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An intelligent expert system for academic advising utilizing fuzzy logic and semantic web technologies for smart cities education

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Abstract Students attending Higher Education Institutions (HEIs) are faced with a variety of complex decisions and procedures. To provide students with more sustained and personalized advising, many HEIs turn to online academic advising systems and tools as a way to minimize costs and streamline their advising services. However, in such systems, uncertainty in the learner's parameters is a factor, which makes the decision-making process more difficult. Fuzzy logic, a multivalued logic similar to human thinking and interpretation, is highly suitable and applicable for developing knowledge-based academic advising systems that conserve the inherent fuzziness in learner models. In this paper, an innovative hybrid software infrastructure is presented which integrates expert system, fuzzy reasoning, and ontological tools to provide reliable recommendations to students for the next appropriate learning step. The software comprises a fuzzy logic component that determines the student's interest degree for a specific academic choice accompanied by an ontological model and a conventional rule-based expert system for the composition of personalized learning pathways. In order for the system to recommend the next step of the learning pathway, the output of the fuzzy logic component together with the knowledge that is modeled as part of the multi-facet ontology and the machine perceptible academic advising guidelines expressed as semantic rules interoperate in a dynamic and seamless manner. The paper presents the key modeling artifacts of the proposed approach and the architecture of the implemented prototype system. During the case

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study, the developed system yielded satisfactory results in terms of overall inter-rater reliability and usefulness.

Keywords Academic advising · Fuzzy logic · Expert system · Semantic web technologies · Higher education

Introduction

Academic advising is an important part of a cohesive strategy for HEIs to educate and retain students. However, although most of the stakeholders in higher education concede that academic advising is a key to student success, viable solutions have eluded the institutions (Henderson & Goodridge, 2015). Academic advisory services in many HEIs rely on personal meetings between students and counselors, which allegedly have problems with inconsistencies among different advisors and inefficient utilization of resources, since many advising sessions are spent answering recurrent and trivial questions without focusing on deeper conversations about the student's academic goals and plans (Aly et al., 2017). In this regard, the use of computer-aided academic advising tools could have positive impacts on the abovementioned challenges.

Academic advising systems (AAS) and tools can be utilized for the provision of consistent decision support for students by processing specific student parameters derived from the learner model in order to produce personalized advice (Iatrellis et al., 2017). In contrast to the traditional course management and registration systems offered by many HEIs, an AAS provides students with a higher level of informed recommendations, which can be considered as an emulation of an academic advisor's role, rather than a registration assistant's role. Traditional course management and registration systems focus mainly on program corequisites, prerequisite rules, and other registration restrictions. On the other hand, an AAS requires reasoning over the current information and knowledge at each decision node of the education plan, taking into account both the available academic options and circumstances inside a HEI and the uncertainties, subjectivities, implicit, and vague information, which is often hidden in learner parameters. Since the fuzzy inference approach is suitable at modeling human knowledge, it is often used to deal with those types of problems in the literature. The fuzzy methodologies can broadly be grouped into two main types: linguistic fuzzy systems (Mamdani) and precise fuzzy systems (Takagi–Sugeno–Kang) (Abduldaim & Sabri, 2019). Both of them contain the expert knowledge of fuzzy logic with their own problem-solving capability; however, Mamdani approach is widely used in particular for decision support applications (Prasad et al., 2017) such as the academic advising systems.

This paper proposes a fuzzy hybrid academic advising system named EDUC8EU (EDUCATE EUROPE) to provide the recommendation of the most appropriate learning step for each student. The architecture of EDUC8EU comprises two core subsystems where the first one receives the personal parameters and characteristics of the learner that affect the decision-making process and the second one is a conventional rule-based expert system. Initially, the fuzzy inputs of the learner model are processed to determine the interest degree for a learning pathway according to student's individual characteristics, needs, and requirements, not just in terms of academic goals, but also in terms of planning, costs, etc. The output of the first subsystem is entered to the second one, which is based on an expert system in order to decide upon the next learning step to be proposed. The technological backbone of EDUC8EU utilizes semantic web technologies to achieve a holistic conceptualization of the domain of educational provision, in order to be further utilized for the formalization of the academic advising rules. The core of the semantic model is based on an ontology that provides an integral conceptual model covering all the involved knowledge streams for the consistent representation of the specific domain as well as for the implementation of the rule repository.

The proposed platform has been developed in the context of the INVEST4EXCELLENCE European Universities H2020 program,[1] which aims at establishing transnational university alliances for developing joint and innovative education and research study programs and curricula, as well as for the implementation of multilingual learning, blended and work-based learning, and European mobilities. The EDUC8EU platform will provide support to students at all three study cycles—bachelor, master, and doctoral, together with the living labs, Vocational Education and Training (VET) certifications, Massive Open Online Courses (MOOCs), and other extracurricular educational activities. Consequently, the establishment of an effective computer-aided academic advising solution that can actively guide the students and react to changes would be of major importance for the participating universities in the alliance since the offered learning pathways will encompass a wide variety of educational options in diverse settings, languages, and disciplines.

In the rest of the paper, we review the related work in "Literature review" section and present our learner model. Section "The EDUC8EU approach" presents the key concepts of the implemented approach, while "EDUC8EU technical architecture" section overviews the technical architecture of the implemented EDUC8EU integrated software environment. Section "Case study" presents our case study and "Our contribution" section describes our contribution in the specific domain. Finally, in "Conclusions and future work" section, we provide conclusions and discuss future research directions.

Literature review

The learner's profile has been gaining an increasing attention in education research discipline. There is a growing number of academic studies that highlight the role played by—what constitutes—a learner model, in Academic Advising Systems. This paper crawled through the following scientific databases to retrieve the existing research supporting that role: IEEE, Science Direct, and Springer Link.

[1] https://www.invest4excellence.eu.

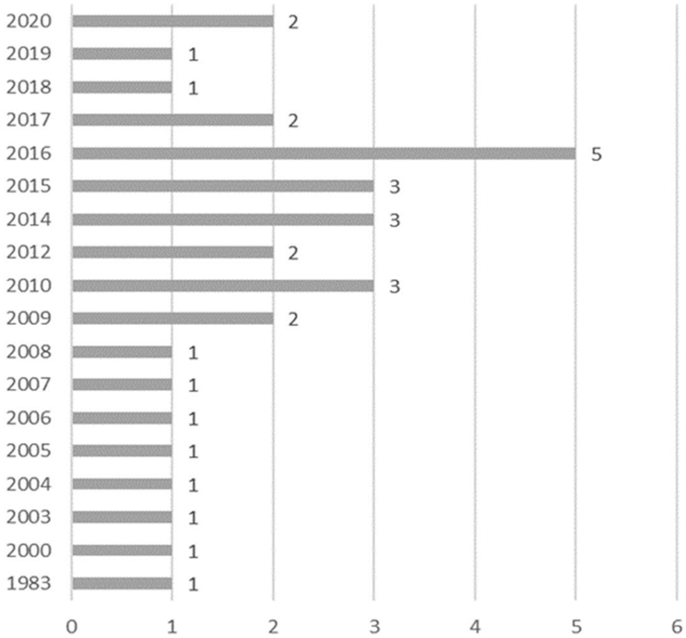

Fig. 1 Classification of research papers by year of publication

The purpose of this search is to find studies that pinpoint the traits and characteristics a learner model comprises, which may be used in recommending more effective learning objects and pathways, thus elevating the accuracy of academic advising systems. The key words that were used to perform this search include the following: "learner profile and recommender systems," "learner profile and personalized learning," and "learner profile and learning pathway." The outcome of this search process yielded 32 research papers related to this study. The selected papers are categorized by publication year and scientific database (Park et al., 2012).

Classification by publication year

Figure 1 depicts the classification of the research papers by year of publication. The time period from 2014 to 2020 is shown to be more productive with regard to papers related to learners' profiles and their association with recommender system.

Classification by scientific database

The research papers were published in three different scientific databases. The classification by scientific database is shown in Table 1 and Fig. 2. Springer Link yielded most of them, 12 out of 32, which corresponds to a quota of 37,50%, followed closely by Science Direct in second place with 11 papers out of 32 at a quota

Table 1 Classification of research papers by scientific database where they were published

Scientific database	Amount	Quota (%)
IEEE	9	28,13
Springer link	12	37,50
Science direct	11	34,38
Total	32	100

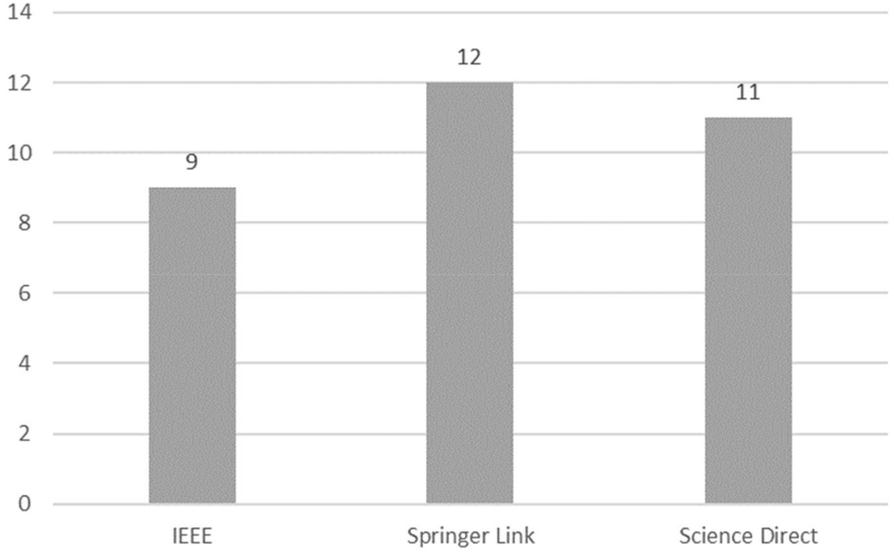

Fig. 2 Classification of research papers by scientific database

of 34,38%. Lastly, third place goes to IEEE with 9 out of 32 papers at a quota of 28,13%.

Most of the research papers showcase the incorporation of a learner's traits, features, behavior, and preferences into recommender learning systems to improve the recommendation process and the personalization of learning pathways.

Related work

Examining the learner's traits, features, and preferences, such as cognitive state and learning style, effort, and behavior (Troussas et al., 2020), and inducting them into the recommendation process, is an essential ingredient of successful recommendations in academic advising systems. The importance of the learner's profile is also highlighted in this extensive, state-of-the-art review on 82 recommender systems (RS) from 35 countries (Drachsler et al., 2015), which analyzes a number of papers (Bielikovà et al., 2014; Casali et al., 2011; Kaklauskas et al., 2013; Martín & Carro, 2009; Santos et al., 2014; Schoefegger et al., 2010), outlining the significant aspects of Technology-Enhanced Learning that include also the user's prior knowledge, skills, and abilities in the process. Since grades, scores, exams, GPA, SATs, etc., offer a way to quantitatively measure/capture these different learner features, past performance gets promoted as a key concept to be considered when devising frameworks and methods for building intelligent recommender systems (Aguilar et al., 2017; Thanh-Nhan et al., 2016), recommending personalized learning pathways (Xu et al., 2016), applying predictive analytics to find out the suitable courses for a student's admission to a college (Upendran et al., 2016), or even establishing a prediction model for the potential of a student opting for early admission in a university (Chen et al., 2014). This key concept alone cannot encapsulate the learner acquired knowledge and skills, as it needs to be complemented by their *Perceived Difficulty of the Learning Pathway* and/or *Object*. Also, variations like advanced learner or beginner learner, as well as time constraints (limited time available for studying) can add up to the difficulty factor (Drachsler et al., 2015). Therefore, matching up learners' abilities with the difficulty levels of a recommended learning object and/or pathway makes the difference for academic advising systems in avoiding disorientation or cognitive overload during (Wigfield & Cambria, 2010) the learning process (Chen & Duh, 2008; Chen et al., 2005).

A learner's motivation plays a significant role in their learning behavior and cognitive engagement (Essa, 2016; Pintrich, 2003). This analysis breaks the value of motivation down to goal orientation and task value, the latter comprising three components, the importance of the task for the learner, their personal interest for the task and how they perceive the task for future goals, e.g., pursuing a career (Anderman et al., 2012; Eccles, 1983). In other words, the learner's career goals, their personal interests, and the manner they perceive the relevance of the selected learning objects to these goals, combined with the learner's prior knowledge, skills, and abilities and an estimation of the workload needed for accomplishing these courses (Farzan & Brusilovsky, 2006), would result in an amalgamation of fundamental criteria that an academic advising system should incorporate into its recommendation process in order to showcase the value of the course/pathway to the learner (Garrido & Morales, 2014; Wigfield & Cambria, 2010). Career goals prove of high value to the learner, providing a powerful incentive to opt for a learning object, even in cases that this course appears difficult to accomplish (Upendran et al., 2016). The same principle applies also to mature learners that participate in Higher Education, whose motivational dynamics is strongly associated with extrinsic and intrinsic factors that stem from sources like career progression, professional improvement, development of professional and personal competences, economic advantage, new career opportunities, etc. (Duarte et al., 2018). The higher value a learner perceives for a task, the higher the commitment and learning outcome (Du Boulay et al., 2010; Ryan & Deci, 2000). Consequently, this adds *Perceived Career Opportunities* into the blueprint for modeling a learner's profile.

Social networking, being an immense, omni-present phenomenon in everyday life's various aspects (personal and professional), is a significant factor to be taken into account in recommender systems for learning objects (Dias & Wives, 2019). Ubiquitous e-learning systems that blend real-world learning with virtual, personal, and shared space consider the learning process as a social transfer process of knowledge (Li et al., 2004). When opting for a learning object, “what to learn” proves as important as “with whom to learn” or “where” this learning object was discussed (e.g., forum), highlighting the importance of social networking in the creation and selection of knowledge. According to (Dias & Wives, 2019) when a recommender system combines a learner’s choices with “with whom to learn,” it generates results with the highest usage prediction accuracy. Other studies highlight the importance of trust that a learner may extend toward certain peers of theirs, regarding what learning objects they have selected or rated. Trust and reliability among peers is a force to be reckoned with; recommender systems that incorporate this parameter can turn out to be effective and efficient (Carchiolo et al., 2010). The learner’s profile needs to be extended to include additional information about their opinions, critiques and relationship with other learners (e.g., their friend groups) in order to increase the knowledge base of an academic advising system to perform more intelligent and precise recommendations (Aguilar et al., 2017). Therefore, *Friends & Peers in Learning Pathway* gets promoted as a complementing concept into the Learner Model.

This social facet of the learning recommendation process is manifested through social signals, interests, and preferences of the learners, which, in turn, adhere to the process as enablers for improving the accuracy of recommendation. These signals can derive from learners’ interactions with other learners, during the learning process, by using forums, chats, or private messaging, as it happens with Moodle. They can also derive when learners rate, comment on, share, or bookmark learning objects in social learning networks, e.g., MERLOT. Besides these explicit manifestations, implicit feedback can be extracted as informational behavior, through the learner’s search actions and use of information in the system (keyword searches, selection of results, clicks, page views, and saves, etc.) (Takano & Li, 2009), or as social media behavior through user bookmarks in social networks (Durao & Dolog, 2009). By exploring other learners’ behavior during the learning process and combining it with these social signals, academic advising systems can alleviate the burden of excessive information on learning objects, filtering, and recommending the most relevant courses to the interested learner through a user-centric approach (Dias & Wives, 2019). The aforementioned recommending approach introduces what can be characterized as the *Reputation of Learning Pathway* concept when modeling the learner. Building a reputation for a learning object in a recommender system can be achieved through various methods and techniques. For instance, the system may form a neighborhood of learners considering their profiles (prior knowledge, performance, learning styles) to discover associations among learning objects and identify thereafter the useful ones that have been accessed by similar learners, thus constructing a personalized recommendation list of courses upon the visit history of the members in that neighborhood (Imran et al., 2016). Other recommender systems calculate an item’s reputation by aggregating ratings provided by multiple users, hence reflecting the formulated opinion of a community on that item (Abdel-Hafez et al., 2014). Hybrid approaches are also used to match up learner profiling—based on their interests, preferences, and historical access records—with learning objects—based on multi-dimensional attributes of the courses (Salehi &

Table 2 Parameters pertaining a learner model

Parameter	Deducing literature
Past performance	Aguilar et al. (2017), Thanh-Nhan et al. (2016), Xu et al. (2016), Upendran et al. (2016), Chen et al. (2014)
Perceived difficulty of learning pathway/object	Drachsler et al. (2015), Chen et al. (2005), Chen and Duh (2008)
Perceived career opportunities	Essa (2016), Pintrich (2003), Eccles (1983), Anderman et al. (2012), Farzan and Brusilovsky (2006), Garrido and Morales (2014), Wigfield and Cambria (2010), Upendran et al. (2016), Duarte et al. (2018), Du Boulay et al. (2010), Ryan and Deci (2000)
Friends & peers in learning pathway	Dias and Wives (2019), Li et al. (2004), Carchiolo et al. (2010), Aguilar et al. (2017)
Reputation of learning object	Takano and Li (2009), Durao and Dolog (2009), Dias and Wives (2019), Imran et al. (2016), Abdel-Hafez et al. (2014), Salehi and Kmalabadi (2012), Adomavicius and Tuzhilin (2015), Kerkiri et al. (2008), Drachsler et al. (2015)
Cost of learning pathway	Díaz-Díaz and Galpin (2020), Ricci et al. (2015), Aly et al. (2017)

Kmalabadi, 2012). Inducting reputation metadata that record the learners' opinion and ratings about learning objects, into recommender learning systems, transforms them into context-aware recommender systems (Adomavicius & Tuzhilin, 2015) and can improve the learner's satisfaction on the recommendation results (Kerkiri et al., 2008). Lastly, the "Panorama of Recommender Systems to Support Learning" (Drachsler et al., 2015) review in the field of technology enhanced learning, records systems that "guide learners to relevant resources that have been previously found as valuable by other learners"; "consider user evaluations of learning resources and propagate them to users with similar tastes"; "manage learners' properties based on learning styles and reputation metadata"; and consider "multidimensional ratings provided by the users on learning resources."

Wrapping up the learner model, there is an extrinsic factor related to an attribute of a learning object that can affect their decision-making process in following that learning path: its financial cost. Although this is subject to a person's social and financial status, hence varies from learner to learner, following a higher education course is an once-in-their-lives choice for most people, because such a decision entails investing in time and money (Díaz-Díaz & Galpin, 2020) Furthermore, if that decision proves wrong, it may have significant ramifications to that person's life. Recommender systems from other domains (e.g., financial investments, car buying / renting industry) consider the true monetary value and final cost of the item when selecting the most suitable or applicable recommendation approach (Ricci et al., 2015). The same consideration fed this next fuzzy expert system for academic advising with the input variable "Cost of Course," to be included in the recommendation process of a learning object (Aly et al., 2017). Thus, the parameter *Cost of Learning Pathway* is the last key concept to complement the learner model of this research.

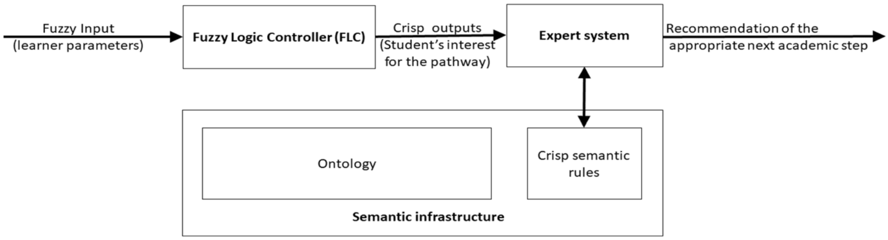

Fig. 3 The conceptual architecture of EDUC8EU

Conclusively, Table 2 summarizes the main concepts that constitute the learner model of the proposed EDUC8EU system, as defined according to this study's literature review:

These parameters in the EDUC8EU learner model constitute fuzzy linguistic variables that are dynamic estimators of student's interest for a specific learning pathway.

The EDUC8EU approach

EDUC8EU conceptual architecture

As illustrated in Fig. 3, the conceptual architecture of EDUC8EU consists of three main components: (a) the semantic infrastructure, (b) the Fuzzy Logic Controller (FLC), and (c) the conventional rule-based expert system.

The core of the semantic infrastructure is a multi-facet ontology, which encapsulates the needed knowledge streams for the representation of all the participating entities in the academic advising process and leverages the utilization of semantic rules that model the academic advising knowledge and experience acquired by domain experts. The semantic infrastructure is utilized for (a) the modeling of the entities of the learning pathways in a clear and unambiguous way, (b) the academic advising recommendations formalization, and (c) the knowledge discovery through the dynamic generation of new facts and conclusions from the rule engine.

The aim of designing the FLC subsystem is to process the parameters affecting decision-making workflow and to determine student's interest for a specific learning pathway. Notions that are included in the learner model like "perceived career opportunities" or "past performance" are not crisp concepts. Learners implicitly interpret them as approximate concepts, which can assume different degrees of truth. Using the FLC subsystem, the classification of these learner parameters becomes a graded matter of possibility instead of a Boolean assignment. Thus, to determine the student's interest for an academic choice, several factors are examined by the FLC and the interactions between them as well. The FLC subsystem involves all pieces of the fuzzy inference process (membership functions, fuzzy logic operators, and if–then rules) that determines the student's interest corresponding to fuzzified learner inputs.

The second subsystem of the EDUC8EU software infrastructure incorporates a conventional rule-based expert system that receives the output of the FLC, combines it with other knowledge streams enclosed in the semantic model, and executes the crisp semantic rules in order to generate the final recommendation for the appropriate next step of the academic plan. These streams of knowledge reflect upon a different dimension of a learning pathway related to the operational and organizational aspects in order to cover various possible learner needs (such as scholarships, hands-on labs, placements among others) and program requirements (such as admission process, course prerequisites, tuition fees, or language proficiency). For example, the "Admission Process" requirement refers to the administrative and functional procedure a learner has to go through in order to be admitted (exams, interviews or screening process), which is an essential criterion in learning pathway selection. An important component of the EDUC8EU approach is the assumption that these organizational related concepts be crisp input variables, which can be processed by a conventional expert system and can be implemented as class instances inside the ontology in order to provide extensibility and flexibility to the model of the academic advising rules. This aligns the EDUC8EU approach with the hybrid development strategy in intelligent systems as identified in Medsker (1995) and more specifically with the transformational model. Thus, in our approach, a tight integration of three forms of reasoning is introduced namely (a) the ontological, (b) the fuzzy-like, and (c) the classical rule-based, resulting in an intelligent hybrid system that incorporates a more "open world" view of the input and output variables for the case of an AAS. This is achieved because the synergy between the abovementioned techniques allows, on the one hand, the representation of the whole "universe" of the participating entities and their relationships in the decision-making process, and, on the other hand, attempts to address the vagueness in academic advising scenarios. Another benefit of implementing the EDUC8EU architecture as a hybrid transformational model is that development can occur in the most appropriate subsystem and therefore a faster implementation and less maintenance is achieved (Medsker, 1995). In this regard, the modeling of the crisp semantic rules is grounded in an existing semantic model utilized by another software platform that already operates at the University of Thessaly, in Greece, and handles the dynamic orchestration of educational processes of the HEI (Iatrellis et al., 2019a). This was a technical decision that promotes interoperability and maintainability through the establishment of a common knowledge base, which in turn can lead to increased inference validity and enhanced ontology enrichment. In this way, the utilized semantic model constitutes a totally dynamic and evolving knowledge space, which can be considered as an asset for the EDUC8EU environment.

Fuzzy logic controller

The fuzzy inference engine of the present system uses Mamdani inferencing, which is widely accepted for describing expert knowledge in a more intuitive and human-like manner (Molina-Solana et al., 2017). Following the Mamdani-style inference approach, the FLC inference process is performed in four steps (Irfan et al., 2019):

Table 3 Learner input parameters and linguistic values pertaining the learner's interest

Parameter	Linguistic variable
Past performance	Very good
	Good
	Fair
	Poor
Perceived difficulty of learning pathway	Hard
	Average
	Easy
Perceived career opportunities	Many
	Some
	Few
Friends & peers in learning pathway	High
	Average
	Low
Reputation of learning pathway	High
	Moderate
	Low
Cost of learning pathway	High
	Moderate
	Low

(a) *Fuzzification of* the *learner variables:* determining the degree to which these inputs belong to each of the appropriate fuzzy sets
(b) Academic *advising rule evaluation (inference):* for each rule, applying the result of the antecedent evaluation to the MF
(c) *Aggregation of the rule outputs (composition):* unification of the outputs of all rules into a single fuzzy set
(d) *Defuzzification:* Calculation of the final output of the FLC in a crisp format

The EDUC8EU learner model was built based on existing literature as described in "Literature review" section. Thus, the proposed system uses six main inputs and produces a single output. Table 3 lists these inputs that represent fuzzy linguistic variables alongside with their corresponding values.

EDUC8EU ontology

The first step toward automatic computer-based academic advising recommendation is knowledge representation. In our case, it involves the abstraction of domain-specific knowledge in terms of concepts that model the academic advising aspect of learning pathway, its organizational dimension, and the important learner parameters affecting decision-making process.

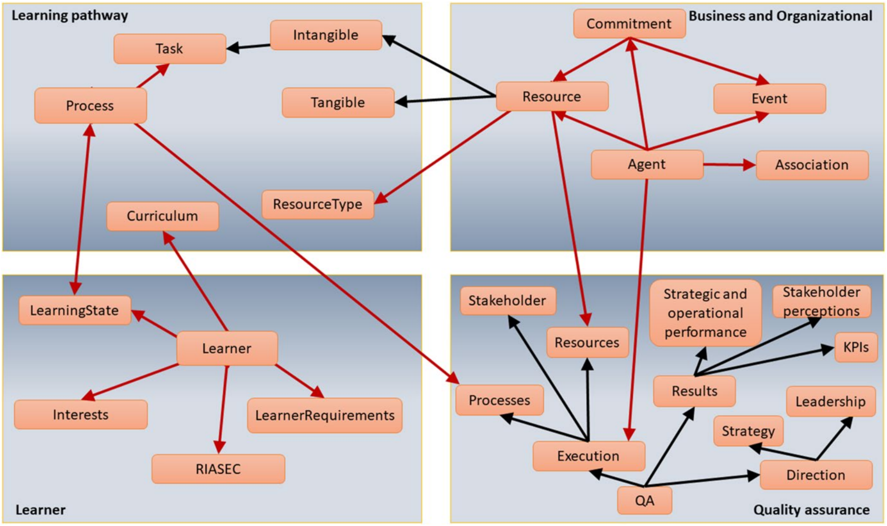

Fig. 4 EDUC8EU ontology abstract diagram

According to Fig. 4, the ontological model, the core of the semantic model is defined as a combination of concepts stemming from four knowledge streams, namely: 1) the Learning Pathway, 2) the Learner, 3) the Business and organizational dimension, and 4) the Quality Assurance. The first part of the implemented ontology contains the semantics to be utilized by the software environment for the recommendation of the appropriate learning steps. The respective subdomain is combined with the building blocks of the EDUC8EU learner model, which describes the main actor of the academic advising process. In addition to the Interests and Requirements concepts of the Learner model, the RIASEC acronym is derived from the research of Dr. John Holland and provides a preliminary way to identify learning pathways that might match students' personality. Holland's theory of career choice is widely accepted (Nauta, 2010) and forms the basis of many popular and heavily researched career inventories including the free online database O*NET (Occupational Information Network) maintained by the US Department of Labor ETA.[2] The utilized semantic model, besides the learner and learning pathway subdomains, covers the business and organizational dimensions of an HEI both on an intra- or inter-organizational level by incorporating a well-distinguished business modeling ontology, namely the Resource-Event-Agent ontology (McCarthy, 2003). The abovementioned parts are combined with a "Quality assurance" module by encapsulating a set of related quality assurance concepts derived from the revised 2020 European Foundation for Quality Management business excellence model.[3] The four domains that are modeled and interfaced as part of the ontology are described in detail in

2 https://www.onetonline.org/.
3 https://efqm.org

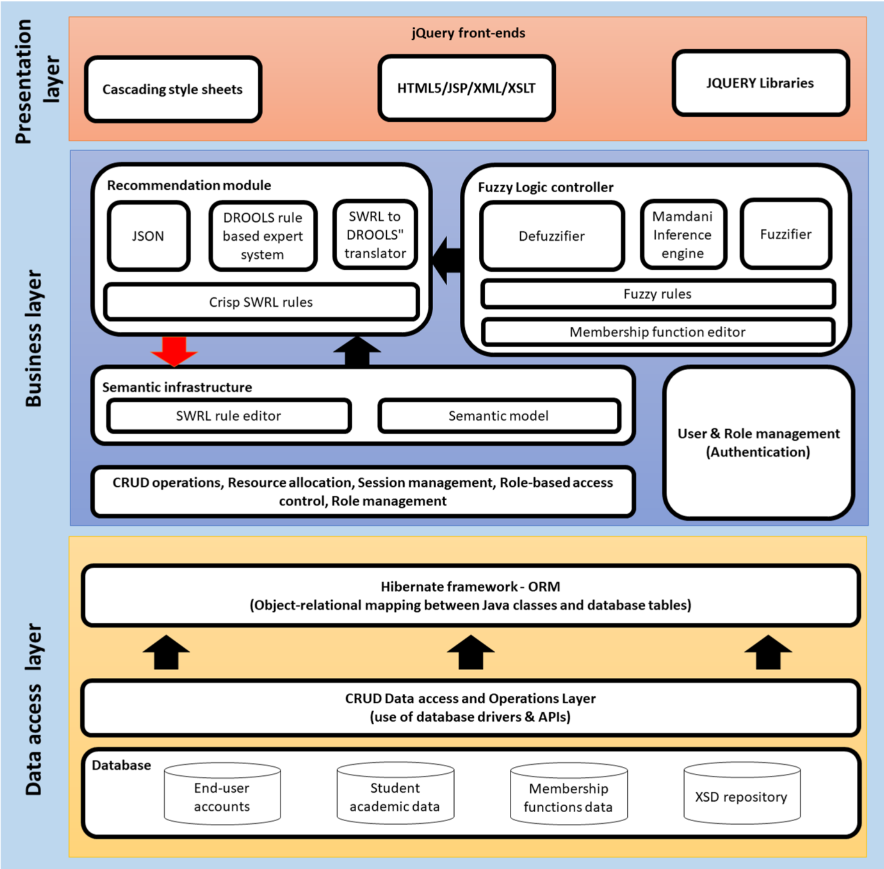

Fig. 5 EDUC8EU technical architecture

(Iatrellis et al., 2019b) and facilitate the semantic interoperability among EDUC8EU and other third-party applications that already exist in the higher education sector.

EDUC8EU technical architecture

The EDUC8EU technical architecture is based on a 3-tier web architecture model to maximize flexibility, adaptability, and stability (Fig. 5). Moreover, the specific architecture enables reusability, integration, and composition of components at different levels. During each execution cycle, the knowledge inside the ontology, the student data, and the rule-set are interoperating in order to offer personalized academic advising guidance and achieve the most optimized outcomes. The core of the business layer utilizes the DROOLS expert system technological solution[4] to provide a unified and integrated platform for rule-based event processing.

Data access layer

The specific layer is responsible for the storage and maintenance of the EDUC8EU data and information and it is implemented based on MySQL platform, which is considered as one of the most popular relational database management system (RDBMS), licensed under the GNU GPL. The Data access layer also includes the "CRUD Data Access and Operations" Layer and provides the appropriate mechanisms for Creating, Retrieving, Updating, and Deleting data records. Moreover, the Data Access layer mechanisms are based on and include the basic principles and properties of the "Hibernate Framework," which provides a "classical" object-relational mapping between Java classes and database tables, permitting the EDUC8EU developer to access instances of such classes (actually stored in a database) as if they were true Java objects. Finally, "Data Access" layer is responsible for the storage, management, and creation of all the necessary modeling components and meta-models used by the upper layers of the EDUC8EU integrated platform. More specifically, it encapsulates the following components:

(a) *the XSD repository* which encloses the complete set of standardized and electronic templates of all types of the predefined learner parameters and linguistic values required during the reasoning process. The primary use of these standardized formats concerns the dynamic creation of the corresponding web form elements that are presented to the end-users.
(b) *the End-User Accounts Directory*, which includes detailed information about end-user accounts combined with their profiles based on their expertise and their position on the organization chart of the HEI. This particular directory provides the privileges concerning the access and interaction with the design tools in order to update the knowledge stored inside the semantic model.
(c) *the Membership Functions Data*, which is part of the database, and stores the necessary values that define how each point in the input space is mapped to a degree of membership between 0 and 1. As elaborated in the ensuing subsection, during the design mode, the domain knowledge experts can perform all the necessary reconfigurations using the EDUC8EU backend, which provides the benefits of a user-friendly graphical interface for the tuning of the MFs.
(d) *the Student Academic Data*, which is also part of the EDUC8EU database, and includes learner's parameters and academic data that in turn enhance the learner's profile. This part of the database is updated at the end of each reasoning process and after the data entry of the respective student information.

4 https://drools.org.

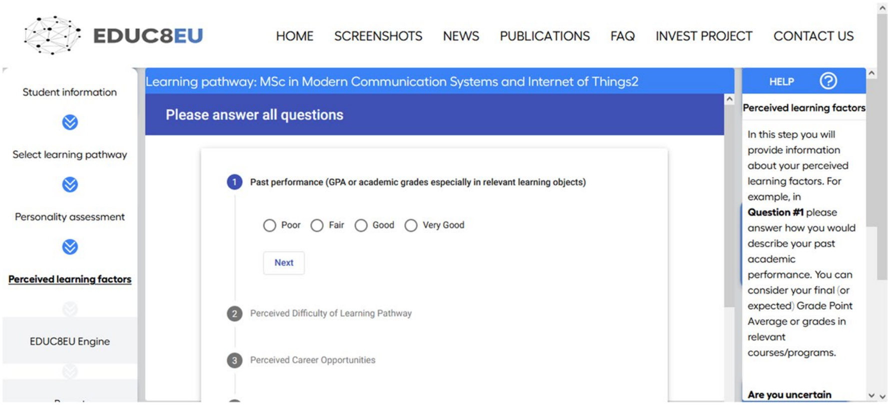

Fig. 6 Reasoning process

Business logic layer

The specific layer is responsible for processing the business logic of EDUC8EU components (without taking into account the presentation and graphical user interface requirements) and for accessing the data layer to retrieve, modify, and delete data to and from the RDBMS. JBoss Application Server is used as the application engine of choice because it provides an integrated platform for development and includes the following:

Semantic sub-layer

During the design mode, the end-user interacts mainly with the semantic layer in order to ensure the constant update and evolution of the academic advising, operational, organizational, and quality-related knowledge that is stored inside the semantic model. The domain experts (academic advisors) are responsible for the maintenance of the ontology and rule-set repository to be utilized during the reasoning process by the expert system. In order to facilitate the continuous maintenance of the semantic rule base in an integrated way by the domain knowledge experts, a graphical rule generator interface was implemented, which offers a better viewing experience for rules and rulesets to facilitate the understanding, knowledge, and manipulation of them.

Fuzzy inference

The FLC subsystem is partially based on an open source Mamdani-style inference engine.[5] Server-side Java Server Pages technology is used to extend the

[5] https://github.com/marcingol1/fuzzy.

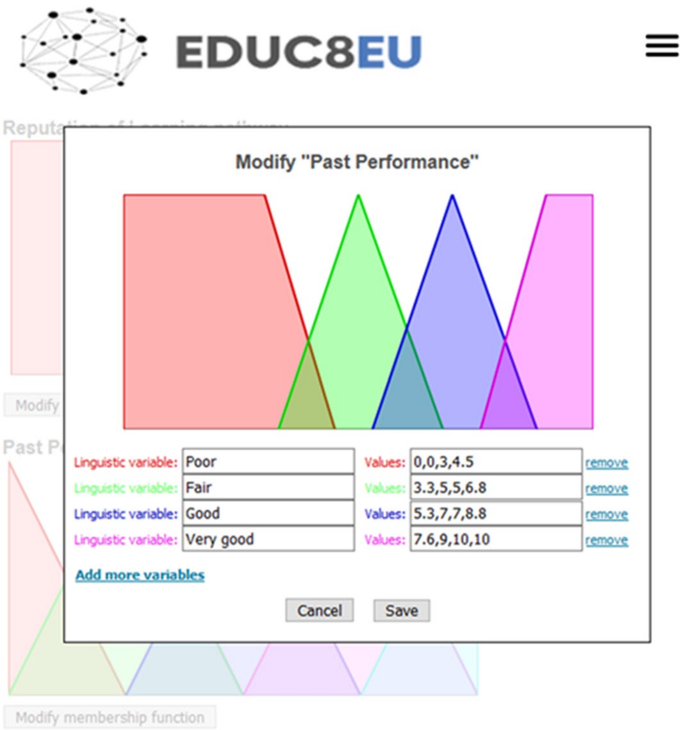

Fig. 7 MF of "Past performance" variable

capabilities of the application by adding dynamic server-side web scripting features and seamless integration with the database.

As it is depicted in Fig. 6, within the FLC subsystem, the end-user has to enter values for all the inputs defined in the learner model. The subsystem will respond with the student's interest degree to be forwarded to the second subsystem.

Fuzzifier Choosing an efficient MF in fuzzy algorithms plays a vital role to achieve the appropriate results. In order to facilitate the tuning of the MFs, an online membership editor UI was implemented. The tool lets the end user display and edit all of the MFs associated with all of the input and output variables for the EDUC8EU system. Figure 7 shows the graphical representations of the "past performance" factor as an example. Both the choice of triangular and trapezoidal shape are supported by the implemented tool because of the simplicity of specification and the satisfying results (Fallahnejad & Moshiri, 2014). More specifically, the triangular function can be defined in the tool by a lower limit a, an upper limit b, and a value m inserted twice in the corresponding textbox, where $a < m < b$ and is calculated by the following formula:

Table 4 Sample of Fuzzy rules used

R1	If [Reputation of Learning Object is low] then [Interest is low]
R13	If [Friends & Peers in Learning Pathway is High] and [Perceived Difficulty of Learning Pathway/Object is average] then [Interest is moderate]
R17	If [Reputation of Learning Object is average] and [Past Performance is veryGood] then [Interest is high]
R19	If [Past Performance is veryGood] and [Friends & Peers in Learning Pathway is many] then [Interest is veryHigh]
R24	If [Cost of Learning Pathway is high] and [Perceived Difficulty of Learning Pathway/Object is easy] then [Interest is veryLow]

$$\mu_A(x) = \begin{cases} 0, x \leq \alpha \\ \frac{\mathrm{x}-\alpha}{\mathrm{m}-\alpha}, a < x \leq m \\ \frac{\mathrm{b}-\mathrm{x}}{\mathrm{b}-\mathrm{m}}, m < x < b \\ 0, x \geq b \end{cases} \tag{1}$$

The trapezoidal function can be defined in the tool by a lower limit a, an upper limit d, a lower support limit b, and an upper support limit c, where a < b < c < d and is calculated by the following formula:

$$\mu_A(x) = \begin{cases} 0, (x < a) or (x > d) \\ \frac{\mathrm{x}-\alpha}{\mathrm{b}-\alpha}, a \leq x \leq b \\ 1, b \leq x \leq c \\ \frac{\mathrm{d}-\mathrm{x}}{d-c}, c \leq x \leq d \end{cases} \tag{2}$$

The output variable, which represents the student's interest for the specific pathway, is defined by five linguistic degrees as "Very Low," "Low," "Moderate," "High," and "Very High." Once the result is processed, the student's interest degree is forwarded to the second subsystem in order to be fed into the rule engine to lay out the pathway.

Fuzzy rules Based on the fuzzy values obtained from the fuzzifier, the rules were acquired from a group of academic advisors, incorporating their knowledge and experience. The academic advisors were tenured faculty members of University of Thessaly in Greece whose experience ranged from 12 to 25 year and whose professional tasks ranged from being solely an educator to being an educator, researcher, and department chair simultaneously. All of 24 rules were approved by 100% of the domain experts participated in the research. The rules are of the structure (IF antecedent(s) THEN consequent) where the antecedents are the learner's factors and the consequent is the student's interest degree. A sample of the rules used is the following (see Table 4):

Defuzzification The defuzzifier component utilizes the centroid method, which is probably the most popular and useful defuzzification technique. It finds the point where a vertical line would slice the aggregate set into two equal masses. Mathematically, this center of gravity (COG) is calculated as follows:

$$\mathrm{COG} = \frac{\int_a^b \mu_{\mathrm{A}}(x)x dx}{\int_a^b \mu_{\mathrm{A}}(x)dx} \tag{3}$$

Recommendation module

To describe the rules for the recommendation module, we employed the Semantic Web Rule Language (SWRL) (Horrocks et al., 2010). SWRL uses the rule syntax "Antecedent→Consequent" to represent semantic relationships. Both antecedent and consequent are formulated as conjunctions of atoms written $a_1 \wedge \ldots \wedge a_n$. Variables are denoted using the standard convention of prefixing them with a question mark (e.g., ?V). Furthermore, SWRL provides many useful built-ins to support comparisons, math, date, or string functions. This module comprises:

The crisp SWRL rules Which model the knowledge and experience of the domain expert. The SWRL rules can perform complex reasoning and calculations by including i) the output of the first stage, ii) other inputs derived from the EDUC8EU semantic model to be used in the reasoning process, and iii) the final recommendations, which are the output of the EDUC8EU system. An indicative set of the crisp SWRL rules for the EDUC8EU prototype is presented shortly:

Rule A

1	Learner(?L) ^ Process(?P) ^
2	hasRIASEC(?L, IRC) ^
2	LearningState(?S) ^ hasLearningState(?L,? S) ^ hasInput(?P,? S) ^
3	hasName(?P, "orientation") ^
4	Interests(?I) ^
5	hasInterest(?I, computerNetworks) ^ hasInterestDegree(?I, high)
6	Curriculum(?C) ^ hasType(?C, handsOnLabs) ^
7	hasRequirement(?P1, admissionProcess) ^
8	hasSatisfactory(?P1, engishSkills) ^
9	hasSatisfactory(?P1, computerBasics) ^ Process(?P1)
10	→
11	hasName(?P1, "CCENT")

Rule A describes the following situation: if the student has a high level of interest in "Computer Networks" (line 5), wishes to gain hands-on experience (line 6) and there is an estimation of "IRC" (Investigative, Realistic and Conventional) as his Holland/RIASEC code pattern (line 2) then the next step of the procedure foresees the registration to the CCENT certification (line 11), which requires an initial admission screening process (line 7). Good knowledge of English and basic computer skills are also important prerequisites according to rule A (lines 8, 9).

Rule B

1	Learner(?L)^Process(?P) ^ LearningState(?S) ^
2	hasInput(?P,? S) ^ hasName(?P, "CCENT") ^
3	hasSatisfactory (?S, CCENTexams)
4	Interests(?I) ^ hasInterest(?I, ICTSecurity) ^
5	hasInterestDegree(?I, veryHigh)
6	hasRequirement(?P1, hasTuitionFees) ^
7	Resource(?C) ^ hasQA(?C, MinimumEnrolledStudents) ^
8	Process(?P1)
9	→
10	hasPart(?P1,? P) ^ hasName(?P1, "CCNASecurity")

Rule B describes the decision concerning the CCNA pathway selection performed once the CCENT cycle is completed. The first hypothesis of the specific rule is that the student has a "very high" level of interest in the "ICT Security" field (lines 4, 5). So, if the student is considered to have satisfactorily completed the CCENT exams (line 3) then the next step of the pathway foresees the enrollment in the "CCNASecurity" pathway (line 10) provided that the specific track has more than a prescribed minimum number of students enrolled to make it viable. It has to be noted that the "minimumEnrolledStudents" indicator is derived from the quality assurance ontological module and is instantiated in Rule B in order to demonstrate the flexibility the current approach provides.

The "SWRL to DROOLS" translator Which takes as input the SWRL rules and translates them into a DROOLS world using a collection of available software components and Java-based APIs.[6] Initially, the appropriate SWRL rule-set is selected by the specific component and transformed into DROOLS compatible format so as to be further processed by the rule engine.

The DROOLS rule-based expert system Which is one of the key components of the business logic for the personalized recommendation of learning pathways. The DROOLS rule-based expert system fires the semantic rules in order to reason upon them and produce the result in JSON format. The JSON file generated is defined as an asset for the EDUC8EU platform so as to be further utilized for the composition of a detailed report containing well-founded recommendations tightly integrated into the available learning pathways (Fig. 8). An important feature of the specific component is that in any execution cycle, a negative recommendation is also possible to be created if the learning pathway is considered not appropriate for the learner. Thus, when-

6 https://github.com/protegeproject/swrlapi/wiki.

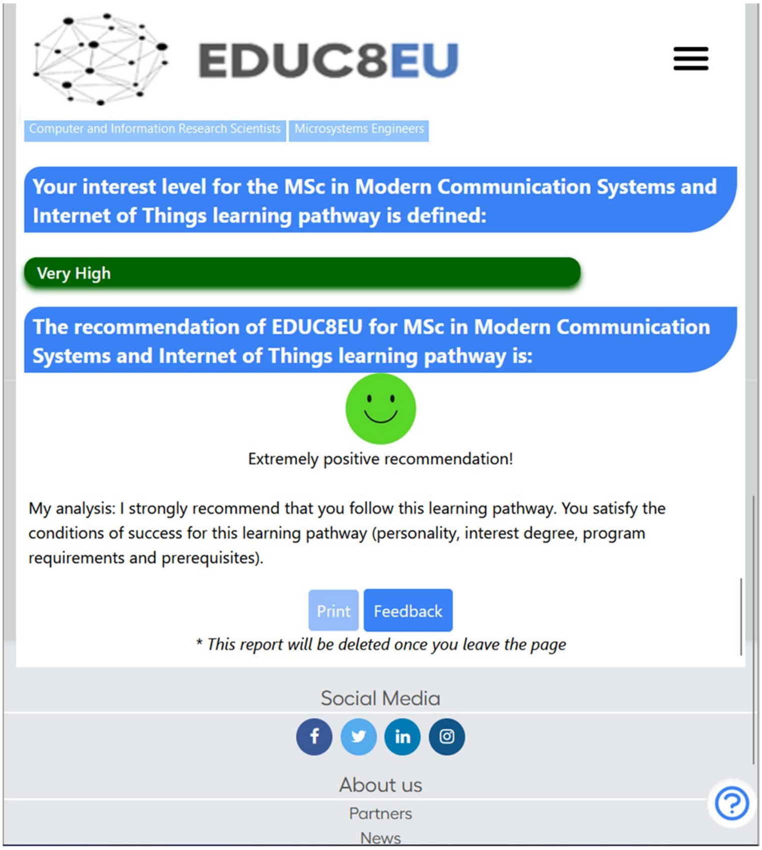

Fig. 8 EDUC8EU recommendation

ever the conditions specified in the antecedents of the semantic rules are not fulfilled, no rule is triggered and hence a negative recommendation is generated by the EDUC8EU system. Moreover, once the rule-set execution is completed, the expert system produces a feedback message (Fig. 5), which contains new DROOLS world facts that can update respectively the knowledge inside the EDUC8EU ontology and the rule base ensuring its perpetual maintenance. Thus, this component provides exception detection functions with semantic rules in order to handle the recommendation of the most appropriate learning step for each student as well as the knowledge evolution.

Presentation layer

The Apache Tomcat[7] software will play the role of the web server that interacts with Java servlets and JSPs, thus enabling transparent access to the platform through

[7] https://tomcat.apache.org/

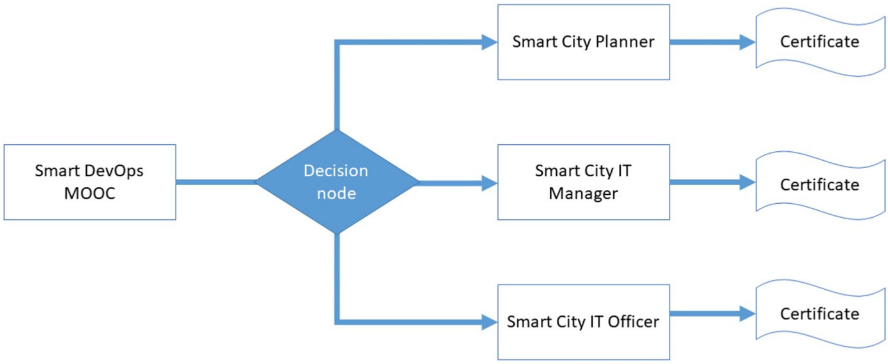

Fig. 9 Smart DevOps Learning pathways

simple web browsers. Moreover, the use of XML data and XSLT transformations serves the adaptation of web pages according to the role and the respective access rights of the specific user. The presentation layer allows the integration and presentation of several client-side JavaScript components based on jQuery for various tools and applications of the EDUC8EU software environment. Finally, the specific layer serves for the triggering of applications, tools, and services of the integrated EDUC8EU software environment.

Case study

The performance and completeness of the implemented prototype were tested during the selection of a set of appropriate academic advising recommendations regarding the MOOC for Smart City professionals offered through Moodle's Open Education platform.[8] The specific MOOC was developed under the framework of the Smart DevOps project to offer high quality educational course that will enable the students to develop and acquire essential competencies needed to tackle the challenges of managing and evolving of smart cities. Students who completed all modules successfully were qualified for the second round of specialized training, which included three different learning pathways leading to the certification of three smart city job profiles: (1) Smart city Planner, (2) Smart City IT manager, or (3) Smart City IT office job profile (Fig. 9) (Kaufmann et al., 2020).

According to the analysis performed by the researchers of the Smart DevOps project, each job profile requires a different curriculum stemming from four learning objectives: (a) Development the transversal skills, (b) Building an adequate IT knowledge background, (c) Developing advanced software development and operation skills, and (d) Developing smart city management skills (Iatrellis, Panagiotakopoulos, et al., 2020). The case study focused on the decision node prior to starting

[8] https://smartdevops.eu/.

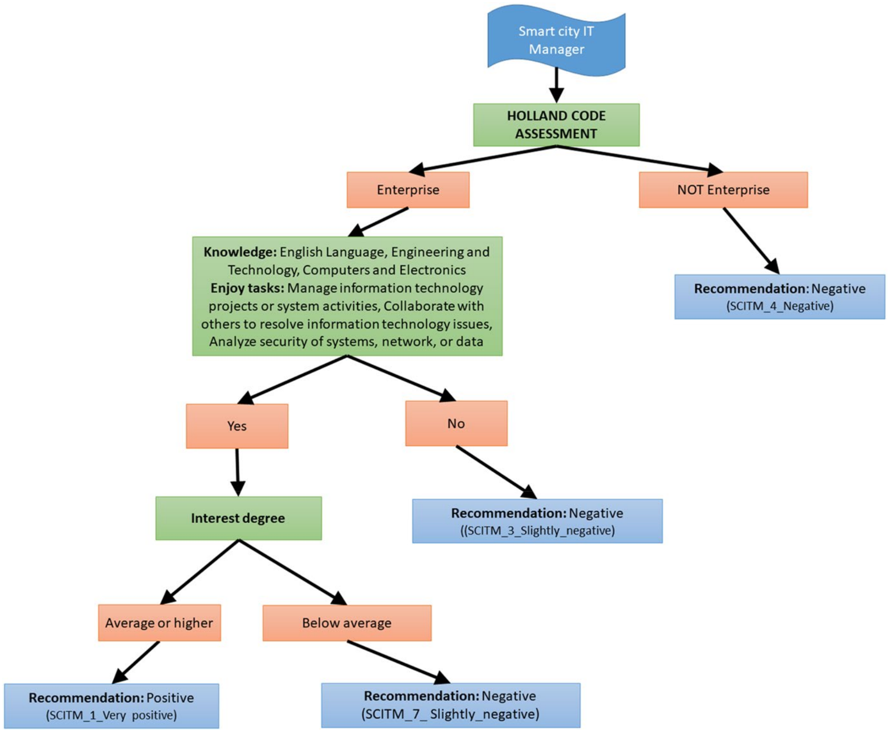

Fig. 10 Smart city IT Manager academic advising guidelines

the specialization training in order to evaluate the output of the EDUC8EU subsystem. Initially, the academic advising guidelines for each learning pathway were represented as a decision tree, since it constitutes a simple way to understand and interpret (Iatrellis, Savvas, et al., 2020). Figure 10 depicts the decision tree for the "Smart city IT manager" learning pathway according to which students were checked by their personality code, their knowledge and skills, and interest degree. It has to be noted that each leaf node of a decision tree features a recommendation ID that associates the output with an explanatory text documenting the reasoning process. Subsequently, the decision tree was translated into SWRL language and imported into the EDUC8EU semantic model. The three decision trees were developed by analyzing the data from popular and heavily researched career inventories such as the ESCO[9] classification, O*Net,[10] and ILO.[11] For example, the Holland code node in Fig. 10 was defined to "Enterprise" in alignment with the "Information Technology Project Managers" profile of the O*net library where it has a 96 out of 100 importance rating. In the O*NET library, the personality type is called "Interests," but

[9] https://esco.ec.europa.eu/.

[10] https://www.onetonline.org/.

[11] https://www.ilo.org/.

it uses the same control measures from Holland's occupational themes (Realistic, Investigative, Artistic, Social, Enterprising, Conventional).

For each student, the knowledge that is modeled as part of the semantic model combined with the student's parameters triggers the rule execution engine. The result of the specific interoperation is a recommendation of the learning pathway to be proposed. In this case study, we used 124 student cases to create the dataset for validation. More specifically, five academic advisors were engaged in the procedure with the aim of providing recommendations for finding the learning pathway that best fits each student. All participants were tenured faculty members with considerable experience in MOOCs and deep knowledge of learning pathways' requirements, prerequisites, and policies and whose experience ranged from 13 to 31 years in Higher Education. The consistency of performance is evaluated using Cohen's kappa statistic, which measures the level of agreement between two raters (EDUC8EU and academic advisors) by using the term of chance agreement. Cohen's kappa coefficient can be calculated as follows:

$$\kappa = \frac{P(a) - P(e)}{1 - P(e)} \tag{4}$$

where P(a) refers to the observed probability of agreement while P(e) is the expected probability of agreement.

During the execution of the case study, the EDUC8EU system only achieved fundamental agreement ($\kappa = 0.6231$) with the academic advisors, thus a series of changes and adaptations to the academic advising guidelines incorporated in the three learning pathways of the MOOC was required. The main cause of the disagreement that was identified was that the academic advisors unanimously considered that the Holland Code assessment decision node should not be used as a root node, since the lack of IT skills, knowledge, or interest poses a major obstacle to fulfilling the requirements of under study learning pathways. The academic advisors recognized that this is a strength of the way the EDUC8EU system is conceived and works since it mimics the human expertise instead of relying solely on easy and sometimes simplistic personality-based matching techniques that automatically link to a range of options. Multicriteria matching of recommendations to learner's parameters and their detailed and comprehensive analysis that is displayed as the final output to the student increase the likelihood that the provided advice by EDUC8EU will be followed. Thus, with the system's help, the goal of optimizing the quality of the academic advising services provided in conjunction with alleviating any inconsistencies will be achieved. Therefore, using the EDUC8EU backend, the corresponding changes were made in the decision trees, which for the case of the "Smart City IT Manger" learning pathway took the following form (see Fig. 11):

Once the semantic model was corrected, the evaluation resulted in a higher concordance with the opinion of the experienced academic advisors. Table 5 lists the results of agreement of the tested cases and the process of calculating Cohen's Kappa coefficient is as follows:

Based on Table 5, the value of kappa value was $\kappa = 0.8831$. The result shows that EDUC8EU has a strong correspondence with the opinion of the academic advisors.

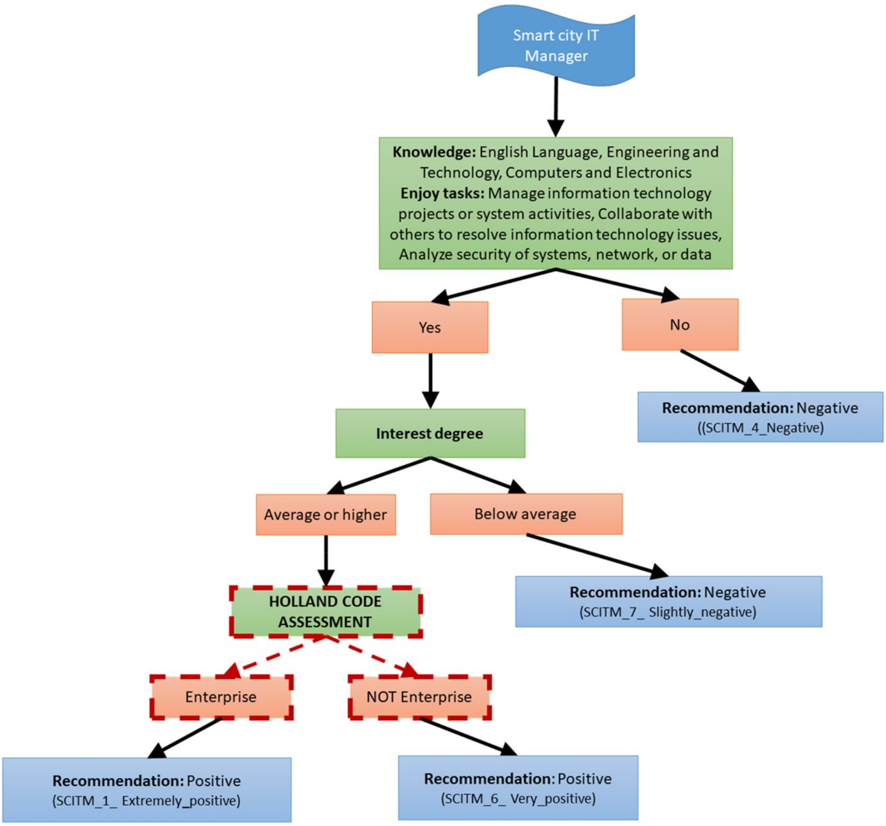

Fig.11 Smart city IT Manager modified academic advising guidelines

Table 5 Agreement table

	Academic advisor positive	Academic advisor negative
EDUC8EU positive	94	3
EDUC8EU negative	2	25

Furthermore, the usefulness of the overall implemented EDUC8EU software environment was evaluated by the five academic advisors who were granted full privileges for the backend system. To mitigate the risk of academic advisors not understanding the way that backend features should be used, academic advisors received a 3-h long instruction that was aimed to explain each feature including the reasoning process, the semantic model, fuzzy logic controller, and the rule generator. The following seven questions were asked to the academic advisors using a feedback questionnaire and 5-level Likert scale where a score of “1” represented strongly unfavorable to the proposed software solution and a score of "5" represented strongly

Table 6 Evaluation questionnaire

#	Question	Score
1	It is simple to use the EDUC8EU system	3.8
2	EDUC8EU can effectively support the academic advising process	4.0
3	The method is able to efficiently deal with the uncertainty and fuzziness of the academic advising process	4.2
4	It was easy to learn to use EDUC8EU backend tools	3.4
5	I believe EDUC8EU can be parameterized to serve various educational programs and scenarios	4.8
6	I believe EDUC8E increases the chances of proposing the most appropriate academic advising guidelines for each student	4.6
7	Overall, I am satisfied with EDUC8EU system	4.4

favorable (Table 6). We provide the average score that the EDUC8EU received for each of these questions along with the question:

The participants in the case study felt that the EDUC8EU has a positive effect on the academic advising process, while at the same time addressing the fuzziness in learner's parameters, required for leveraging personalized learning. Moreover, it was pointed out that the simplicity and effectiveness of the implemented software environment makes it usable and practical for various educational programs and scenarios.

Our contribution

Our proposed approach led to the development of EDUC8EU platform, which supports the provision of highly personalized recommendations for every individual student by combining fuzzy logic with an evolving expert system and semantic web technologies. Our platform constitutes a novel combination of fuzzy, ontological, and rule-based reasoning techniques in academic advising systems that tackle the following research problems:

(1) The probabilistic nature of student data / outcomes and the vagueness in the formulation of academic advising recommendations can potentially create uncertainty in an academic decision support architecture (Mohamed Baloul & Williams, 2013).
(2) The formalization of academic advising recommendations constitutes one of the major challenges for the area (Shatnawi et al., 2014), (Iatrellis et al., 2017).
(3) From HEI's perspective, the academic advising recommendations reflect on the academic, the techno-economic, and the administrative aspects of the higher education processes (Iatrellis et al., 2018); therefore, it is important to be academically adaptable to the modern educational trends and responsive to administrative business process changes or transformations.

Our research addresses the first problem by determining a suitable learner model for representing the important factors affecting decision-making process, through extensive study of the literature and bibliography in the specific domain of our interest. EDUC8EU approach utilizes fuzzy logic to absorb the vagueness that may exist in these factors alongside with the imprecision in judgments regarding the student's next academic step. The adaptation of academic advising guidelines is performed by the establishment of a semantic model the core of which is the EDUC8EU ontology. EDUC8EU ontology is further utilized for the implementation of a rule-set of semantic rules. The reasoning process is performed by utilizing an expert system as the backbone of the EDUC8EU system. Thus, the academic advising workflow for each student is totally personalized and based on their personality, interests, prior skills, and knowledge and requirements of the learning pathway offered to them.

The second problem is counter-measured by achieving academic advising guidelines formalization, both in terms of content and structure, by means of the semantic rules, which can facilitate the establishment of a mechanism for the consistent recommendation of the next appropriate step of an academic plan. The resulting formal rules can be used as a valuable online enchiridion by the HEI to provide consistent academic orientation and guidance.

EDUC8EU tackles the third challenge by offering a complete toolkit to the academic personnel in order to maintain and update the stored rules, thus covering the complete lifecycle of the academic advising process (both design and execution mode). In order to facilitate the tuning of the fuzzy parameters in an integrated way by the domain knowledge experts (academic advisors), an online membership function editor tool was implemented for creating and editing the membership functions (MFs) for every input and output variables. Moreover, EDUC8EU infrastructure encompasses an extensible semantic model utilized for the representation of the required domains of knowledge, as well as for the creation of a set of semantic rules for the modeling of the academic advising experience and knowledge. The rules are used in the inference process to discover new facts from given ones and redefine the rule base of the EDUC8EU platform accordingly.

Conclusions and future work

The EDUC8EU software platform offers a "tight integration" of ontological, fuzzy reasoning and rule-based tools all together. It is implemented exploiting state-of-the-art technologies, starting from a conventional rule-based expert system and building upon it to perform fuzzy reasoning. Successful determination of student interest in a specific learning pathway through fuzzy logic enables the propagation of fuzzy truth values along the triggered semantic rules. In this way, fuzzy reasoning, conventional expert system, and semantic web technologies are combined to form a unified reasoning process to produce personalized recommendations for the next academic step in an integrated way. The cornerstone of the EDUC8EU infrastructure is a multi-facet ontology coupled with the implemented rule-set and the enhanced expressivity inherited from the SWRL language, which can be easily adapted to serve various educational needs and scenarios. The development of the expert system was realized by utilizing the Drools system, while the online membership editor has been developed as an add-on for the online software platform, a technical decision that greatly enhances the accuracy and robustness of the system. At the same time, the Drools rule engine can enrich the semantic model by inducing new implicit knowledge as each pathway progresses. As rules are fired, new facts are inserted into the fact base, which can be used in further inference and ontology evolution. Currently, we are exploiting our system for assisting students on their academic paths in the context of the INVEST4EXCELLENCE H2020 project that encompasses programs of study with a wide variety of educational options and experiences in diverse settings.

In future, a type-2 fuzzy approach may be explored to determine the rules and values of the parameters. Moreover, future work will be devoted to investigate the adoption of learning analytics techniques to support the decision-making process through predictive analysis. To this regard, we plan to develop a data-driven prediction model that will utilize machine learning methods to perform clustering according to their students' past decisions on learning pathways.

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