL to represent the LMS users’ attitude in terms of their QoI.
Probing to the future, some additional aspects related to the FCM-QoI model could be considered. In particular, here, the five courses involved in the training and testing data were unified; in this way, a course effect analysis could be performed and related with the estimated FCM-QoI outputs, so to examine how the course content affects the users’ QoI. Since the structure and functionality of the proposed FCM-QoI model are not related to a specific educational context, it could easily be expanded to the analysis of LMS data from various fields, e.g., Social Sciences and/or Engineering Education (Lawton et al., 2012), exploring possible dis/similarities and correlations in the LMS users’ QoI, from an institutional perspective. Moreover, the data used here refer to the LMS Moodle usage from one year only; the FCM-QoI model, however, could also be applied to similar data from consequent academic years (e.g., 2010/2011-2013/2014), revealing possible causal dependencies, converged and/or dispersed interaction trends, all reflected at the FCM-QoI model response, in order to promote a more objective interpretation of the way LMS Moodle-based b-learning environments could be realized within the online learning context.

Finally, a hybrid model (e.g., FISFCM-QoI) could also be examined, by considering the intermediate variables outputted by the FIS1-FIS3 of the FuzzyQoI model, i.e., View, Addition, Alteration, respectively, along with the two inputs to the FIS5, i.e., Time Period and Engagement Time (Dias & Diniz, 2013), as five-input concepts to the FISFCM-QoI, keeping the QoI as its desired output. In this way, the number of concepts will be reduced from 15 of the FCM-QoI model down to six of the hybrid FISFCM-QoI one, reducing, simultaneously, the computational complexity.

The exploratory study presented here aims at providing a framework for possible rethinking of the LMS-based b-learning modeling, extending its views as a more fruitful source of information about the attitude of its users’ interaction.
Acknowledgments

The first author has been supported by the Foundation for Science and Technology (FCT, Portugal) (Postdoctoral Grant SFRH/BPD/496004/2013). Moreover, this work was realized within the framework of the EU FP7-ICT-2011-9-ICT-2011.8.2, under the grant agreement n° 600676: “i-Treasures” Project (http://i-treasures.eu). Finally, the authors would like to thank Dr. C. Ferreira of the Faculty of Human Kinetics, University of Lisbon, Portugal, for his assistance in the retrieval of the LMS Moodle data.
Appendix A: FCM Parameter Updating Process

Adopting the general FCM 4-tuple \( \{C, W, A, f\} \) defined in Methodology section, the FCM parameter updating process involved in the proposed FCM-QoI model is realized through the Nonlinear Hebbian Learning (NHL) (Papageorgiou et al., 2003) as follows.

Under the view of NHL, the value of each concept at the iteration \((k+1)\) is calculated taking into account the influence of the other concepts with which it is interconnected via the updated interconnection weights, i.e.:

\[
A_i^{(k+1)} = f\left(A_i^k + \sum_{j=1}^{N} A_j^{(k)} \cdot w_{ji}^{(k)}\right), \quad k = 1, 2, ..., K, \tag{A.1}
\]

where \(N\) is the number of concepts involved in the FCM, \(K\) is the maximum number of iterations, \(A_i^{(k+1)}\) denotes the value of the \(C_i\) concept at the iteration \((k+1)\), \(A_j^{(k)}\) is the value of the \(C_j\) concept at the previous iteration \((k)\), \(w_{ji}^{(k)}\) corresponds to the weight of the interconnection between \(C_j\) and \(C_i\) concepts at the previous iteration \((k)\), whereas \(f\) is the sigmoid threshold function, i.e.,

\[
f(x) = \frac{1}{1 + e^{-\lambda x}}. \tag{A.2}
\]

The updating equation of the \(w_{ji}^{(k)}\) in Eq. (A.1) is given by (Papageorgiou et al., 2003):

\[
w_{ji}^{(k)} = w_{ji}^{(k-1)} + \eta_k A_j \left(A_i^{(k)} - A_j w_{ji}^{(k-1)}\right), \quad k = 1, 2, ..., K, \tag{A.3}
\]

where the coefficient \(\eta_k\) is a very small positive scalar factor, namely learning parameter. As Tsadiras (2008) demonstrated, the inference capability of FCM may be strongly influenced by the selection of the concept transformation function. To this end, Eq. (A.2) can take the more general form of:

\[
f(x) = \frac{1}{1 + e^{-\lambda(x-\mu)}}, \tag{A.4}
\]
where $\mu$ is a constant. Moreover, as Papageorgiou, Oikonomou and Kannappan, (2012) suggest, if convenient, the Eq. (A.1) could be used in a rescaled form, like:

$$A_i^{(k+1)} = f((\nu A_i^k - \sigma) + \sum_{j=1}^{N} (\nu A_j^k - \sigma) \cdot w_{ji}^{(k)}), k = 1,2, ..., K,$$  \hspace{1cm} (A.5)

where $\nu, \sigma$ are constants. The Eq. (A.5) is employed in order to remove the spurious influence of inactive concepts (with $C_i = 0$) on other concepts, and avoids the conflicts emerge in cases where the initial values of concepts are 0 or 0.5 (Papageorgiou et al., 2012).

In the FCM-QoI model, the iterative process is terminated when a criterion is satisfied. The latter depends upon the phase of the FCM, and has the form of:

- **Training phase criterion:**
  $$|QoI_{FCM}^{(k+1)} - QoI_{FIS}^{(k+1)}| < \varepsilon, \hspace{0.5cm} k = 1,2, ..., K,$$ \hspace{1cm} (A.6)

- **Testing phase criterion:**
  $$|QoI_{FCM}^{(k+1)} - QoI_{FCM}^{(k)}| < \varepsilon, \hspace{0.5cm} k = 1,2, ..., K,$$ \hspace{1cm} (A.7)

where $0 < \varepsilon \ll 1$ is a tolerance level keeping the variation of the values in Eqs. (A.6) and (A.7) as low as possible. Apparently, if Eq. (A.6) or Eq. (A.7) is not met during the iterative procedure, the $QoI_{FCM}^{(K)}$ is adopted as the output of the FCM-QoI model. In the training phase, when the termination conditions are met, the final weight matrix $W^{up}: \{C_j, C_i\} \rightarrow w_{ji}^{up}, j, i = 1,2, ... N$, is derived and used as the one that expresses the concepts interconnection knowledge within the FCM of the FCM-QoI model. Consequently, the Eq. (A.5) during the testing phase of the FCM-QoI model takes the form of

$$A_i^{(k+1)} = f((\nu A_i^k - \sigma) + \sum_{j=1}^{N} (\nu A_j^k - \sigma) \cdot w_{ji}^{up}), k = 1,2, ..., K.$$  \hspace{1cm} (A.8)
Appendix B: The FCM-Viewer Application

Figure A.1(a) illustrates the interface of the developed FCM-Viewer application. As it can be seen from the latter, a series of user-selection categories is available. In particular, the requirement for the FCM-Viewer to function is the loading of the concept interconnection weights matrix. This could be realized in two ways, i.e., either from a Matlab format (.mat) file or as a variable from the Matlab workspace. As soon as the weights matrix is loaded, a series of concept layout parameters becomes available. With the navigation buttons (PREVIOUS-NEXT-GO TO), the user could navigate to each concept and alter/save its characteristics or use the defaults button that directly corresponds the default values to all variables. Moreover, the user could set the weights layout, select the FCM layout type, enable/disable nodes auto size, set the scaling factor (values greater (smaller) than 1 shrink (expand) the FCM representation), select the arrows characteristics and the weights layout. Via the HELP button, a help video is automatically triggered that visually explains all the functionalities of the FCM-Viewer.

When the aforementioned parameters are set, the FCM could be created and visualized in a new window (Figure A.1(b)) with available menu functionalities of saving, exporting, moving, zoom in/out, and node right-click functionalities, such as highlighting of the ancestors/descendants or both, along with the node properties. The visualized FCM could also be exported as a visual object handle and loaded again as a separate object (see Figure A.1(a)-bottom), to facilitate the easy access to existing FCMs.

----------- (Fig. A.1 about here) -----------

It should be noted that the FCM-Viewer requires prior installation of the Matlab Bioinformatics Toolbox; hence, with the initiation of the FCM-Viewer application, the user is automatically informed about the existence or not of the specific toolbox in the currently
running Matlab version (>R2011 version is preferable). Finally, a mouse-over help is available for each button of the FCM-Viewer, whereas a series of warnings/information messages or returns to previous states is evoked when a wrong selection is performed by the user.
References


Figure captions

Fig. 1. A schematic representation of a FCM model with four concepts (i.e., C1,...,C4), corresponding to the interconnection weight matrix W of (1).

Fig. 2. A schematic representation of the proposed FCM-QoI model, with the LMS Moodle user’s interaction metrics (M1,...,M110) categorized into 14 input parameters (C1,...,C14) fed to (a) the FuzzyQoI model (Dias & Diniz, 2013) outputting the estimated QoI_{FIS} and (b) the FCM-QoI model as input concepts interconnected with the FCM-QoI as an output concept to estimate the QoI_{FCM}. Note that the estimated QoI_{FIS} is fed to the FCM-QoI model during the training phase only, to correctly adjust the interconnection weights of the latter towards the minimization of the error in the knowledge representation process.

Fig. 3. A schematic representation of the time-period segmentation of the examined academic year 2009/2010, spanning 51 weeks, involving three distinct periods, i.e., Lecture, Interruption (from left to right: Christmas, Carnival, Easter, Summer) and Exam, corresponded to specific weeks, for the first (soft-stems) and the second (heavy-stems) semester.

Fig. 4. (a) The estimated P - QoI_{FCM_{minRMSE}} (dense black line), which corresponds to the iteration 291 that exhibits the minimum RMSE, and (b) the estimated P - QoI_{FCM_{maxRMSE}} (dense black line), which corresponds to the iteration (415) that exhibits the maximum RMSE. In both subplots, the corresponding P - QoI_{FIS} (light gray line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-dependent training phase of the FCM-QoI model is superimposed for comparison reasons. The vertical lines illustrate the time-period segmentation of Fig. 3.

Fig. 5. The estimated professors’ P - QoI_{FCM_{(p-wup,w_{testing})}} (thick grey line) during the testing phase of the time-dependent scenario, along with the corresponding P - QoI_{FIS_{testing}} (light black line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-dependent testing phase of the FCM-QoI model. The vertical lines illustrate the time-period segmentation of Fig. 3.

Fig. 6. The estimated P - QoI_{FCM} (diamonds) along with the P - QoI_{FIS} (dots), corresponding to the double averaged (across the professors and across the weeks) P - QoI_{FIS} values estimated from the FuzzyQoI model (Dias & Diniz, 2013), across the 1000 iterations of the training phase of the time-independent scenario. The solid lines correspond to the mean[P - QoI_{FCM}] = 0.1529 and mean[P - QoI_{FIS}] = 0.1768, respectively.

Fig. 7. The FCM corresponding to the interconnection weights matrix P - W_{up,y} between the 15 concepts [14 input concepts and P - QoI as the output concept of the FCM-QoI model], shown in Table 1. The Ci,i = 1,4,5,6,7,12,14, enclosed by thick circle border, correspond to the concepts that are directly connected to the output P - QoI concept.

Fig. 8. The estimated professors’ P - QoI_{FCM_{(p-wup,w_{testing})}} (dense black line) during the testing phase of the time-independent scenario, along with the corresponding P - QoI_{FIS_{testing}} (light grey line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-independent testing phase of the FCM-QoI model. The vertical lines illustrate the time-period segmentation of Fig. 3.

Fig. 9. (a) The estimated S - QoI_{FCM_{minRMSE}} (grey line), which corresponds to the iteration 87 of Fig. 12 that exhibits the minimum RMSE, and (b) the estimated S - QoI_{FCM_{maxRMSE}} (grey line), which corresponds to the iteration (554) that exhibits the maximum RMSE. In both subplots, the corresponding S - QoI_{FIS} (black line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-dependent training phase of the FCM-QoI model is superimposed for comparison reasons. The vertical lines illustrate the time-period segmentation of Fig. 3.

Fig. 10. The estimated students’ S - QoI_{FCM_{(s-wup,w_{testing})}} (grey line) during the testing phase of the time-dependent scenario, along with the corresponding S - QoI_{FIS_{testing}} (black line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-dependent testing phase of the FCM-QoI model. The vertical lines illustrate the time-period segmentation of Fig. 3.

Fig. 11. The estimated S - QoI_{FCM} (diamonds) along with the S - QoI_{FIS} (dots), corresponding to the double averaged (across the students and across the weeks) S - QoI_{FIS} values estimated from the FuzzyQoI model
across the 1000 iterations of the training phase of the time-independent scenario. The solid lines correspond to the mean $S - QoI^{FCM} = 0.131$ and mean $S - QoI^{FIS} = 0.148$, respectively.

**Fig. 12.** The FCM corresponding to the interconnection weights matrix $S - W^{up,y}$ between the 15 concepts [14 input concepts and $S - QoI$ as the output concept of the FCM-QoI model], shown in Table 2. The $Ci,i = 2,3,5,7,14$, enclosed by thick circle border, correspond to the concepts that are directly connected to the output $S - QoI$ concept.

**Fig. 13.** The estimated students’ $S - QoI^{FCM}_{(S-wup,y,testing)}$ (grey line) during the testing phase of the time-independent scenario, along with the corresponding $S - QoI^{FIS}_{testing}$ (black line) derived from the FuzzyQoI model (Dias & Diniz, 2013) and used for the time-independent testing phase of the FCM-QoI model. The vertical lines illustrate the time-period segmentation of Fig. 3.

**Fig. 14.** The estimated FCMs from the training phase of the time-dependent scenario that correspond to the week-pairs of (a) professors (P-PR1, P-PR2, P-PR3, P-PR4) and (b) students (S-PR1, S-PR2, S-PR3, S-PR4), visualised using the FCM-Viewer (see Appendix B). For both cases, PR1={15,16}, PR2={17,18}, PR3={22,23} and PR4={37,38}, representing the transition from Lecture (1\textsuperscript{st} semester) to Interruption (Christmas), Interruption (Christmas) to Exam (1\textsuperscript{st} semester), Exam (1\textsuperscript{st} semester) to Lecture (2\textsuperscript{nd} semester) and Lecture (2\textsuperscript{nd} semester) to Exam (2\textsuperscript{nd} semester), respectively. In (a) and (b), the $Ci$ concepts with thick border represent those that are directly connected to the corresponding output concept, i.e., $P,S - QoI(w#)$, where $#$ denotes the current week. Note that in all FCMs, the interconnection weights have been omitted to facilitate the visualisation of the FCMs.

**Fig. A.1.** (a) The interface of the FCM-Viewer developed application with the main user-selection categories, including: loading of the weights matrix, selection of the layout type, nodes auto size and scaling, concept navigation, concept layout characteristics selection, concept settings saving, arrows characteristics selection, weights layout, default use, help recall, exporting/loading visual object handles and, finally, creation and visualization of the FCM in a new window, as shown in (b), with additional menu and node right-click functionalities of the FCM.
Table 1
The concept interconnection weights of the FCM-QoI model corresponding to the $P - W^{up, y}$ embedded within the FCM of Fig. 7.

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Table 2
The concept interconnection weights of the FCM-QoI model corresponding to the $S - W^{ip,y}$ embedded within the FCM of Fig. 12.

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$S - QoI^{FCM}$
Highlights

- Fuzzy modelling of LMS Moodle users’ quality of interaction within b-learning
- $FCM$-$QoI$ model efficiently identifies LMS interaction trends
- $QoI$ dependencies exist with the time-period of the LMS use
- $FCM$-$QoI$ supports better understanding of the LMS users’ interaction behaviour
LMS MOODLE

METRICS CATEGORIZATION

FuzzyQoI model

Training Phase

Fig 2

FCM-QoI model

$QoI^{FIS}$

$QoI^{FCM}$

$M_1$

$M_{110}$
Fig 9

(a) (b)
Fig14

(a)