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A Social Web of Things Approach to a Smart Campus Model

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***Abstract*—New technological advances in user mobility and context immersion are enabling novel adaptive and pervasive learning models in ambient environments. In this paper, we aim at developing a novel ubiquitous learning model within a pervasive smart campus environment. We define a model of a smart campus, and advocate learning practices in the light of new paradigms such as context-awareness, ubiquitous learning, pervasive environment, resource virtualization, autnomic computing and adaptive learning. In this environment, we profile learners and augment physical campus structures to advocate context-aware learning processes. We also suggest a social community platform for knowledge sharing which involves peer learners, domain experts as well as campus physical resources.**

***Keywords*-Ubiquitous learning, pervasive environments, smart campus**

I. Introduction

A smart environment is a digitally augmented physical world where pervasively and non-invasively instrumented objects and spaces are intelligently perceptive and made responsive to the state of the environment and its inhabitants. We adopt a user-centric approach, which aims at learning about the users' profile, to adapt services and applications according to their preferences and needs. Universities have made a substantial investment in bricks-and-mortar construction to facilitate learning, and are continually renewing the physical space in which learning occurs. Several research studies show that today's learners favor autonomy over strict guidance, to construct their own knowledge using personalized means. In these environments, the use of computing and communication services is not limited to solitary moments at an office desk, or a classroom but extended in multifaceted ways to all aspects of daily life, and exposed through the Web for wider informational accessibility and remote operational control. Web-enabled real-world physical things are a reality today with cars that email their owners about tires that need to be changed and sports companies connecting their training shoes to the Web to compare performances. The opportunity to transform the value of physical resources with augmented digital services is poised to boost learning experiences tremendously. Towards that perspective, we introduce Ambient Learning Spaces [6] (ALS) as virtual spaces within an application context. ALS represents one or more physical learning resources, and use Web services to render their informational states and operational functions to interoperate with pervasive educational applications. An example of an ALS may be a Computer System. Each bench of the lab is equipped with a tiny Web server to enable its Web connectivity through which the bench indicates its availability, its procedure (such as assembling a PC) and its learning outcomes. Learners may adopt this ALS member in their social circle and figure out for example previous students who used that same bench for possible assistance. The integration of ALSs creates the possibility of realizing pervasive learning in our smart campus environment.

Our goal is to situate learners in a smart campus environment that provides context-based personalized learning and feedback. We achieve this goal by integrating real-world learning resources in a campus-wide social network. Moreover, the proposed approach is able to profile learners and record their behaviors. In addition, the provision of a smart campus environment provides support for collaborative learning in a cost-effective way, using sensing technologies, tiny web servers and mobile learning devices [4].

The remaining of this paper is organized as follows: Section 2 states the problem and reveals some background and related works. Section 3 reveals our approach and methodology to formulate the smart campus concept. Section 4 further presents the design of and processes involved in the proposed smart campus. Section 5 concludes the paper with a work summary and some future extensions.

II. Problems and Background

The ubiquitous environment should be personalized according to every learner's profile which is standardized as LIP following IMS Learner Information Package [1]. Personalization tailors information and services to match the unique and specific needs of an individual learner. Typically, learners are immersed in ambient spaces, which compose our smart campus which communicates seamlessly with its inhabitants in a persuasive way that drives learners through a continuous learning cycle such as the one shown in Figure 1.

The learning continuum shown in Figure1 is actually based on Kolb's theory of Experiential Learning [8], which states that learners perceive and process information according to this continuum, which dictates learning transitions from initially sensed perceptions, to observations followed by abstract conceptualizations and then concrete experiences to test implications. Depending upon the context or the ambient environment, learners may enter the learning cycle at any point.

In this research, we support the deployment of these patterns into ambient learning spaces and social connections, where actors are both people and campus-wide instructional resources. We view a smart campus as a social environment where campus students have lots of social interactions with peers,

[1]Learner Information Package (LIP) specification, available at: http://www.imsglobal.org/profiles/

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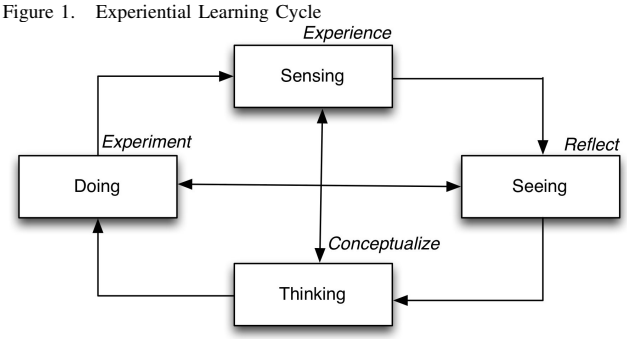
Figure 1. Experiential Learning Cycle



instructors and even instructional things (like lab resources). In this social ecosystem, both learners and instructional sources are profiled and may feed their data into one another (for example, a lab tells learners about relevant workbenches).

The purpose of this paper is to support learner-centered approaches and improve teamwork spirit across the various facilities of a university campus, in order to monitor learning needs and assess learning outcomes autonomously. A substantial part of this research is geared towards defining and developing the mechanisms and processes that allow a smart learning environment to be continuously sensitive to the learner's capabilities and responsive to his or her learning objectives.

Using current advances in Internet of Things, real-world objects get digital identities and can then be integrated into a network and associated with digital information or services. These objects can facilitate access to digital resources and support their interaction. Regular mobile devices (such as tablets or smart phones) are used to physically interact with NFC[2]-tagged objects in order to facilitate interactions with their associated instructional information and operation services [2]. Due to its ease of use and straightforwardness, this physical interaction can make mobile interaction with "people, places, and things" an enriching and intuitive learning experience. In this environment, the user-interface is formed by the tagged objects themselves to free users from the drudgery of a mouse or a keyboard, through pointing directly to virtual information. They intuitively point to the actual physical instructional object that advertises pervasive information to facilitate their inner information and operation discovery. Several research works attempted similar efforts to exploit the social and pervasive learning context of a campus. RFID tags have been earlier deployed on various objects at University of Tokyo to enable people to learn while on campus [7]. More recently, a context-aware ubiquitous learning approach has been integrated at Taiwan University of Science and Technology [5] in the form of a collaborative mind-tool based on a concept map methodology. A related approach has also been earlier proposed for Tokushima University in Japan, which utilizes ubiquitous technologies to recommend educational materials and peer helpers according to a learner's current task and location [3]. This trend will continue and is poised to transform contemporary education venues with the emergence of current social networking services, mobile devices, cloud computing, tiny Web servers and NFC technologies.

III. Approach and Methodology

Mobile devices are increasingly NFC-enabled which could unlock the gateway to information hidden in physical objects in an a u-learning environment. Physical books for example, could be augmented with 3D virtual imagery via a mobile device to enrich the instructional value of the book contents (for example viewing a 3D model of a molecule discussed in the book by simply pointing a mobile screen to the molecule in the book). Another simple example may enable students to create smart posters and then attach touch-tags to allow visitors to listen to an audio description of that object or even view a video-demo related to their poster through their mobile device. Next we discuss our methodical approach to model learning processes, learners, and the learning environment to meet u-learning attributes of a smart campus.

A. Ubiquitous Learning Model

A smart campus provides connectivity between learners and their surrounding environments. For students, learning-goals are inherently identified to trigger didactic models which guide their instruction around 'real-world' data, based on their unique learning contexts and delivered in the right time at the right location. For academics, this is a new enhancement of pedagogical processes through which learning is diffused Just-in-Time like a production process, when individual learners are ready to achieve a targeted level of instruction. The proposed smart campus transcends inner intelligence and becomes aware of the context in which it operates. Contextual information is central to the effective realization of the smart campus initiatives as it facilitates personalized instruction. Context is formed around a number of roles and multiple data sources, captured through Cloud-based services and intelligent agents as illustrated in Figure 2. Web-based agents address a number of functions; e.g., organize, fetch and personalize learning services in the smart campus. Our model aims at unleashing the instructional power of three prevailing sources of intelligence in a smart campus which are: individual intelligence provided by instructors or field experts, social intelligence produced by peer learners and spatial intelligence which is embedded in surrounding smart things [1], as illustrated in Figure 2.

B. Pervasive Learning Object Metadata

Learning resources are packaged following IEEE LOM[3] standard to facilitate their integration in the social learning environment of the smart campus. We extend this standard specification to Pervasive LOM or PLOM to accommodate the context-acquisition and the social immersion in a ubiquitous learning environment (as discussed earlier in Figure **??**). PLOM objects form the building blocks of the smart campus structure and a specification of a PLOM object is depicted in Figure 3. The complexity of modeling context-aware learning

[2]Near Field Communication (http://www.nfc-forum.org)

[3]Learning Object Metadata specification is available at: http://ltsc.ieee.org

Figure 2. Pervasive Learning Environment

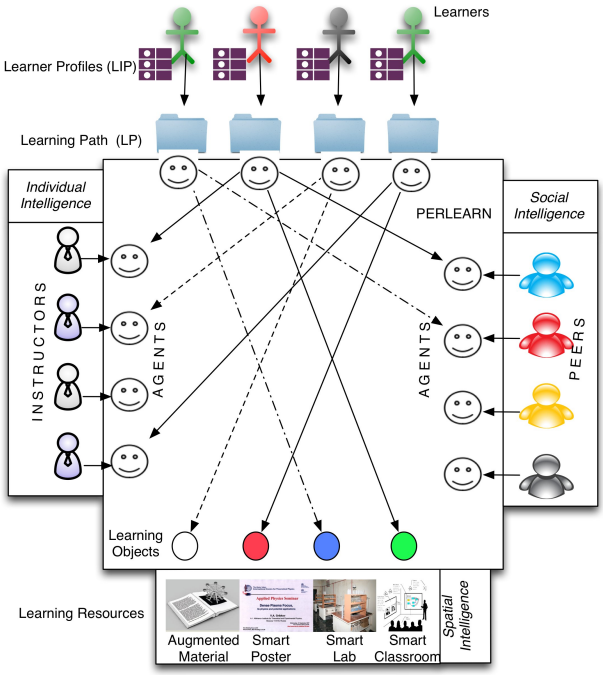
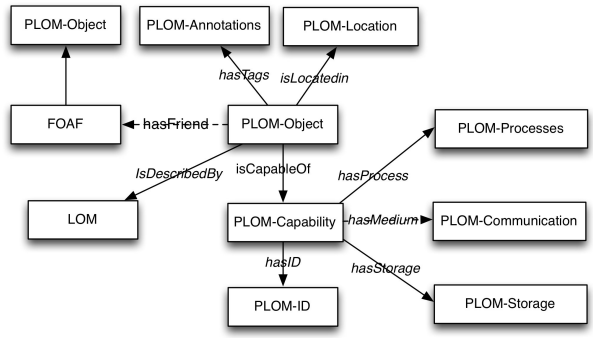


Figure 3. Pervasive Learning Object Metadata



scenarios using a common approach to interface with a wide range of learning sources and resources, is harnessed through the proposed Pervasive Learning Object Metadata or PLOM representations. This extended definition of a learning unit standard eases the deployment of learning resources in a pervasive environment, and expose them as standard Web services. This common structure is described through a semantic Web framework using OWL and SPARQL ontological definitions to capture and reason about the semantics of learning resources in ambient learning spaces. PLOM instances generated by this model map the capabilities, context, state and rules of learning resources to shape the behavior of ubiquitous learning resources as social entities. PLOM ontological structures enable social partners of PLOM individuals to know about a resource's availability, capability, and when and how to use it.

The metadata of a PLOM object comprises various ontological definitions as shown in Figure 3. PLOM-Annotations ontology provides rich semantic-content to capture user experiences and feedback about the learning resource. PLOM-Location provides a record of how an object can be traced from the virtual space to its physical whereabouts. PLOM-Capability ontology recognizes four capability dimensions of candidate pervasive learning resources to be Identity (ID), Processing, Communication, and Storage, referred to as the IPCS capability set [6]. PLOM-Profile matches the standard resource's LOM specification of the learning resources, and also integrates additional variables to enable social and ambient integration. PLOM-Capability ontology mandates the minimum requirement for a physical resource to participate in an ALS to be a unique ID within the application context of ALS. This taxonomy refers to resources as "Smart Learning Resource" when it has all four IPCS capabilities and referred to as pervasive when it accumulates all PLOM specification attributes, including LOM-based profile, location, social and the extensible annotations dimensions.

Pervasive learning resources in a smart campus are inherently dynamic and proprietary in nature i.e., during the lifespan of a resource [6]. They include various context values and also adapt to various ownership. Moreover, these resources also have various inherent characteristics like manufacturer/author details, date of manufacturing/authoring, version number, user experiences, and ownership history. PLOM-Profile hosts the structure and content of the semantic information that describes a learning resource. These XML descriptors, and the other PLOM ontologies contribute to the semantic representation of a pervasive learning resource. PLOM-Profile has actually two sets of elements, <plom:preset> which is a representation of all inherent properties that are instantiated at the time when a physical resource is virtualized (as resource's capabilities, LOM instances and manufacturer/author details are initialized), and <plom:dynamic> which is a representation of properties that augment over time (owner history and user experiences).

Software components that essentially enable pervasive learning resources are illustrated in Figure 4. A PLOM object is realized by augmenting a resource with a tiny Web server adapter and then providing RESTful Web services to interact with the resource. PLOM-Object Handler receives the requests for resource's services. The adapter provides the necessary drivers to interact with a resource's information or operations. We represent resource's states and functions in XML, to ensure interoperability between PLOM objects. The HTML presentation enhances human perception of PLOM objects. The XML conveys the dynamic context of learning resources and then the HTML is updated in real-time based on the XML. Both XML and HTML are lightweight and provides structured constructs for resource's representation. An Ambient Learning Space or ALS provides a mashup of PLOM objects Handlers of various resources within an application context as discussed further in the next section.

C. Ambient Learning Space

As illustrated in Figure 5, learning resources are augmented with pervasive and social capabilities and clustered

Figure 4. Transforming Learning Resources into PLOM Objects

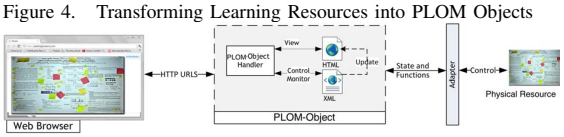
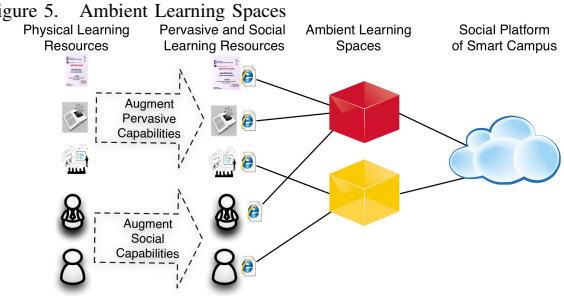


Figure 5. Ambient Learning Spaces



into ALSs. The collaborations and compositions of ALSs create the social platform of our smart campus to share and integrate direct interactions with learning resources. Similarity criteria based on spatial, temporal or topical dimensions are used to cluster resources into ALS communities . Besides similarity criteria, communities can be sporadically formed using other types of relationships like complementary relationships or simply "friendship". The smart campus integrates people and physical resources within communities represented by ALSs. Both member types are represented through their socially-augmented LIP (for people) and PLOM profiles (for resources). These XML profiles can be parsed to determine the context and similarities with other members of the smart campus to match dynamically their participation in a pervasive learning session.

As an illustration of an ALS, consider a scenario where the ambient space within an application context is a Chemistry Lab. The lab has a number of weighing balances spread across several venues of the smart campus, which are associated with faculty members who are then aware about the availability and operational features of these balances. Some of these faculty members have defined certain schedules and restrictions for the use of these balances. When a new PLOM-enabled digital balance is ordered and arrives at one of the lab venues, it first associates itself inherently with its own kind i.e., joins a group of similar balances on campus, and then sends friendship requests to faculty members associated with the older balances in the group who may then use it to schedule experiments for students.

Similarities are examined among profiles of the smart campus members. For physical resources, these could be PLOM-Annotations, PLOM-Location, PLOM-Capability, or FOAF. We adopt a threshold-based technique for the clustering to determine the suitable cluster assignment based on a resource's similarity with any of the existing ALSs' members. We develop a scalable clustering algorithm to create and maintain the community of learning resources. Namely, given a threshold μ, a similarity function σ, and resources $d_1 ... d_n$ to cluster, the algorithm considers each resource d_i and calculates the corresponding similarity $\sigma(d_i, c_j)$, for each existing cluster c_j, for $j = 1, \ldots, l$. If no matching cluster is found (i.e. $(d_i, c_j) > \mu$, $j = 1, \ldots, l$), either d_i is considered at the next clustering cycle or we manually create a new cluster c_l for d_i. Alternatively, d_i is assigned to cluster c_j with the highest $\sigma(d_i, c_j)$.

In this first stage, we create ambient learning spaces (ALSs) like the above Chemistry Lab, which suits the context of an application, for example the group of weighing-balances. These are groups with at least one member (manually inserted) which acts as a seed or centroid to adopt future members. Similarities that exist between the preset parts (<plom:preset>) of the resources' PLOM-Profiles are used to create clusters around the predefined seed. During a clustering process, every new resource (for example our newly procured weighing-balance) that is PLOM-enabled but not in an ALS is adopted into an ALS by comparing similarities of its PLOM-Profile (<plom:preset>) with the available cluster seeds. If a resource is not matched into any cluster then the resource could be adopted during another periodic clustering process or manually administered as a new seed to form a new ALS. The seed in each ALS provides a common representation for similar things . The clustering process ensures the re-election of the seed i.e., the clustering process may change the centroid of the cluster. Hence, over a period of time the seed becomes a *purified* representation of a cluster.

Our approach is to drive smart campus resources to build a presence in the induced pervasive environment through joining an ALS, which bridges PLOM objects and social campus communities. This hierarchical structure facilitates the organization of the multitude PLOM objects available in the smart campus. To achieve this organization, we first integrate a resource into a topical ALS (such as Chemistry Lab), and in the second stage we use opportunistic social relationships of a member of that ALS with campus people (or other resources) to dynamically infer the integration of the other ALS members into social communities. This social propagation of PLOM objects aims at increasing the pervasiveness of learning resources accross a smart campus environment.

D. Social Collaboration Specification

The success of a smart campus lies on its ability to populate communities based on social links that exist between its members. The social networking platform suggests possible links between members based on ties that are assumed to exist between them. Learning resources whether tangible or abstract have heterogeneous properties, but they can be inherently grouped based on profile, spatial , or social ties . These communities of a smart campus thrive in a conglomeration of ALSs as part of the campus PERLEARN model.

Campus people and resources are members of the campus-wide social network platform. The social link of ALSs uses the dynamic (<plom:dynamic>) part of the PLOM-Profiles to contain say members' feedback. ALSs are initially set up with at least one such social connection (i.e. manually assigned) which acts as a seed or centroid for inferring the social connections of future ALS members. Social connections to

ALS members are iteratively suggested to members (people) of existing groups in the social network where the ALS seed is already a member. A social group can for example be a course offered in the smart campus and gathering members enrolled or interested in that course as well as ALSs' members which support that course, for example a Chemistry course as a social group and the Chemistry lab ALS members (i.e. weighing balances).

To build ALSs and advocate social inferences within PERLEARN, we measure the content and the structural similarities among PLOMs' content (i.e. LOM data) and structure (i.e. PLOM tags) separately and combine the results with different weights. This gives relative importance to the structure and content depending on the type of resources under consideration.

Content similarity invites an ALS potential candidates to join the ALS membership based on their LOM content. For example, a chemistry balance joins the Chemistry Lab ALS. The Chemistry Lab in this case may already be represented by a current member such as a lab book which guides experiments planning and records personalized data entry, to run and record the results of some lab related experiments. This is a digital resource but represented by its PLOM profile and manually inserted into the Chemistry Lab ALS.

The structural similarity depends on how intrinsic PLOM profiles properties are organized and tagged. However, given the XML tree structure of each profile, the elements in the profile are naturally organized in a tree-like structure. We match the structure of PLOM-Profiles by dividing the profile into distinct paths. These paths are used to measure structural distances between different PLOM profiles.

Using the similarity measures, a pair-wise PLOM-Profile comparison is computed, to generate a similarity matrix for clustering things into ALSs. K-Means algorithm is applied to determine clusters or ALSs from the similarity matrix.

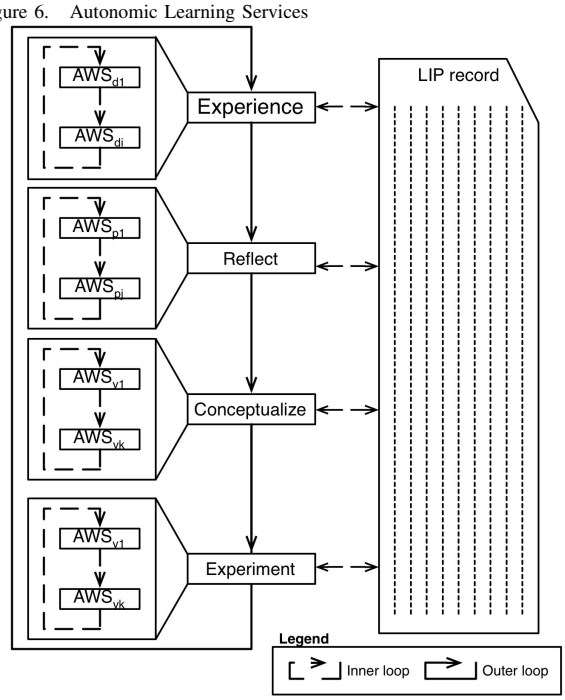
E. Learning Design and Processes

Our goal is to associate each ALS with a learning pattern in the experiential continuum shown in Figure 1 to encompass the places in which learning occurs, and advocate appropriate ALSs for each phase in the continuum. For example, the workbench of a Chemistry Lab ALS is associated with the "Experiment" stage of the continuum, whereas a PLOM-enabled poster exhibit could be associated with "Experience" stage and the associated video, viewed through the embedded NFC tag could be associated with the the "Reflect" stage and finally, a classroom where related concepts are presented could represent the "Conceptualize" stage. Hence, this approach supports pedagogically-supported immersive learning experiences to meet LIP-specified learning objectives.

While learners navigate throughout the smart campus premises, virtually they move across multiple ALSs, which contents and services are advocated. PLOM objects populate inherently ALSs and hence the pervasive learning space of the smart campus inherently, as discussed in the previous section. The system maintains the status of each learning objective and its associate continuum stage to notify learners whenever they navigate across appropriate ALSs.

PERLEARN exploits the inter-relationships between LIP and the smart campus elements to define learning paths alongside the proposed experiential continuum for an individual learner, to match preset objectives and cognitive preferences, and record acquired competencies. The access to ambient learning content from multiple, distributed sources allows learning applications to transparently update learners' profile. This shift requires changing learning design focus to developing learning applications formed out of distributed learning networks that are largely self-managing, self-validated, and transparent to the learner. Learning becomes flexible, accessible, and transparent. These three benefits are traditional autonomic computing functionalities adapted to learning technology in this research. Different Autonomic Web services (AWS) intervene at different levels of a learner's LIP record. The autonomic activities in a learning system can broadly be categorized into four areas to match the proposed learning continuum: Monitor_Context_AWS, Reflect_AWS, Conceptualize_AWS and Experiment_AWS. These four areas of autonomic activities as well as the synergistic correlations they provide in a closed-loop format are illustrated in Figure 6. Each AWS is followed by a validation step to record acquired competency. It is possible that this process be reiterated or composed of a set of iterative sub-tasks until validation succeeds. Hence, the inner-loop in each phase shown in Figure 6. The successful outcome of the validation process leads to an amendment in the learner's LIP profile by updating his competencies.

Figure 6. Autonomic Learning Services



Similar to complex autonomic systems, which are built using intelligent agents, u-learning applications can implement their functionalities through AWSs. As illustrated earlier in Figure 2, an AWS is a proactive entity that possesses the

social ability to instruct other agents to change their behaviors. It uses fine-grained components in the development of the autonomic learning processes. AWS enables an autonomic behavior to sense the context and collect LIP data to compare them alongside ambient PLOM objects' related ontologies. It perceives changes and, in response to goals and ambient PLOM object settings, invokes dynamically appropriate Web services to reveal the required instructional session.

AWSs are geared by a six-tuple generic model [9] $< K, A, G, P, I, L >$, where K is a set knowledge base rules, A is the set of behavior capabilities,G is the set of goals, P is the set of plans, L is the set of policies, and I represents the behavior preferences. K represents a set of rules that transcend learners into a new learning state provided certain Boolean conditions are evaluated to True. Basically, they specify the conditions under which a given learning re-configuration could be enabled to fire appropriate learning Web services. The behavior capability A describes the capabilities represented as a set of domain-specific learning design patterns. These are ontological learning patterns to match the continuum learning phases. The goal G reflects the desired state or behavior changes after executing a specified learning. AWS continuously fetches learning goals from the corresponding LIP record. The plan P determines the approaches to reach the goals. A plan connects the knowledge base rules in K, the capabilities$A$, and the goal G together, which illustrates what actions to take for completing the specified learners' goal based on the domain knowledge and capabilities. The plan P is the result of the learning-process controlled by the inner-loop of AWSs shown in Figure 6. The policies L describe the rules to validate a learning outcomes. For example, these may include assessment criteria to satisfy some competency requirements. The policy rules are specified as part of the output of the learning- validation controlled by the inner-loop of AWSs shown in Figure 6. Finally, the behavior preferences I records the learner's preference indicated in LIP record (such as accessibility preferences). Based on this model, an AWS will repeatedly execute the following steps:

1) Monitor the environment and based on K rules,
2) Fetch learning objectives from LIP and add to G
3) Decompose a candidate goal into sub-goals $\delta \in G$ that match post-conditions of a capability in A,
4) Find a plan $(a_1, ..., a_n)$ in P where a_i is a learning action to achieve a goal δ according to the policy L and preferences I,
5) Execute the plan and feedback to LIP activity, goal, and competency fields.

IV. Conclusion

In this study we proposed a framework specification for ubiquitous learning in a smart campus model. We identified and modeled the main components of a smart campus environment to support ubiquitous learning experiences. We proposed PLOM, a structure to capture pervasive learning resources which meet the expectations of smart campus stakeholders, and provided the semantic PLOM relationships to achieve multi-modal u-learning and automatically generate instructional paths in a smart campus environment. We introduced the concept of Ambient Learning Space (ALS) to harness the complexity induced by a multitude of PLOM objects and used it as a gateway to the smart campus wide social platform. We also specified an autonomic u-learning ecosystem that exhibits capabilities such as self-organization and self-adaptation. To do this, we introduced the autonomic Web service (AWS) concept to reason about ALS members in inferring personalized learning paths to meet learner-declared goals.

On the basis of the existing work, we will complete the realization of PLOM and ALS structures as well as AWS learning processes. We will conduct experiments in a university campus settings. After this, we will continue to study the upper layers of the Ubiquitous Learning Resources Management and Sharing Architecture to administer the social infrastructure of the proposed smart campus. This includes the study of the knowledge base gearing the behavior of AWSs and domain-oriented learning workflow applications.

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