Personalized Students' Profile Based On Ontology and Rule-based Reasoning

Shaimaa Nafea[1], Leandros A. Maglaras[2,*], Francois Siewe[2], Richard Smith[2], Helge Janicke[2]

[1]School Of Business, Arab Academy For Science Technology & Maritime Cairo, Egypt
[2]School of Computer Science and Informatics De Montfort University Leicester, UK

Abstract

Nowadays, most of the existing e-learning architecture provides the same content to all learners due to "one size fits for all" concept. E-learning refers to the utilization of electronic innovations to convey and encourage training anytime and anywhere. There is a need to create a personalized environment that involves collecting a range of information about each learner. Questionnaires are one way of gathering information on learning style, but there are some problems with their usage, such as reluctance to answer questions as well as guesses the answer being time consuming. Ontology-based semantic retrieval is a hotspot of current research, because ontologies play a paramount part in the development of knowledge. In this paper, a novel way to build an adaptive ontological student profile by analysis of learning patterns through a learning management system, according to the Felder-Silverman learning style model (FSLSM) and Myers-Briggs Type Indicator (MBTI) theory is proposed

1. Introduction

In an educational environment, learners with diverse learning capacities and foundation information require particular learning ways [1]. For example there exist two kinds of learners, the visual (prefer images) and the verbal learner (prefer words, both in speech and writing), which affects both their educational behavior and also and their learning capabilities [2]. Learning can be characterized as the procedure of obtaining knowledge [2]. It includes three key structures of cooperation:

- learner-learner.

- learner-instructor.

- learner-content. [3].

Personalization is proposed as an approach for overcoming these limits. Personalized (or "user-adaptive") systems have become increasingly popular and have gained substantial impulse with the rise of the web technologies.

These systems should be able to make the appropriate recommendations to improve the efficiency of the education process [4]. Based on learning theories, every

learner has a particular learning style, furthermore, using the learning style check in any educational system has a wide impact on the learning and learner satisfaction [5]. Also, the more a learning system knows about a learner, the greater is the chance of delivering learning content that matches his/her needs. Consequently, a learning system has to have access to the learner information and handle learner profiles to figure out which content is the most appropriate and to provide the learner with learning resources or complete learning paths tailored to his/her needs [6]. Generally, there are two approaches to extracting learners' styles:

- Questionnaire;

- Behavior learning pattern [6].

Traditionally, learning styles have mainly been assessed using surveys and questionnaires; asking students to self-evaluate their own behaviors. This is suitable in the traditional way of learning, where it is difficult to observe and analyze students' preferences over the entire learning process. However, as with every qualitative survey, this type of assessment endures numerous downsides. Firstly, it can be biased as it relies on upon student judgment. Secondly, it is performed only at a single point in time, while learning styles, according to several theories, can change over time. Some

*Corresponding author. Email: leandros.maglaras@dmu.ac.uk

of these surveys can reach over 40-questions long, such as Vermunt [7] and Felder–Silverman's [8] and hence, students' dispositions are not easy to keep updated. The uncertainty in the majority of the data gathered from a questionnaire is another drawback of this method. It has direct negative influence on the quality of learning personalization.

Adaptive e-learning frameworks that depend on learning styles by and large utilize distinctive learning style models. This raises the issue of what models and hypotheses are suitable and effective. Likewise, there is an absence of amazing observational assessment with respect to their viability [9] and a scarcity of similar work in connection to these frameworks [10]. Adaptive e-learning systems are based on learning styles generally by utilizing different learning style models. One major issue is the selection of the correct models and theories that are more suitable in order to build an effective adaptive learning environment. In addition, there is a lack of high quality empirical evaluation regarding their effectiveness [9] and a paucity of comparative work in relation to these systems [10]. Most of the existing learning management system focuses on personalization in general, whereas others focus more specifically on personalization based on learning style [11].

The objective of this paper is to build an adaptive student profile by analyzing the user's behavior through a learning management system and by matching the learners learning style with their personality with the use of ontologies and rule-based techniques (inference engine). An initial concept of our adaptive learning management system was presented in [12].

1.1. Motivation of the research and problem statement

The aim of this research is to present an adaptive student's profile based on ontology and inference rules (rules-based) to match their learning style according to two different models. The first model is the FSLSM (Felder and Silverman Learning Style) and the second is the MBTI (Myers-Briggs Type Indicator). Our research differs from these previous works in relation to several aspects:

- We provide personalized student profile based on learner's behavior patterns using two different models namely FSLSM and MBTI.

- We support adaptive learning using ontological architecture featuring an independent adaptation engine and inference rules (rule-based reasoning). Additional adaptation using rule-based reasoning offers personalisation in real time based on the interaction of the learner with the system.

- The proposed work is not only intended to ensure the learner's ability to learn, but it is also expected to be useful in providing a learning path and guidance based on individual differences (learning style and personality). Through the interaction of learners with the system, the provided knowledge is updated. After the knowledge is changed, specific rules are executed and based on these, the knowledge base is again updated with the new inferred knowledge.

- Personalized guidance is accomplished by gathering a student's initial capabilities and preferences from analyzing their behavior pattern from AAST'S MOODLE (Arab Academy for Science and Technology and Maritime Transport - Modular Object-. Oriented Dynamic Learning. Environment) toward utilizing semantic rules and rule-based reasoning in order to detect learner behavioral changes. That way the system can determine which learning style is more suitable for the user.

This proposed model addresses the limitations of existing adaptive e-learning models, the principal ones being as follows.

- Most of the existing models assume that the teacher and learner meet frequently during the learning process and that the learning style of the learner is obvious to the teacher.

- The existing models need the complete dataset of the learner's behavior. Since in real environments most of the times incomplete or vague information exist, it is necessary to be able to make effective conclusions from incomplete data in order to identify an individual's learning style.

We have organized the rest of this paper in the following way; Section 2, discuses the background which include different learning style models as well as semantic web. Section 3 presents our proposed adaptive student profile model, in addition to ontological representation of the existing adaptive models (Adaptive e-learning models). Section 4 illustrates proposed adaptation process flowchart. Section 5 presents current e-learning systems. Finally, Section 6 concludes the article.

2. Background

2.1. Learning style models

Kolb's Experiential Learning Theory [13] identifies four learning styles, namely, diverging, assimilating, converging and accommodating. They can be tested using the metrics watching, thinking, feeling and doing. Under these lens, experience is very important to the learning process. Whilst Kolb's model is suitable for the conventional type of learning, where the learner meets the tutor directly, this model cannot be applied directly in web based e-learning [13].

According to Honey and Mumford's model [14] , behaviors are very important for identifying learning styles. They contended that learners fall into one of the categories of: Reflectors, Theorists, Pragmatists and Activists. They introduced the concept of adaptiveness in learning based on behavior and in order to implement this in e-learning, it is necessary to introduce a neural network model for adjusting the cognitive load dynamically.

Gregorc's model [15] is a cognitive model that refers to four learning preferences: concrete sequential, abstract random, abstract sequential and concrete random. This classification helps to form learning groups that can then be provided suitable learning assistance. However, it is essential to have an effective mechanism for forming such groups, which is possible with the application of clustering algorithms.

Flemming's VAK model [16] is a Meta learning theory that terms the different learning styles: Visual, Auditory and Kinaesthetic. This consequently places emphasis on the audio visual features with regards to learning. Audio, video and text mining techniques can be employed with this perspective to understand learner's behavior.

Dunn and Dunn's model [17] is a biological and experimental model which considers environment and emotion with regard to learner preferences, and is validated using the noise level and persistence metrics. Jackson's model [18] is based on the neuro-psychological theory, where the learning preferences are based on the individual learners' sensation, goal, willingness to achieve, emotion and deep learning to achieve. Both these models consider emotion as a parameter for learning. In the e-learning era, measuring emotion requires user interaction integrated with machine learning algorithms to derive suitable conclusions.

Drawing on Carl Jung, Myers and Brigg [19] developed a personality theory, which classifies the personality based on judgment and perception, thinking and feeling, sensing and intuition and extroversion and introversion. They contend that since learning can be adopted based on the personality it is necessary to understand the personality of the learner. However, understanding it is very hard and hence, suitable agents must be introduced into this model for monitoring and comprehending the learner's personality.

Felder–Silverman's psychological theory [8] is helpful to understand the learner's mood, which can be active or reflective. Moreover, he/she can be sensing or intuitive while learning and the learning itself can be either based on Visual or verbal features. Finally, it considers the sequential and global nature of learners. This we consider to be the most important contribution on learning styles for our purposes when compared with the other perspectives. This is due to the fact that it can be used in e-learning where the psychology of the learners is considered in advance so that flexible courseware can

learning style model	system
Felder and Silverman [8]	CS-388 [20]
	LSAS [21]
	Tangow [22]
Kolb [13]]	MOT [23]
Honey and Mumford [14]	AHA! [23]
	INSPIRE [24]

Table 1. Adaptive systems summary.

be prepared and provided suiting the learners' behavior. The following table 1 shows a summary of some existing adaptive systems.

2.2. Learning Styles and Personality

This study is based on the widely accepted theory that every student has an individual or particular learning style [8]. A learner with a particular learning style can confront difficulties while learning, when there is not bolstered by the instructing environment. Numerous authors have proposed distinctive definitions for learning style. Learning style can be characterized as student's preferences in the way of learning and differences in students' learning, and it is considered as one of the factors influencing learner's achievement [25].

A wide importance, definition is provided by Keefe[26] "Learning styles can be defined as characteristic cognitive, affective, furthermore psychological behaviors that serve as generally stable indicators of how learners perceive, interact with, and respond to the learning environment". James and Gardner (1995) define learning style as the "complex manner in which, and conditions under which, learners most efficiently and most effectively perceive, process, store, and review what they are endeavoring to learn ". There is a definition of learning style that was presented by Merriam and Caffarella (1991) which is well known in grown-up education, as the "individual's characteristic method for processing information, feeling, and behaving in learning circumstances" [27].

In our research, we concentrate on two models as explained below. First, the Felder-Silverman model [8] (FSLSM) is selected because the authors provide the questionnaire and a comprehensive guide on how to use it its can be linked easily to e-learning systems. In addition, this model has been turned out to be powerful in numerous adaptive learning systems and it has often been used in technology-enhanced learning [28] [29]. In addition, this model is adequately accepted in numerous different situations [30], [31], in order to deliver personalised contents adapted to student's learning styles. Moreover, the FSLSM describes the learning style of a learner in more detail than other models, distinguishing between

Preferences	Definition
Extraversion/Introversion	Where a person prefers to focus his attention
Sensing/Intuition	The way a person prefers to take in information
Thinking/Feeling	How a person deal with the external world
Judging/Perceiving	Where a person prefers to focus his attention

Table 2. Basic four MBTI dimensions

preferences across four dimensions: active/reflective, sensing/intuitive, visual/verbal and sequential/global. The dimensions sensory/intuitive and visual/verbal refer to the mechanisms for perceiving information. Whilst the active/reflective and sequential/global are concerned with the way of understanding and processing information [32]. The associated questionnaire, named the Index of Learning Styles (ILS), consists of 44 questions with two options, A or B, each one related to just one of the four dimensions.

The second model we use is the Myers-Briggs Type Indicator (MBTI), that has been widely used and validated in the education domain [33] and has long been considered an important instrument by educational psychologist's [34]. The MBTI questionnaire examines personality traits in four distinct domains: extraverted (E)/introverted (I), sensing (S)/ intuitive (N), thinking (T)/feeling (F), and judging (J)/perceiving (P). The Myers-Briggs Type Indicator reports a person's preferences on four scales as presented in Table 2[35].

The various combinations of these preferences result in a total of sixteen personality types and are typically denoted by four letters to represent a person's tendencies on the four scales For example the dominant preference found in ISFP, INFP, ESFJ and ENFJ is sensing. For those with ISTP, INTP, ESTJ or ENTJ type, the dominant preference is thinking. For reasons of simplicity we can define four MBTI classes or MBTI clusters[36]:

$S = (ISTJ, ISFJ, ESTP, ESFP)$
$N = (INFJ, INTJ, ENFP, ENTP)$
$F = (ISFP, INFP, ESFJ, ENFJ)$
$T = (ISTP, INTP, ESTJ, ENTJ)$

As briefly discussed above, not only can the learning style impact learner performance, but also, additionally, personality has very high impact while determining learners preferences in order to include them in the learning processes. There appear to be critical variables for deciding learner personality while we adapt their profile; Personality is closely related to preferences for learning materials in that a specific configuration or format reflects learner's preferences regarding receiving an information and making decisions.

Most of personalized e-learning systems did not consider these elements while building student models, because there is no easy way to model adaptive profile that is based on both learning style and learner personality. The only method available so far is AHA! [23], which identifies the learner's style as "activist/reflector", in view of a self-evaluated personality type. As previously stated there is a relationship between the Felder-Silverman model and MBTI model. The following figure 1 show the correlation between FSLSM and MBTI personality.
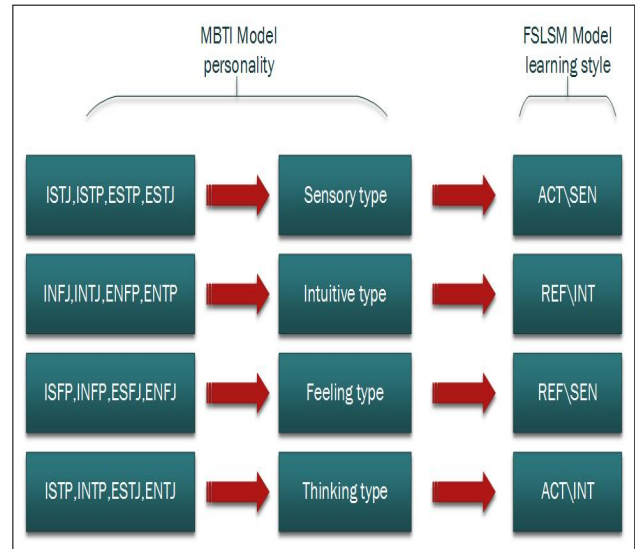

Figure 1. Matching the four Myers-Briggs Type Indicator dominant preferences with the Felder-Silverman learning style model dimensions

2.3. Semantic Web and Ontologies

The Semantic Web [37] is defined as "an extension of the current web in which information is given well-defined meaning." It imagines a machine-justifiable web with an explicit semantic representation of fundamental web pages, web information, and other web assets. Figure 2 [37] demonstrates the semantic web stack.

- XML (extensible Markup Language) allows people to structure their documents by defining and adding their own tags. It plays an important role in exchanging different types of data on the Web. In fact, it is the basis of a rapidly growing number of software development activities. Each document starts with a namespace declaration using XML Namespace.

- RDF (Resource Description Framework). RDF statements come in a type of triples entity-relation-value. XML is used for RDF syntax while Universal Resource Identifiers are used for identifying each of its three components

- Ontology is responsible for knowledge representation. Ontologies models a conceptualization of a certain domain and there exist many forms, which share a taxonomy of domain-specific concepts (classes), featuring a set of properties and relations to other concepts [38]

- Web Ontology Language (OWL) is a an ontology language for the Semantic Web, which allows subclasses of the taxonomy to inherit properties and relations of their ancestor classes.

- Finally, the Proof Layer is used to provide "proofs", e.g. in order to prove that the joined data is acquired from a trusted source.
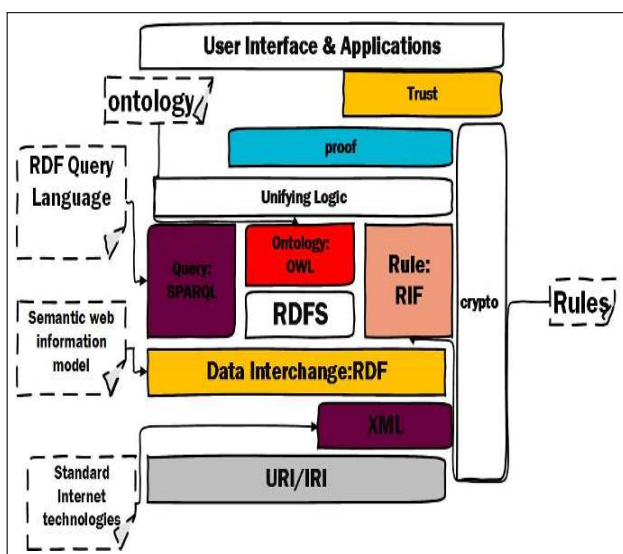

Figure 2. Semantic Web Stack

2.4. Ontology in adaptive Learning

Semantic web technologies are used in various ways in e-Learning systems in order to adapt its content depending on the task they are aimed at delivering.

In the work of ontology based automatic annotation of learning content [39], ontology is used to annotate learning objects with metadata. Similarly, Gasevic et al. [40] have also used domain ontology for semantically marking up the content of a learning object. In the work of Ramezani et al. [41], an algorithm in a Web 2.0 platform is recommended that supports end users collaboratively to evolve ontologies by suggesting semantic relations between new and existing concepts. They use the Wikipedia category hierarchy to evaluate the algorithm and the experimental results show that it produces high quality recommendations.

Gutierrez [42] present the concept of ontology and activity to build an approach of learning activity sequencing. He implements an algorithm to analyze

learning activity and a dynamically updating learner profile. Learning Domain Ontology (LDO) describes the field of learning or teaching in a general manner. It is a generic ontology in the form of a domain classification. It divides in fact, any domain of learning into sub-domains. Every subdomain incorporates points on study that are identifier for that sub-domain[43]. For example, the field of MIS can be described as a sub-domain of Information systems. As it is shown in Figure 3, concepts of LDO are learning, learner and learning style. Relations between them is "*has style*" and "*is style of*".
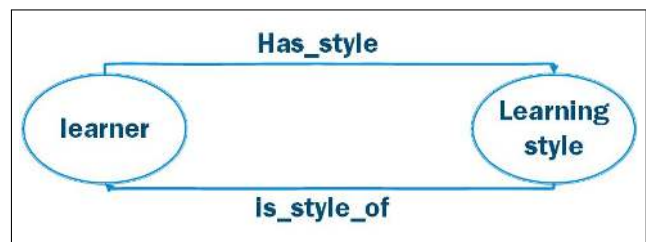

Figure 3. Concepts of LDO ontology

2.5. OWL Reasoners

A reasoner is a program that infers logical consequences from a set of explicitly asserted facts or axioms and typically provides automated support for reasoning tasks such as classification, debugging and querying [44]. Among the large number of reasoners available, the reasoners that can support protégé are: Pellet [45], RACER [46], FACT++ [47], Snorocket [48], HermiT [49], CEL [50], ELK [51] and SWRL-IQ [52], TrOWL [53].

In this study we will use PELLET[54]. PELLET is proven to be very effective in reasoning. Similar to other ontology tools, such as SWOOP12, protégé, Pellet is an OWL DL reasoner using the tableaux algorithms (a decision procedure that aims to determine the suitability of an input formula in a given logic) which is provably complete. Pellet supports reasoning with SWRL rules. Pellet interprets SWRL using DL-Safe Rules notion. There is no need for using any additional utility function to use SWRL in Pellet. It supports the full expressivity OWL-DL including reasoning about nominals (enumerated classes). Therefore, OWL constructs owl:oneOf and owl:hasValue that can be used freely. Currently, Pellet is the first and only sound and complete DL reasoner that can handle this expressivity. Pellet ensures soundness and completeness by incorporating the recently developed decision procedure for SHOIQ (the expressivity of OWL-DL plus qualifiedcardinality restrictions in DL terminology)

Importance of reasoners. The quality and correctness of ontologies plays vital role in semantic representation and knowledge sharing [55]. To ensure the quality of ontologies, there is a need for dealing with

the inconsistency and uncertainty in the ontologies of real-world applications. An inconsistent ontology means that an error or a conflict exist in an ontology, as a result some concepts in the ontology cannot be interpreted correctly. The inconsistency will result in false semantic understanding and knowledge representation. An uncertain ontology+ means that the correctness of the ontology is probabilistic. Ontology reasoning reduces the redundancy of information in knowledge base and finds the conflicts in knowledge content.

Ontology reasoning steps. Ontology reasoning development include the following steps:

- Conceptualization refers to the extraction of classes, subclasses and relationships. Subclass-super class hierarchy can be used for simplifying and understanding adaptive student's profile.

- Formalization refers to the process of analyzing and reasoning upon the domain and characterizing slots.

- Ontology implementation refers ontologies that can be encoded by ontology tool and stored in XML, RDF-XML, and OWL-XML language.

In this paper, ontology implementation will take three stages as shown in figure4:

1. The creation of student ontological model

2. The creation of the adaption mechanism rules (OWL/SWRL)(The SWRL rules are created using a built in reasoner within Protégé.)

3. The development of adaptation reasoning, with the use of the Pellet reasoner in order to perform rule-based inference and logic reasoning.

2.6. Student profile

A personalized student profile is defined as the ability to provide content and services tailored to the individual based on the knowledge about his preferences and behavior [56]. The information regarding these is gathered in the student model. User profile is practically the normal representational of student's data that can be gathered in two ways: from the student or by analyzing his behavior through a learning management system. If the details are gathered directly from the learner, then subsequently the profile made is called explicit or static profile. Whereas if this information is collected by observing the behavior of the learner then the profile created is known as the implicit or dynamic profile. If we build a learner profile, then the data can be effortlessly adjusted for every learner according to his/her preferences.
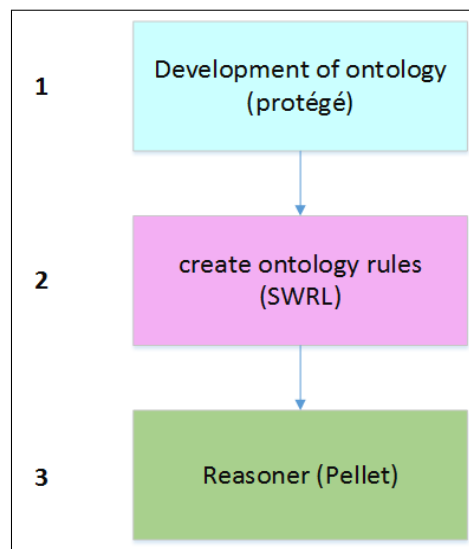

Figure 4. Adaptive ontological stages

Describing Learner Data. Learner data are those pertaining to an individual learner, including the learner profile (personal data), completed content (progress made) and performance data. Moreover, the developed ontology complies partly with well-known standards for student modeling for example, IEEE, PAPI (Public And Private Information) [57] learner and LMS learner information package (LIP)[58].

It is a common belief that (PAPI) and LIP are the most significant and important among the known standards due to their benefits while they adapt learner profile [59]. These vary in terms of their main purpose and the way in which a given system can use their embedded information. Some e-Learning systems use meta-data from more than one standards to produce a learner profile; for example, the PAPI standard considers both the student's progress and performance.

2.7. Advantages of Using Ontological Profile

There are numerous benefits of building ontological based profile

- We could use reasoning toward building the ontologies. We can utilize ontology relations, conditions and restrictions as a premise for deducing extra learner characteristics[60].

- Ontologies control the uncertainties compared into the data and the user profiles that are acquired by the Ontology model give better results compared to other adaptive techniques.

- Ontology provides shared understanding of the area which helps reuse of the outcomes. Furthermore imparting of learner profiles is the most vital

point in utilizing ontological based client profile [60].

3. Proposed adaptive learner profile

We propose a learner ontology model which displays the individual data and learning qualities of distinctive learners. Figure 5 depicts the graphical representation of the learner model.

3.1. Student interface

The student Interface is the communication component that controls the interaction between the student and the system. It deals with the account of learner's such as (registration and login) after that student fill learning style questionnaire which is based on the FSLSM model.

3.2. Data collection

In this section we present, the data that are collected from AAST's (Arab Academy for Science and Technology and Maritime Transport) faculty of business. Two types of data are collected from the learners:

1. When they log into the AAST student portal for the first time, they need to fill in the questionnaire based on the index of learning styles (ILS) developed by Felder-Silverman model.

2. The learner behavior data collected from two sources namely MOODLE and Student portal.

- MOODLE (Modular Object-Oriented Dynamic Learning Environment) includes learner Personal Information as far as the essential individual data, for example, name, date of conception, email, login record etc.

- Student portal holds information about the learner behavior Such information comprises categories of knowledge, preferences and behavior such as the number of visits, time spent on exercises etc.

3.3. Data processing

Reference ontology. The system should have a reference ontology for student profile modelling. Ontology creation can be broken down into two main parts; the first one is static profile and the second one is dynamic profile which are used in order to match the behavior of the user with the suitable learning style according to FSLSM and MTBI model. The data are collected from two sources, the data repository and the learning style model.

adaptation engine. In this stage, the system compares the outcomes from questionnaire to these from the reference ontology using inference rules (association rules). Subsequently, it starts to recommend adaptive content based on the personalized profile for the student, Figure 6 illustrates adaptation engine components .

1. Knowledge base: is an information repository in the form of ontologies. After constructing the ontological knowledge model (e.g. questionnaire), OWL is employed for representing the knowledge base. OWL can define the structure of data by describing and categorizing concepts within the domain and relations between pairs of concepts. It can be used to model the domain and support reasoning about the concepts. The adaptation model is established using SWRL rules in order to empower the knowledge base. The inferred knowledge is used to update the knowledge base real time. The updated knowledge base contains all the knowledge necessary for the adaptation process.

2. Inference Engine: is the crucial component for constructing adaptive learning. It includes comparing recommendation agent and updating agent that provide personalized student profile dynamically. Whenever new information is available it is send to the inference engine, which works based on rule-based reasoning. Rule based is most often used to build rukes using a series of if then functions for instance:

- $Rule_1 : If \quad student = reflective \quad then \quad learning \quad object = problem \quad statement \quad or \quad narrative \quad text$

- $Rule_2 : If \quad student = active \quad then \quad learning \quad object = exercise \quad or \quad experiment$

3. Rule-Based adaptation Mechanism

This study demonstrates how the student Profile Model can be utilized to effectively model the preferences of different students and how the execution of associated Semantic Web rules (using SWRL). These semantic rules are used to adapt student profile based on their learning style and personality. Figure 6 presents the adaptation main components. These components consist of a User Model (or Ontology Model) to hold all relevant user characteristics/information, a Reasoning Engine (such as Pellet) to enable logical inferences to be made from existing User Model information and finally, a set of adaptation Rules which are used to specify certain concepts relating to a particular user.

4. OWL Reasoner (Pellet) A semantic reasoner or rules engine is able to infer logical consequences from a set of asserted facts or axioms. Pellet is an open source java based OWL-DL reasoner developed by The Mind Swap group. It is based on the tableau algorithm and supports expressive
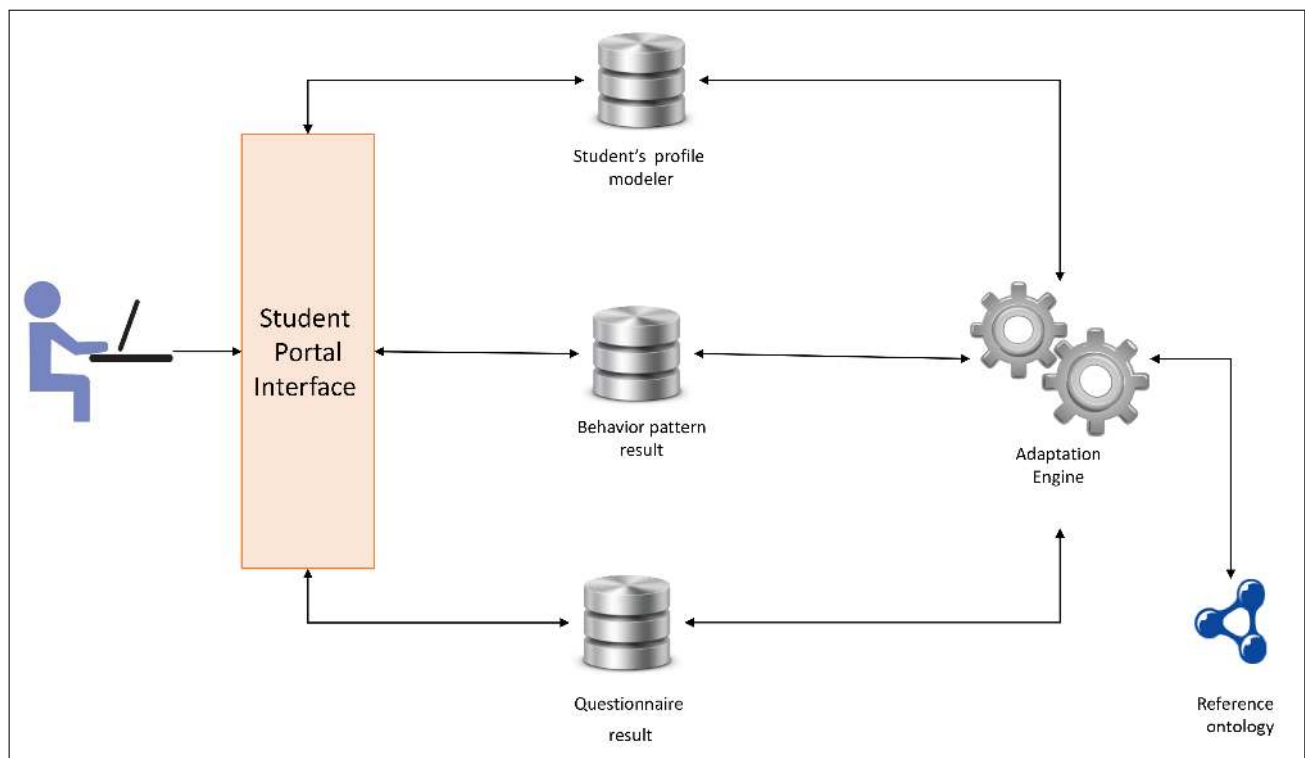
Figure 5. Proposed student profile architecture

description logics. It is the first reasoner that supported all of OWL DL SHOIN (D) and has been extended to OWL2 (SROIQ (D)) [61]. Pellet supports OWL 2 profiles. It reasons ontologies through Jenaas well as OWL-API interfaces. Pellet also supports the explanation of bugs. Fig1 shows various components of the pellet reasoner.

5. Student profile modeler makes a copy of the learner model and keeps it in an accessible memory. It increases the performance of the system as the frequency of accessing the learner model in the knowledge base is considerably reduced. Learner modeler reads and writes information to/from the ontological student model in a variety of syntaxes including OWL. It also facilitates accessing OWL reasoners such as Pellet.

The framework utilizes this data as a part of request to adjust to learner's individual needs. The framework regulator upgrades the learner models during the learning procedure, so as to stay informed concerning learner's activities and advancement and perhaps manage the learner appropriately. Learner model is in charge of recovering the attributes of a specific learner, rolling out the fundamental improvements and sending it to the adjustment model through collaboration with the storehouse. The framework additionally gets the information about new learners from the User Interface and stores it in the learner model. Learner

model is overhauled when it gets new data about the learner from the adaptive engine. The learner model gets continuously upgraded by incorporating learners' interaction with the framework. In points of interest, learners are occupied with adapting adroitly pre-characterized subjects, complete activities and take tests, while the framework ought to consistently perceive changes in the learner's information and capacities as they advance and upgrade the learner model in like manner.

3.4. Used tool (Protégé)

In this proposed ontology based mechanism the broadly accessible ontology editor Protégé 4.3 [62] is utilized as a development tool. Ontologies and learning bases can be adjusted intuitively inside Protégé, being accessed with a graphical client interface and Java API. Protégé can be extended using pluggable components to include new functionalities and administration. There is an expanding number of plug-ins offering an assortment of extra elements. Protégé implements a rich arrangement of information demonstrating structures and activities that support the creation, perception, and control of ontologies in different representation designs. There are various structures, for example, RDF(s), OWL and XML Schemes in which protégé philosophy can be exported. Besides, this ontology editor is picked because it enables the construction of domain ontologies and customized
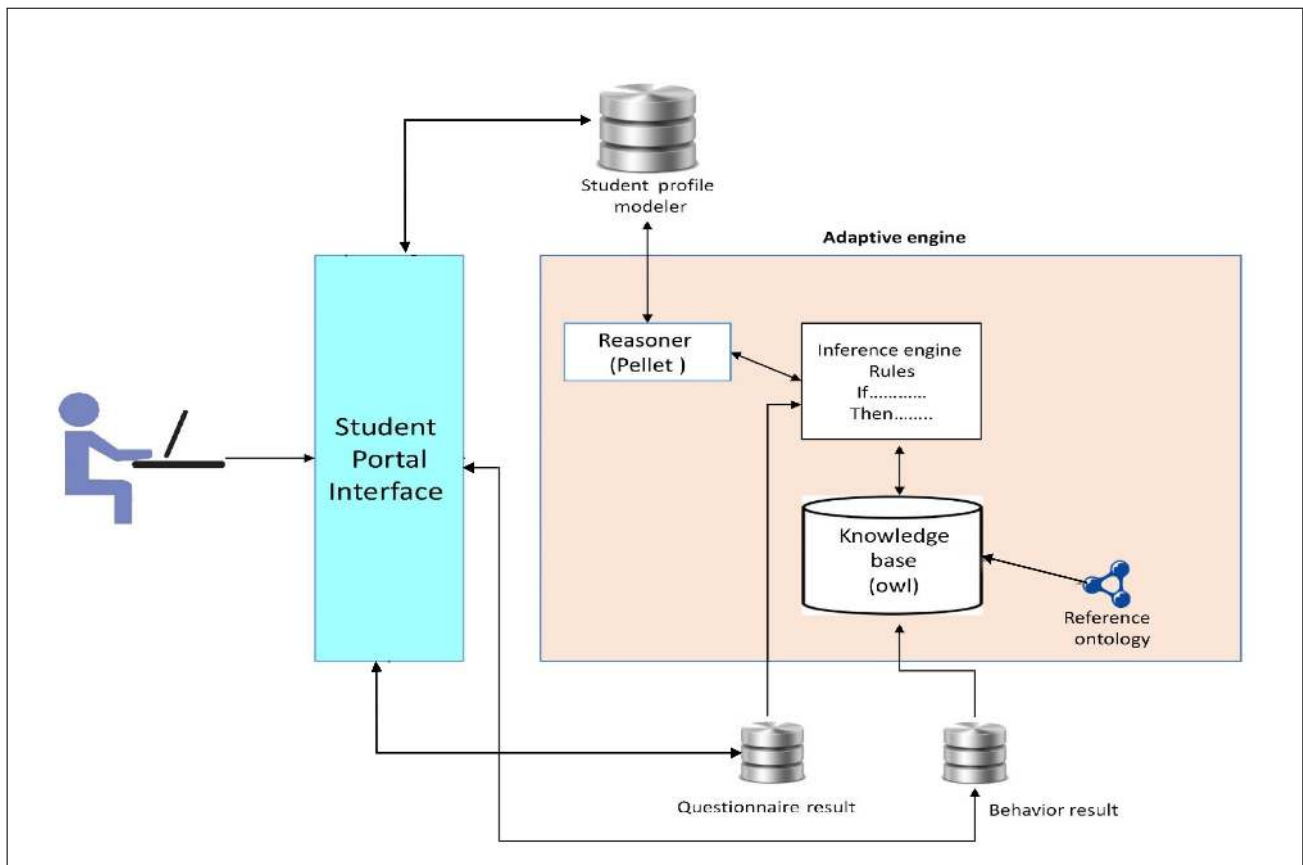
Figure 6. Adaptive engine components

data entry forms. In addition, it allows for the definition of classes, class hierarchies, variables, variable-value restrictions, and the relationships between classes as well as the properties of these relationships.

4. Proposed Adaptation Process Flowchart

The following adaptation flowchart represents the adaptation process. On the one hand, the instructor is responsible for adding course material in different formats and adding student cases, which is illustrated in the following figure 7.

On the other hand, Figure 8 shows the cycle when creating an adaptive learning environment. A new student signs up by completing the learning style questionnaire (FSLSM questionnaire) to create his/her learner model. If the student has already a profile associated then he/she could just use his/her credentials to log into the system. A learning session starts when a registered learner logs into the system. According to the information taken from the questionnaire the system starts to build the student profile in order to present the course content that matches his/her learning style. The adaptation model generates adaptive learning content based on the learner's profile. After that the learner starts to interact with the interactive IOs in
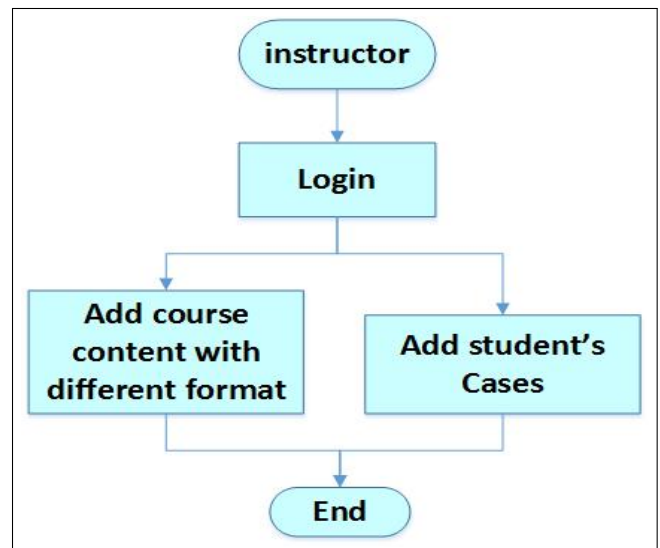

Figure 7. Instructor flowchart

order to analyses his/her learning patterns and from that point the adaption engine starts to recommend the most suitable course content and updates the student model based on student's behavior patterns.
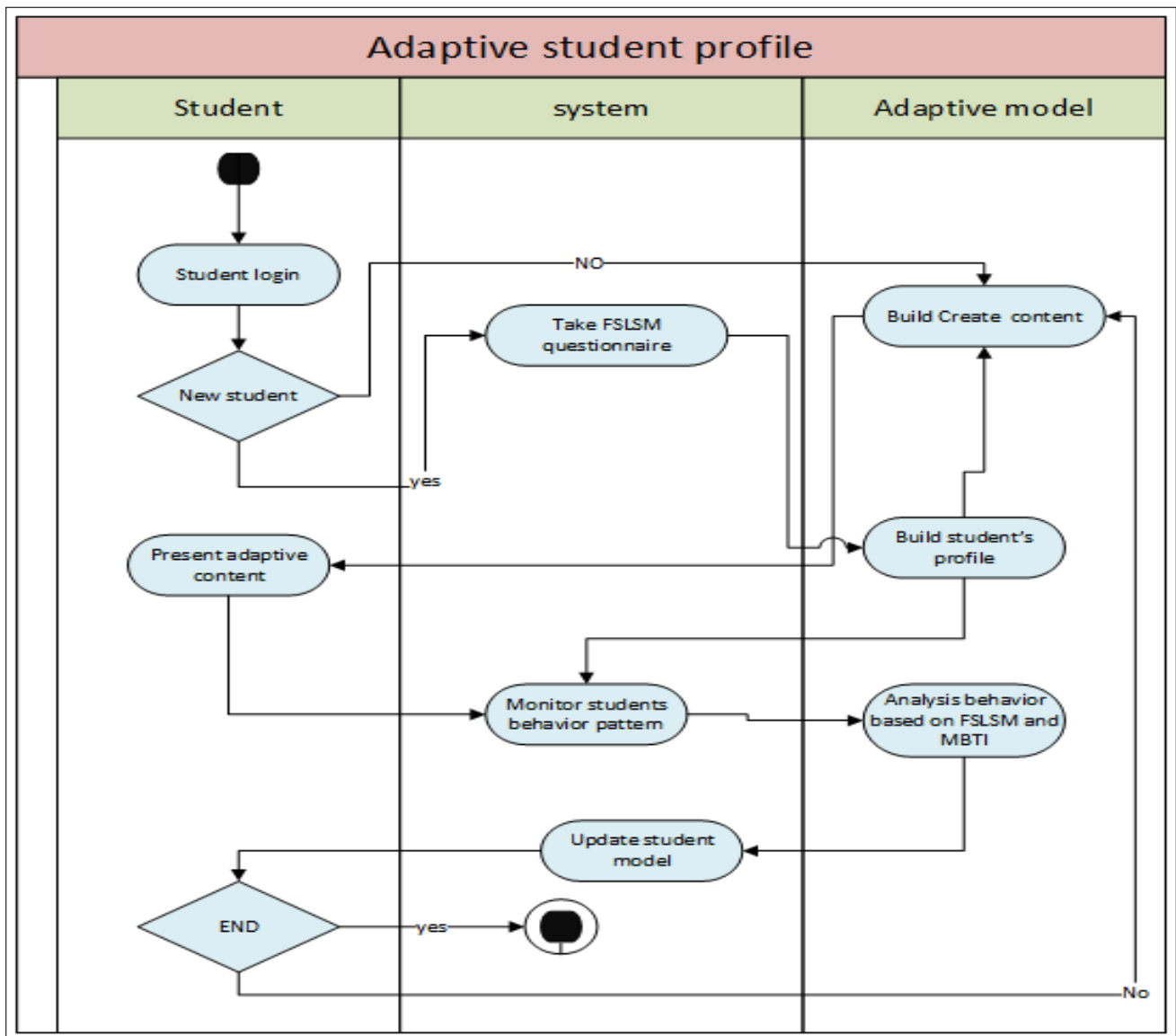
Figure 8. Proposed student profile flowchart

4.1. Ontology representation

The first phase of the ontology building process is identifying the ontology goal and scope, in order to specify the domain ontology and identify the required resources. Figure 9 illustrates ontology implementation graphics using the OWLViz . OWLViz enables the class hierarchies in OWL Ontology to be viewed, allowing comparison of the asserted class hierarchy and the inferred class hierarchy. The components of an ontology are presented that pertain to an adaptive student profile, which is divided into main three classes: basic, static and dynamic information. Students' basic information details are collected from AAST's MOODLE for the faculty of business, comprising name, date of birth, email address etc. which are then divided into several subclasses. Students' dynamic information

details are then collected from AAST's Student portal. Such information comprises categories of Knowledge, preferences and behavior like No. of visits, No. of visits and time spent on exercises Amount of time dealt with reading material etc. student learning style and personality can be obtained by analyzing student's behavior while using student's portal. On the one hand learning styles typically refer to how tends to learn according to Felder-Silverman's. On the other hand learner personality is based on analysis according to Myers-Briggs Type Indicator.

.

4.2. Object properties (relations)

Relationship is an Object in ontology which links between instances as well as between an object and an
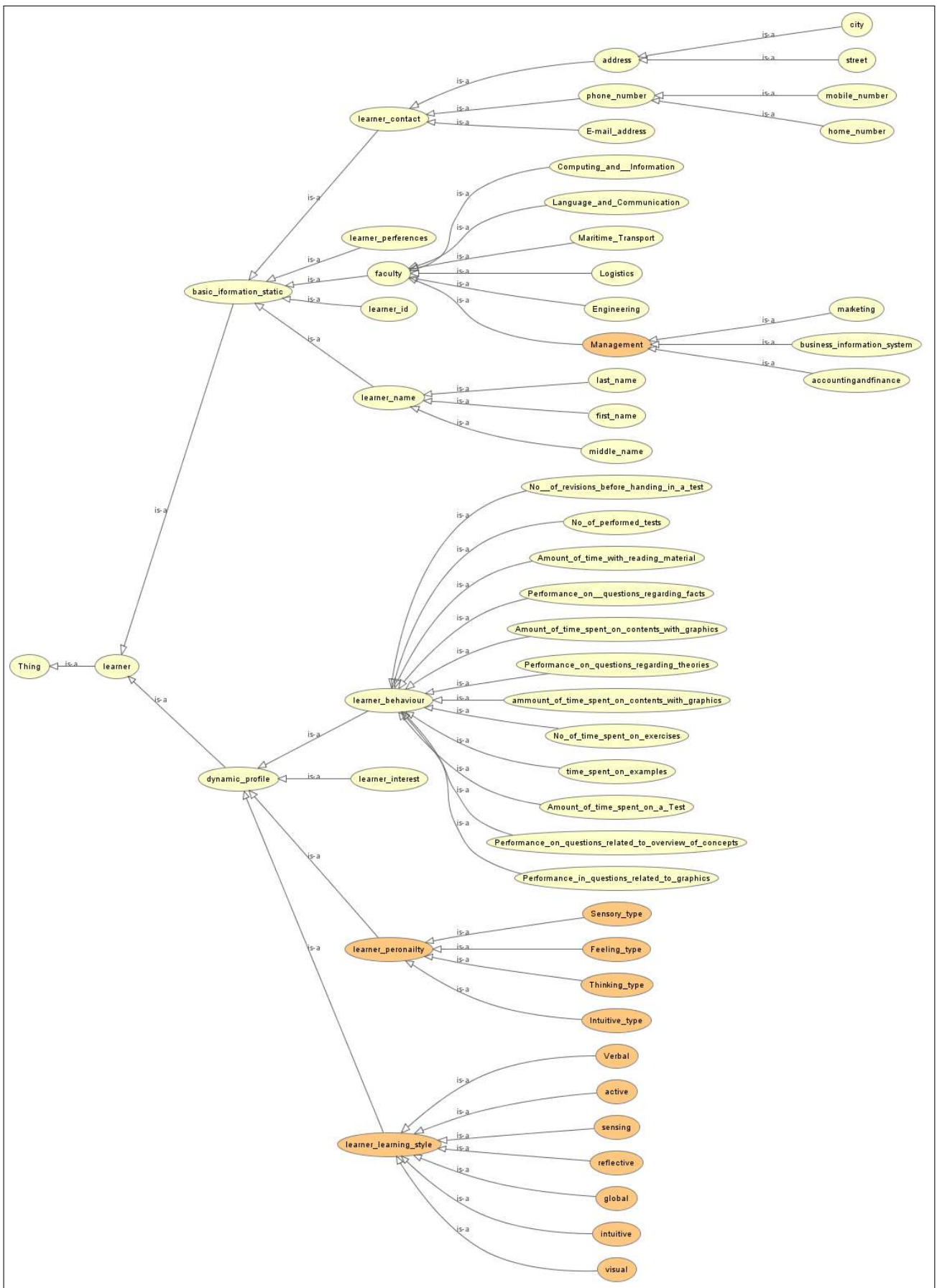
Figure 9. Ontology representation

attribute which is related to. Some of the Relationships and their properties made for the proposed student profile are illustrated in Table 3 where we have listed properties and their corresponding inverse properties along with domain and range of the properties.

Property	inverse	Domain	Range
Has interest	*Is interest of*	*Learner id*	*Learner interest*
Has behavior	*Is behavior of*	*Learner id*	*Learner behavior*

Table 3. classes and properties

4.3. Modeling relationship between personality and learning style

Figure 10 shows the graphical representation of the ontology obtained through domain ontology. The graphical representation of the ontology is generated using the software protégé 4.2 (Protege). The ontological model for the relationship between student personality is based on MBTI and the learning style is based on FSLSM. For instance, for a student who has a thinking personality the most suitable learning style is active and intuitive.
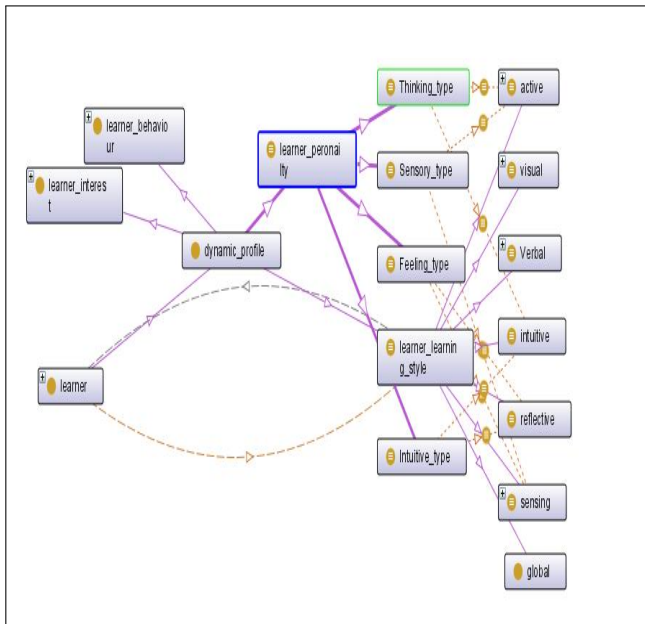

Figure 10. Modeling relationship between personality and learning style

4.4. Relation between behavior and style

The style of the learner can be acquired by investigating the learner's behavior while using the framework. Learning styles ordinarily allude to how a user tends to utilize faculties in order to learn. It can be spoken to the learning style in generalization model as indicated by

the Felder-Silverman learning style classifications. Figure 11 shows the relationship between student behavior and learning style based on FSLSM model.
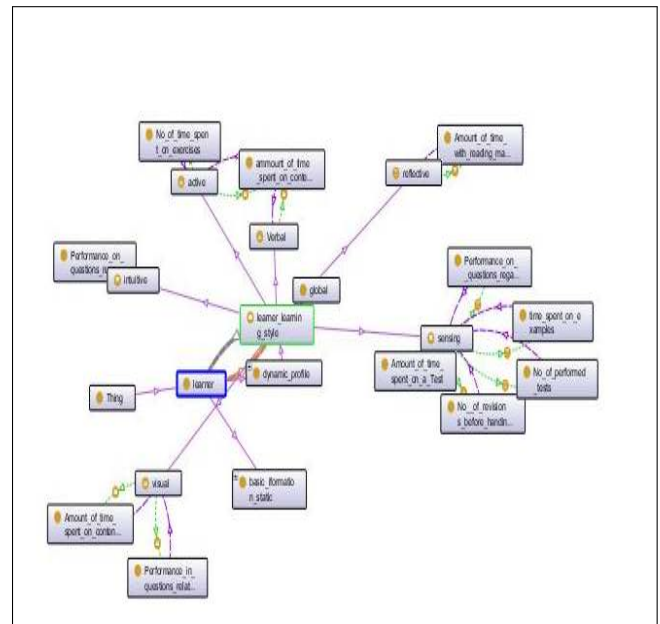

Figure 11. Modeling the relationship between student behavior and learning style

4.5. Ontology reasoning

learning style involves different types of learning's style such as active and reflective. Figure 12 shows the reasoning results of learning style (active) based on student's behavior while learning management system which is AAST'S student portal .

5. Related work (Adaptive e-learning models)

In recent years, several researchers have focused on applying different data mining techniques in order to analyze learner log files, match them with the appropriate learning style and build personalized learner profiles. In this section we present these works. In our model, we utilize ontology with an inference engine (rule-based) to represent and build student learning profile and match it with this learning style that suits his/her preferences and personality. Our focus is to further enhance this area of research by not only adapting the process mining tools, but also presenting a way to introduce semantic-based reasoning for adaptation within the learning process. Fahland and Van der Aalst [63] note that process mining has been proven to be one of the existing technologies that is able to extract useful information from user log files.

Due to the huge amount of "irrelevant information" in a web log, the original log file cannot be directly
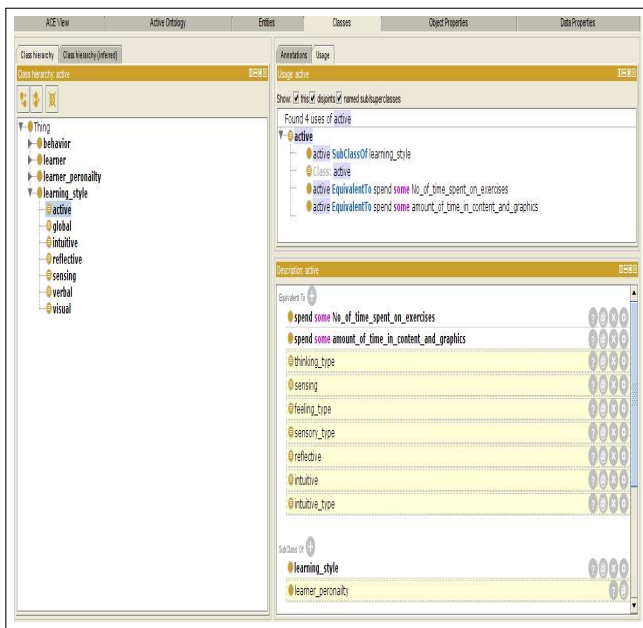
Figure 12. learning style (active)

used in a web usage mining procedure and consequently, pre-processing of the web log file becomes imperative. To this end, the design of a data e-learning web-house as a supporting structure for future personalized e-learning systems has been proposed [64]. Hang jinghua [65] propose a Semantic Web Based Personalized Learning Service for programming courses in e-learning. This model is based on resource base, ontology base, and strategy base techniques. The proposed model although effective is not suitable for all strategies. Another model that is using ontologies for generating a student activity report from the log files inside a Moodle-based e-Learning system has been proposed in [66]. This research combines two concepts that is, using ontologies and giving recommendations inside the e-Learning mechanism based on knowledge-based reasoning. Authors in [67] propose to create a user profile by collecting information through a meta search of his/her blog, personal/organization, web pages, and any other web sites. WordNet and the Lexico-Syntactic pattern for hyponyms were used to extract features from documents. This profile can be further improved by applying an ontology matching approach to enrich the profile with characteristics other similar users.

Authors in [68] have built a user profile by analyzing the web log with the use of WordNet in order to extract data from documents and solve the semantic inadequacy of the VSM model. A fuzzy technique is employed to classify the learners according to their interests and the Felder-Silverman model, we note that this model is narrow, because it only focuses on analyzing assignments submitted by the students. The work in [69] describes a context-aware platform which provides personalized

services to the learners. It uses an ontology-based context model with accompanying rule-based context-aware algorithms. These algorithms capture the behavior of the learner and provide relevant material. However, it only focuses on learning meta-data for personalized context and this method is not suitable for all learning management system. Similarly, PASER (Planner for the Automatic Synthesis of Educational Resources) is a retrieval engine for automatic and personalized curricula construction, based on appropriate learning object combinations. The personalization is designed to take into account the learner's profile and his preferences. This model involves first the creation of a repository metadata which includes learning object descriptions, learner profiles and domain ontology; second a deductive object-oriented knowledge base deductive which is responsible for querying and reasoning about RDF/XML metadata, called R-DEVICE; and finally a planning system called HAPEDU that automatically constructs course plans [70].

The ONTODAPS systems[71] is an ontology-driven disability-aware personalized e-learning system, which personalizes learning resources and services for students with or without disabilities. In addition, it provides appropriate levels of learner control by allowing them to personalize learning resources. The work presented in [71] describes a learning environment that personalizes e-learning relating to pedagogy and a personalized educational process. The framework is based on web services, the description of the semantic information of learning units and the relationship between units.

The work presented in [72] describes a model for building personalized e-learning experiences. This model accounts for different cognitive states and learning preferences of learners. In addition, it supports experts in modeling educational domains using ontologies. Using these models, personalization is achieved through several steps 1- educational domains model based on reference ontologies; 2- modeling of learner cognitive state and preferences (Student Model); 3- build the relationship between metadata and learning objects 4- modeling of E-Learning experiences (E-Learning experience model)". Another adaptive model is described in [73]. This work focuses on the student's cognitive state and cognitive process. It provides a diagnosis related to the student's knowledge state, and achievement quality of the learning objectives. The Student Model is based on ontologies to extract which feature is important in order to build knowledge representation. This design incorporates a number of ontologies including student profile ontology (personal information), a student state ontology (progress) and a learning objectives ontology.

The student model can be used for accessing the knowledge in digital libraries by creating a student ontology in [74], which consists of two parts, general student information and information about student

behavior in the learning domain dynamically. A user profile modeling method has been designed in [75] by combining the keywords and ontology concepts. This model takes into account short-term interest and long-term interest of the user. The authors of the proposed system verified that their model improves the efficiency of the information retrieval procedure. A user profile ontology is proposed in [76], which incorporates the concepts and properties deployed to model the user profile. Ontologies related to the domain have been used to create this model. The model is available in two different areas, personal information management and adaptive visualization.

The ALOCoM ontology [77] is designed to generalize the content models and to provide an ontology-based platform to integrate the different ones by explicitly defining the structure of their LOs (Learning Objects). The revised ALOCoM ontology [78] is divided into two different parts: ALOCoM content structure ontology, in order to define the learning objects and its role as well as their components. CoAKTinG project [79] has developed an ontology based system for distributed e-Science through the application of advanced knowledge technologies. The EUME Onto [80] is an educational ontology system that contains concepts related to learning resources, learning design and learning content.

The LOFinder [81] is an intellectual Learning Object Metadata which enhances knowledge representations, as well as enables intelligent discovery of learning objects. Cakula et al.[66] have developed a personalized e-learning model using methods of ontology. Their aim is to discover overlapping points of KM and build personalised e-learning using ontology and metadata in effective manner. HJia et al. [82] has designed a performance oriented workplace e-learning system which aims to overcome the gaps between individual needs and organizational interests and improve the user satisfaction. In order to do so key performance indicators are used in order to clarify organizational training requirements and to aid learners to set up rational learning objectives. Moreover there is also used to develop formal and machine comprehensible conceptualization of the performance oriented learning environment.

Table 4 summarizes different adaptive e-learning systems.

5.1. Comparing our proposed model other similar Adaptive System

In this subsection we compare our proposed model with other similar adaptive e-learning systems namely:Protus 2.0 [88], TANGRAM [6], ADAPT [91], AHA[92] and Interbook [93]. This comparison is presented in table 5.

System	Adaptive model
LOTTI [83]	Satisfaction survey showed that most of the group "agree" or "strongly agree" with respect to the usability of the system, easiness and time of creation of an intelligent tutoring system
OWES[84]	Ontology based web education System It uses XML and RDF to describe data in system, and uses ontology to describe grammar and relation of data.
TAS [85]	It offers help to the author by making completely comprehensive materials and proposing accentuation on the design of the outline and on the development of the learning objects
AI [86]	Adaptively and Interoperability in e-Learning using Ontologies This is the configuration and improvement of an adaptive system in light of ontology that considers information that is present into the e-learning environment with a specific end goal to create adaptation rules.
ABILO [87]	It gives an automatic suggestion to active learners without requiring the explicit input in view of Automatic personalization approach
Protus 2.0[88]	Architecture for an adaptive and personalized tutoring system that totally depends on Semantic Web models. An ontology-based approach is displayed.
ITS[89]	Authoring tool that permits a high school for web-based intelligent tutoring systems. It takes into account the quick formation of web-classroom applications.
ICALT'06[90]	Presents a service-based architecture for an adaptive system based on ontology that combines technologies to add the personalization capability into the e-learning environment like dynamic, learning networks. Several web-services use the learners' profile to adapt their queries, or to their questions, or to produce suggestions

Table 4. Adaptive e-learning systems

6. Conclusion

In this paper we propose a new model for automatically building s learner profile in an e-Learning environment. It is based on real behavior patterns of students during interaction with the AAST student portal, employing ontology creation and an inference engine to identify learning styles automatically according to the FSLSM model. The ontologies give perspectives of the learner style taking into account the behavior of the student. Personalization can be achieved by coordinating the user's profile with the courses offered in the college. The users subsequently will receive suggestions for courses based on the data collected from their behavior, thereby avoiding inappropriate recommendations being generated.

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system	ontology	rule-based	content-ontology	student's profile	adaptation ontology
Interbook	NO	NO	NO	NO	NO
TANGOW	NO	NO	YES	NO	NO
ADAPT	YES	NO	NO	YES	NO
Protus2.0	YES	FSLSM	YES	FSLSM	YES
TANGRAM	YES	NO	YES	YES	NO
Proposed Model	YES	FSLSM and MBTI	YES	FSLSM and MBTI	YES

Table 5. compare our proposed model with exiting adaptive systems

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