Chatti, M. A., Jarke, M., & Specht, M. (2010). The 3P Learning Model. *Educational Technology & Society*, *13* (4), 74–85.

The 3P Learning Model

Mohamed Amine Chatti, Matthias Jarke and Marcus Specht[1]

Informatik 5 (Information Systems), RWTH Aachen University, Germany // [1]Open University Heerlen, Netherlands

chatti@dbis.rwth-aachen.de // jarke@dbis.rwth-aachen.de // marcus.specht@ou.nl

ABSTRACT

Recognizing the failures of traditional Technology Enhanced Learning (TEL) initiatives to achieve performance improvement, we need to rethink how we design new TEL models that can respond to the learning requirements of the 21st century and mirror the characteristics of knowledge and learning which are fundamentally personal, social, distributed, ubiquitous, flexible, dynamic, and complex in nature. In this paper, we discuss the **3P learning model**; a vision of learning characterized by the convergence of lifelong, informal, and personalized learning within a social context. The 3P learning model encompasses three core elements: **P**ersonalization, **P**articipation, and Knowledge-**P**ull. We then present the **social software supported learning framework** as a framework that illustrates the 3P learning model in action, based on Web 2.0 concepts and social software technologies.

Keywords

Personalization, Personal Learning Environment, Knowledge Ecology, LaaN

Introduction

The world is changing at an ever-faster pace (Brown & Adler, 2008) and the half-life of knowledge (i.e. the time span from when knowledge is gained to when it becomes obsolete) is shrinking (Siemens, 2006). There is a wide agreement that traditional Technology Enhanced Learning (TEL) models failed to cope with the fast-paced change and critical challenges of the new knowledge society (cf. Brown & Adler, 2008, Downes, 2005, Mejias, 2005, Siemens, 2006). In order to align with the shifts and challenges of the new knowledge landscape, a new vision for TEL is required. In this paper, we highlight critical factors that must be addressed to ensure that future TEL models will endure and discuss the **3P learning model**; a new learning model characterized by the convergence of lifelong, informal, and personalized learning within a social context. **P**ersonalization, **P**articipation, and Knowledge-**P**ull build the cornerstones of this model. We then present the **social software supported learning framework** as a possible realization of the 3P learning model, based on Web 2.0 concepts and social software technologies.

Success Factors for TEL Models

Learning and knowledge are two sides of the same coin, and are fundamentally personal, social, distributed, ubiquitous, dynamic, flexible, non-linear, fluid, and complex in nature (Chatti et al., 2007). In this section, we start from these characteristics and derive five critical factors that must be addressed to ensure that future TEL models will endure.

Learning is personal and self-directed

Knowledge is personal and learning is self-directed in nature. Tobin (2000), for instance, states: ”All learning is self-directed ... The learner may not have control over what is taught, but the learner always has control over what is learned” (Preface, p. vii). In general, learners tend to resist to the one-size-fits-all learning approaches that often fail to address their individual differences, expectations, preferences, and needs. Recognizing that learning and knowledge are personal, TEL models require a move away from one-size-fits-all models toward a learner-centric model that puts the learner at the centre and gives her the control over the learning experience.

Learning is social

Knowledge and learning are social in nature, as has been emphasized by many researchers (e.g. Polanyi, 1967; Wenger, 1998), and it resides in networks (Downes, 2006; Siemens, 2006). TEL models thus need to recognize the social aspect of learning and put a strong emphasis on knowledge harnessing within a social context.

Learning is open

Knowledge is distributed and ubiquitous in nature and learning is now happening in a world without boundaries. Downes (2006), for instance, writes: "knowledge - and therefore the learning of knowledge - is distributive, that is, not located in any given place" (para. 1). TEL models need therefore to operate in a decentralized, loosely coupled, and open context.

Learning is emergent

Knowledge is complex and a learning environment is a complex adaptive system comprising many interacting identities in which cause and effect relationships cannot be distinguished (Holland, 1998). A learning environment thus has a non-deterministic character and can evolve in inherently non-linear and unpredictable ways. Emergence is central to the theory of complex adaptive systems (Holland, ibid.). Holland argues that emergence must be the product of self- organization, not centralized control. Consequently, TEL models need a shift from command-and-control to coordinate-and-channel; from hierarchy to wirearchy, defined by Husband (1999) as "a dynamic two-way flow of power and authority based on information, knowledge, trust and credibility enabled by interconnected people and technology".

Learning is driven by knowledge-pull

Emergent and self-organized learning also suggest a shift in emphasis from a knowledge-push to a knowledge-pull model. In a learning model based on knowledge-push, the information flow is directed by the institution/teacher. In a learning model driven by knowledge-pull, the learner navigates toward knowledge.

The 3P Learning Model

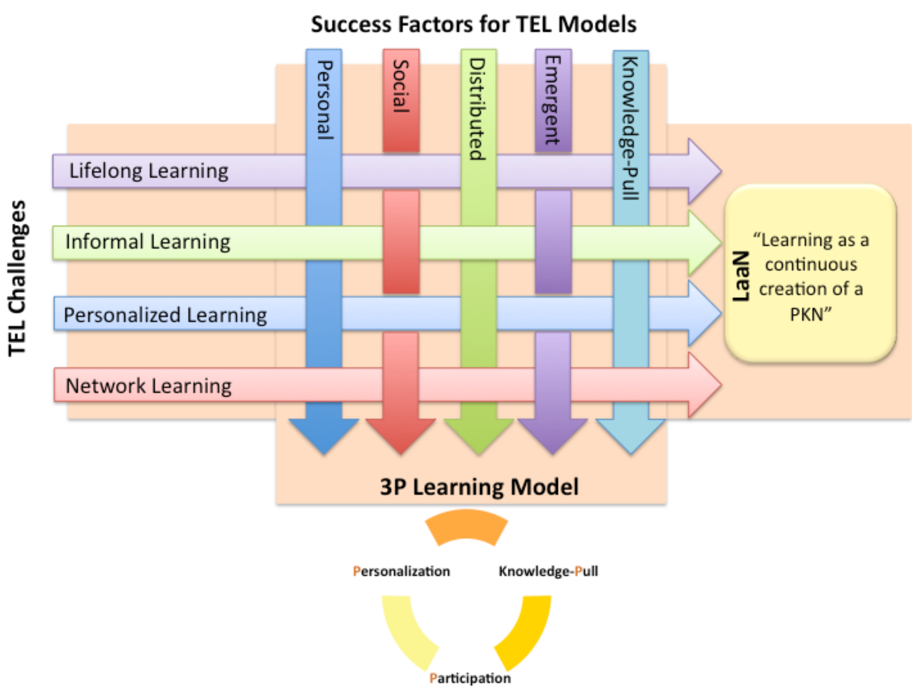

Figure 1: The 3P Learning Model

The five success factors outlined in the previous section suggest a move away toward a more personalized, social, open, emergent and knowledge-pull model for learning, as opposed to the one-size- fits-all, centralized, top-down, and knowledge-push models of traditional learning models. In the following sections, we discuss the **3P learning model**, which captures the characteristics of knowledge and learning and reflects of the five success factors aforementioned. The 3P learning model consists of three main elements, which feed, complement, and reinforce each other: **P**ersonalization, **P**articipation and Knowledge-**P**ull. Figure 1 shows a diagram of the 3P learning model. The next three sections will explore the three elements of the 3P learning model in more details.

Personalization

The first element of the 3P learning model is *personalization*. One of the core issues in learning is the personalization of the learning experience. It is widely recognized that effective and efficient learning need to be individualized – personalized and learner-controlled. Personalization is also a key issue for implementing mechanisms to foster and increase activities in informal and lifelong learning networks.

Traditional Personalized Adaptive Learning Approaches

There are many definitions of adaptation in educational systems. The two main terms usually involved are adaptivity and adaptability. Adaptivity is the ability to modify course materials using different parameters and a set of pre-defined rules. Adaptability is the possibility for learners to personalize the course materials by themselves (Burgos et al., 2007). Most relevant literature on personalized adaptive learning has focused on adaptivity. There, we can identify two main streams of research: (a) Adaptive Intelligent Educational Systems; and (b) Adaptive Instructional/Learning Design Models.

Adaptive Intelligent Educational Systems

Adaptive intelligent educational systems can be partitioned into three historically and architecturally distinctive classes: Intelligent Tutoring Systems; Adaptive Educational Hypermedia; and Adaptive Educational Web-based Systems (Kravcik et al., 2005).

Intelligent Tutoring Systems

An Intelligent Tutoring System (ITS) is educational software containing an artificial intelligence component. The software tracks students' work, tailoring feedback and hints along the way. By collecting information on a particular student's performance, the software can make inferences about strengths and weaknesses, and can suggest additional work (Hafner, 2004). ITS achieve their "intelligence" by representing pedagogical decisions about how to teach as well as information about the learner. ITS encompass five major components: (a) the domain knowledge which contains information the ITS is teaching; (b) the student model which stores information that is specific to each individual learner; (c) the pedagogical module which provides a model of the teaching process; (d) the communications module which controls interactions with the learner; and (e) the expert model which is a model of how someone skilled in a particular domain represents the knowledge (Beck, 1996).

Adaptive Educational Hypermedia

Brusilovsky (1996) defines an Adaptive Hypermedia System (AHS) as follows: "By adaptive hypermedia systems we mean all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible aspects of the system to the user" (p. 88). Brusilovsky (ibid.) and De Bra (2002) identify educational hypermedia systems as one of the main application areas for adaptive hypermedia. In adaptive educational hypermedia a variety of research work about questions on how to adapt curricula and learning content to individuals and groups of learners has been carried out (e.g. Brusilovsky, 1996; De Bra, 2002, Kravcik et al., 2005).

Adaptive Educational Web-based Systems

Adaptive educational Web-based systems inherit from intelligent tutoring systems (ITS) and adaptive hypermedia systems (AHS) (Kravcik et al., 2005). According to De Bra (2002), most adaptive educational Web-based systems can be classified as both ITS and AHS, strongly reflecting the hypertext nature of the Web. Typically, the domain of an adaptive educational Web-based system is represented by a hierarchy of concepts, and the learner model stores a numeric value for each concept in the hierarchy indicating to what extent the learner has mastered the topic (De Bra, 2002). Technically, what most adaptive educational Web-based systems do in terms of adaptation of the learning material is link annotation and link hiding (Kravcik et al., 2005).

Limitations of Adaptive Intelligent Educational Systems

Although implemented in different ways, adaptive intelligent educational systems share three common characteristics: (a) they focus on presentation of and navigation through content; (b) the adaptation engine is usually expressed in the way of artificial intelligence components and nested conditions; and (c) the adaptation process is mainly based on three models: domain model, learner model, and context model.

With their primarily focus on presentation of and navigation through content, adaptive intelligent educational systems follow an objectivist view of learning which asserts that there is a particular body of knowledge that needs to be transmitted to a learner, and that learning is the acquisition and accumulation of a finite set of skills and facts (Tam, 2000). In fact, all adaptive intelligent educational systems follow a static and predefined representation of knowledge. They view knowledge as a thing that can be codified, captured, and passed along. Knowledge, however, is fluid and dynamic; and thus cannot be reduced to a merely conditional selection and sequencing of fixed and pre-packaged content according to pre-defined rules and properties. Moreover, content in adaptive intelligent educational systems is primarily created by the instructor and does not include, for instance, learner-generated content or more up-to-date content available on the Web. Furthermore, in adaptive intelligent educational systems, navigation through the course materials is linear, each page is leading to the following page and each topic is leading to the following topic. Learning, however, is a complex and non-linear process, and cannot be reduced to a predefined string of topics and pages, controlled by a pre-programmed teaching machine.

All adaptive educational systems focus on learner modeling, as the core for achieving adaptive learning environments, which will be able to take into account the heterogeneous needs of learners and provide them with tailored learning material suited for their unique needs. The problem with learner modeling is threefold.

Firstly, learner modeling is an extremely difficult task, due to the dynamics of the learner’s knowledge and the diversity of the parameters that should be taken into consideration, such as the context of the learning environment, the nature of the learning activity, learning goals, preferences, motivation, cognitive capacities, disabilities, etc. (Aroyo et al., 2005).

Secondly, knowledge is complex and multifaceted to be captured within a learner model. The amount of knowledge that can be captured represents only the tip of the iceberg. The bulk of the iceberg below the waterline represents the knowledge in learner’s heads, i.e. their tacit knowledge (Polanyi, 1967).

Thirdly, from a psychological point of view, there are no unique learner models/styles for each learner. Learner modeling approaches assume that a learner systematically uses a single procedure for the task at hand. However, it was shown that each learner applies just one of a family of procedures applicable to the problem at hand, and that the procedure selection strategy is ad hoc (Ohlsson, 1994).

Adaptive Instructional/Learning Design Models

Instructional design is a prescriptive theory based upon descriptive theories of learning (Reigeluth, 1999). In the instructional design literature, three basic learning theories build the foundation of instructional design models, namely behaviorism, cognitivism, and constructivism.

In TEL, instructional design is best represented by IMS Learning Design (IMS-LD). Specht & Burgos (2007) note that the issue of personalized learning can be modeled with the IMS-LD specification. The authors state that Level B of IMS-LD is the key to adaptation in IMS-LD as it provides some powerful resources and elements to model personalized Units of Learning (UoL) and combines several features that make the content and the learning flow more flexible. The authors, then, describe the key elements in the Level B of IMS-LD to create adaptive UoL, based on sequence, groups, content, evaluation and other features.

Limitations of Adaptive Instructional/Learning Design Models

IMS-LD is a powerful language to model learning activities. It, however, suffers from several limitations when it comes to adaptation modeling. In the following, we argue that IMS-LD is neither easy to use nor useful in real learning settings. In fact, IMS-LD has low Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). PEOU is the extent to which a person believes using a particular system is free of effort. PU is the degree to which a person believes using a particular system enhances his or her job performance (Davis, 1989). The low PEOU in IMS-LD is due to the complexity of this specification and the significant effort needed to create adaptive IMS-LD UoLs comprising level B and C constructs. The low PU in IMS-LD is mainly due to the fact that this modeling language is designed with control in mind, and thus cannot be easily adopted by learners. In IMS-LD, the learner is confined to the learning designer's world. In fact, the specification of adaptation strategies within IMS-LD is supposed to be a task for learning designers. The learning design prescribes a sequence of activities for a learner, which are carried out within closed environments initiated and controlled by learning designers, rather than the learners themselves. Learning designers are supposed to make decisions and rely on their experience to guide the design. It has however been argued that there is no perfect learning designers, who are capable of designing learning environments that satisfy the heterogeneous needs of individual learners (Wild et al., 2008). Furthermore, the learning designer's goals and the learner’s goals may differ.

IMS-LD is characterized by a systematic and top-down input-process-output paradigm, where the input can be specified, the design process follows a sequential and linear waterfall model driven by pre-determined goals, and the learning output is pre- defined by the learning designer. However, in learning, which is a dynamic, fluid, and complex process in nature, neither the input can be pre-determined, nor can the process be anticipated or the outcome be predicted. In learning, a wide range of interacting entities produce unpredictable outcomes. It is an illusion that learning can follow a clear pre-determined direction, based on pre-specified inputs, and controlled by pre-defined condition-action rules.

IMS-LD follows a traditional objectivist (i.e. behaviorist/cognitivist) approach to instructional design. Objectivism asserts that knowledge can and must be objectified in order to be transmitted and assessed, and assumes that learning is externally mediated by the instructional strategies that predetermine the required mental activities that give rise to acquiring the elements of an external reality. Learning is thus the process of mapping external reality onto learners. That is, learners are told about the world and are expected to replicate its content and structure in their thinking (Jonassen, 1991). Following an objectivistic approach, learning designers analyze a task, break it down into smaller steps or chunks, and move the instruction process from simple to complex. Information is then delivered to the learner from the most simple to the most complex depending on the learner’s prior knowledge (Mergel, 1998).

IMS-LD, and instructional design in general, is however challenged to accommodate constructivist and connectivist perspectives that engage learners and give them more control over the learning experience.

The constructivist perspective describes learning as a change in meaning constructed from experience (Tam, 2000). While the emphasis in objectivism is on the object of knowing, constructivism is concerned with how we knowledge is constructed. Rather than attempting to map the structure of an external reality onto learners, constructivists recommend that we help them to construct their own meaningful and conceptually functional representations of the external world (Jonassen, 1991).

The connectivist perspective presents learning as a connection/network-forming process (Siemens, 2006). Siemens suggests learning that can reside outside the individual learner, is focused on connecting specialized information sets and the connections that enable us to learn more than our current state of knowing. Later in this paper, we will present a more learner-oriented viewpoint on connectivism by discussing what we call the Learning as a Network

(LaaN) perspective, which puts the learner at the center and represents a knowledge ecological approach to learning. While traditional objectivist instructional design is a top-down approach, a LaaN-driven instructional design approach is learner-centered, open, and emergent.

The Personal Learning Environment Approach

The personalized adaptive learning approaches outlined in the previous sections are very much top-down and ignore the crucial role of the learners in the learning process. The success factors discussed in the first section do not play a significant role in these approaches. A new vision of personalized learning is therefore needed. In this section, we introduce an alternative approach to personalized learning based on the concept of **personal learning environments** (PLE). The PLE concept supports self-organized, informal, lifelong learning and network learning and translates the principles of constructivism and connectivism into actual practice. It mirrors the success factors outlined before and presents a move away from command, control, and passivity toward openness, emergence, flexibility, active participation, and dynamic.

In PLEs, personalization is triggered by the learner, rather than processed by an intelligent system. The PLE-driven approach to learning does not focus on adaptivity, i.e. the top-down configuration of a set of learning elements following some pre-defined rules. It rather focuses on adaptability and emphasizes learner's self-direction, self-organization, and self-control. Consequently, learners are not responsible for adapting themselves to the requirements of the institution or the instructor. They are rather responsible for creating and maintaining their very own learning environments, self-adapted to their individual needs. From this perspective, personalization can be defined as the ability on the part of the learner to learn the way she deems fit.

PLE is a relatively new term, first introduced in 2004 (van Harmelen, 2006). van Harmelen describes PLEs as "systems that help learners take control of and manage their own learning. This includes providing support for learners to
- set their own learning goals
- manage their learning; managing both content and process
- communicate with others in the process of learning
and thereby achieve learning goals."

The PLE is not an application, but rather, an emerging concept and a new vision of learning. It represents a significant shift in pedagogic approaches toward constructivist and connectivist learning that puts the learner at the center and give her more autonomy and control over the learning experience. A PLE is a more natural and learner-centric approach to learning that takes a small pieces, loosely joined approach, characterized by the freeform use of a set of learner-controlled tools and the bottom-up creation of knowledge ecologies (Chatti et al., 2007).

However, to enable the transition from theory to practice, the PLE concept needs to be realized in some practical form and development strategies need to be discussed to help learners create their personalized spaces based on their individual needs.

There is still no agreement on what mechanisms can underpin the development of PLEs. Wilson et al. (2007) note that the PLE pattern suggests several very different strategies may be feasible. The authors state: "a single PLE application may be possible, or on the other hand, the coordinated use of a range of specialized tools may achieve a satisfactory result" (p. 33).

There have been some attempts to define approaches to developing PLEs. van Harmelen (2006), for example, suggests "a PLE may be composed of one or more subsystems: As such it may be a desktop application, or composed of one or more web-based services". Attwell (2007) asserts that "a PLE is comprised of all the different tools we use in our everyday life for learning" (p. 4). Lubensky (2006) discusses different ways of PLE development. According to the author, PLEs can be realized as WebTops, desktop applications; content management systems, or in terms of mashups. PLEs can also exist in an ad-hoc manner, for instance through blogs.

Personalized start pages such as iGoogle or Netvibes were not designed as educational technology, but their design strategies match parts of the characteristics of PLEs. These services, for instance, provide means to facilitate the aggregation of different services into a personalized space, through RSS feeds and widgets.

Participation

The second element of the 3P learning model is *participation*. Participation has been the cornerstone of most of the socio-cultural theories of learning in CSCL. However, most social learning theories put the emphasis on overarching structures where learning is supposed to take place. These include groups and communities. In this paper, we rather view participation from a learner's point of view and discuss the **Learning as a Network (LaaN)** perspective, which puts the learner at the center, and represents a knowledge ecological approach to learning.

The LaaN Perspective

The participation metaphor of learning has mainly been explored in Wenger's social theory of learning. Wenger (1998) presents one of the most influential social learning theories with the primary focus on learning as social participation in communities of practice. According to Wenger, participation "refers not just to local events of engagement in certain activities with certain people, but to a more encompassing process of being active participants in the practices of social communities and constructing identities in relation to these communities" (p. 4). Wenger further stresses that he will use the term participation to describe "the social experience of living in the world in terms of membership in social communities and active involvement in social enterprises" (p. 55).

The Learning as a Network (LaaN) perspective does not view participation in terms of membership in communities, but rather in terms of personal horizontal connections. In LaaN, we are not merely members of groups or communities. Each of us is at the center of our very own personal knowledge network (PKN). A PKN spans across institutional boundaries and enables to connect beyond the constraints of formal educational and organizational environments. Unlike communities, which have a start-nourish-die life cycle, PKNs develop over time. Many communities die mainly because they are none’s priority. PKNs persist because it's everyone's highest priority to hold and sustain her knowledge home.

In contrast to Wenger's social theory, where learning, for an individual, is "an issue of engaging in and contributing to the practices of their communities" (p. 7), LaaN views learning, for an individual, as an issue of continuously building, maintaining, and extending her PKN. LaaN starts from the individual learner and focuses on PKN as the unit of analysis. A PKN is comprised of a myriad of explicit knowledge nodes (i.e. information) and tacit knowledge nodes (i.e. people) with complex connections. In order to learn, we build, maintain, and extend our PKN with new explicit/tacit knowledge nodes and when needed we activate the nodes that we believe are able to help us in mastering a learning situation. The process of developing a PKN is driven by the learning demands of the individual learner. In LaaN, participation suggests permanent listening, active networking, and genuine knowledge sharing with others, thus enabling each participant to build and extend her PKN, and in so doing learn.

Knowledge Ecology

At the heart of the LaaN perspective lie **knowledge ecologies**. We define a knowledge ecology as a complex, knowledge intensive landscape that emerges from the bottom-up connection of personal knowledge networks. As an example of a complex adaptive system, a knowledge ecology holds emergent properties, includes self-organized entities, and can evolve in ways that we may not expect or predict. Knowledge ecologies blur the boundaries of learning and harness the power of personal knowledge networks. They house self-directed learning that occurs in a bottom-up and emergent manner, rather than learning that functions within a structured context, of an overarching framework, shaped by command and control.

In the following sections, we will compare knowledge ecology to other popular social aggregates that have been introduced in the CSCW and CSCL literatures. These include communities of practice (Wenger, 1998), knots

(Engeström et al., 1999), and intensional networks (Nardi et al., 2002). We mainly discuss the difference between those social forms in terms of the success factors previously outlined; i.e. self-organization, decentralization, openness, and emergence.

Knowledge Ecology vs. CoP

As a special type of community, Wenger (1998) introduces the concept of *communities of practice (CoP).* Wenger et al. (2002) defines CoP as "groups of people who share a concern, a set of problems, or a passion about a topic, and who deepen their knowledge and expertise in this area by interacting on an ongoing basis" (p. 4). Wenger (1998) discusses three dimensions of communities of practice: (a) mutual engagement, (b) a joint enterprise, and (c) a shared repertoire. Knowledge ecologies differ from CoP on all these dimensions.

CoPs emphasize membership, mutual engagement, and community maintenance. Knowledge ecologies, by contrast, emphasize independence and autonomy. Rather than being forced to interact intensely with other members of a CoP, within a knowledge ecology, everyone can rely on her personal knowledge network. Consequently, we focus on forming, maintaining, and sustaining our personal knowledge networks rather than maintaining the community of practice to which we belong.

Unlike CoPs, which are shaped by hierarchy, command and control within the boundaries of a joint enterprise, knowledge ecologies are characterized by emergence and self-organization. In knowledge ecologies, the boundaries can be bridged and merged. Knowledge ecologies are not positioned within a broader system and are not bound to the control of any external force. They emerge naturally without strong pre-determined rules or institutional authority. Knowledge ecologies are thus self-controlled and self-organized entities.

In contrast to CoPs, knowledge ecologies lack a shared repertoire and are thus open and distributed domains. The knowledge tools used to learn do not belong to the community and the knowledge resources produced are not "common artifacts" of the "CoP memory". They are rather distributed over all personal knowledge networks within a knowledge ecology.

Knowledge Ecology vs. Knot

Within an activity theory framework, Engeström et al. (1999) introduce the concept of *knotworking* to describe temporal situation-driven combinations of people, tasks, and tools, emerging within or between activity systems. According to the authors, the notion of *knot* refers to "rapidly pulsating, distributed, and partially improvised orchestration of collaborative performance between otherwise loosely connected actors and activity systems" (p. 346). Knowledge ecologies are similar to Engeström’s knots in that they enable the formation of networks between loosely connected individual actors. These networks have no center and rely on distributed control and coordinated action between actors. Knowledge ecologies and knots, however, differ in several important points. Knots are constituted by temporary relationships among Knots' actors who aggregate to accomplish a specific task and disaggregate immediately afterwards. And, knots' configurations are in a sense predictable due to the well-defined practices of the actors and their predetermined individual roles. Knowledge ecologies, by contrast, are formed by long-term personal relationships among individuals who self-organize in highly flexible, dynamic, and unpredictable networks, without pre-determined roles.

Knowledge Ecology vs. Intensional Network

Nardi et al. (2002) develop the concept of *intensional networks* to describe the personal social networks workers draw from and collaborate with to get their work done. The authors further use the term *NetWORK* to refer to the ongoing process of keeping a personal network in good repair. Intensional networks are at the core of the knowledge ecology concept. One of the crucial skills of a knowledge networker within a knowledge ecology is her ability to netWORK; that is build, maintain and activate her personal knowledge network to get her work done or learning goal achieved. Knowledge ecology, however, is a more general concept than intensional networks. Intensional networks are the elementary building blocks of knowledge ecologies which, by definition, are derived from the emergent connection of different intensional networks. Nardi et al. admit that joint activity is accomplished by the assembling of sets of individuals derived from overlapping constellations of personal networks. The authors, however, place a heavy emphasis on the netWORKing process, discuss the characteristics of intensional networks as ego-centric networks that arise from individuals and their communication and workplace activity, but do not address the characteristics of the knowledge domains that emerge out of the interacting intensional networks. We referred to these knowledge domains as knowledge ecologies and we characterized them as emergent, highly dynamic, complex, and self-organized social entities.

Knowledge-Pull

The third element of the 3P learning model is *knowledge-pull*. The knowledge-pull approach to learning is based on providing learners the access to a plethora of tacit/explicit knowledge nodes and hand over control to them to select and aggregate the nodes the way they deem fit, to enrich their personal knowledge networks. One concern with knowledge-pull approaches is knowledge overload. Therefore, there is a need for knowledge filters that tap the wisdom of crowds (Surowiecki, 2004) to help learners find quality in the Long Tail (Anderson, 2006).

The Long Tail in Learning

According to Anderson (2006), our culture and economy are increasingly moving from hits toward niches and demand must follow this new supply. Anderson identifies three forces representing a new set of opportunities in the Long Tail: (a) Democratizing Production, (b) Democratizing Distribution, and (c) Connecting Supply and Demand.

The first force is democratizing the tools of production. The distinction between "professional" producers and "amateurs" has blurred, as the tools of production and creativity has become cheap and ubiquitous. The second force is cutting the costs of consumption by democratizing distribution. “Aggregators” are a manifestation of this second force. The third force is connecting supply and demand, introducing consumers to these new and newly available goods and driving demand down the tail. Anderson stresses the need for “filters” that should help us find quality in the Long Tail.

The Long Tail phenomenon can also be applied in the learning domain. As Brown and Adler (2008) note: "Whereas traditional schools offer a finite number of courses of study, the “catalog” of subjects that can be learned online is almost unlimited ... Furthermore, for any topic that a student is passionate about, there is likely to be an online niche community of practice of others who share that passion" (p. 28).

The Wisdom of Crowds

The concept of the wisdom of crowds is based on observations that when solving cognition, coordination, and cooperation problems requiring decision making, prediction, and estimation, especially if the solutions are fuzzy and less definitive, the many are smarter than the few. Under the right circumstances, groups are remarkably intelligent, and are often smarter than the smartest people in them. Even if most of the people within a group are not especially well-informed or rational, it can still reach a collectively wise decision (Surowiecki, 2004). Surowiecki mentions four conditions that characterize wise crowds: (a) Diversity of opinion (each person should have some private information, even if it is just an eccentric interpretation of the known facts), (b) Independence (people’s opinions are not determined by the opinions of those around them), (c) Decentralization (people are able to specialize and draw on local knowledge), and (d) Aggregation (some mechanism exists for turning private judgments into a collective decision).

The challenge of finding the right knowledge

The immediate implication of the first force of the Long Tail; i.e. democratizing production is that, from a learner’s perspective, the Web evolves into a rich pool of knowledge. It thus becomes crucial to examine some mechanisms that would allow learners to cope with the knowledge overload problem. The second and third force of the Long Tail concept provide a possible solution for this problem. Powerful knowledge "aggregators" and "filters" that would help learners find quality in the Long Tail are needed. The personal knowledge network provides a first filter. Long Tail filters can also be social search engines that build on the wisdom of crowds to locate quality tacit and explicit knowledge nodes.

The Social Software Supported Learning Framework

The next sections present a framework within which to consider the implementation of the 3P learning model, based on Web 2.0 concepts and social software technologies. This framework can be broken into three key points.

Mashup Personal Learning Environments

From a technical point of view, a PLE suggests the freeform use of a set of lightweight and loosely coupled tools and services that belong to and are controlled by individual learners. Rather than being restricted to a limited set of services within a centralized institution-controlled system, the idea is to provide the learner with a plethora of different services and hand over control to her to select, use, and remix the services the way she deems fit (Chatti et al., 2009). A PLE can thus be viewed as a self-defined collection of services, tools, and devices that help learners build their Personal Knowledge Networks (PKN), encompassing tacit knowledge nodes (i.e. people) and explicit knowledge nodes (i.e. information). Consequently, mechanisms that support learners in building their PLEs become crucial. **Mashups**, which have recently emerged as a core technology of the Web 2.0 and social software movement, provide an interesting solution to developing PLEs. In Web terminology, a mashup is a Web site that combines content from more than one source (from multiple Web sites) into an integrated experience. We can differentiate between two types of mashups:

- *Mashups by aggregation* simply assemble sets of information from different sources side by side within a single interface. Mashups by aggregation do not require advanced programming skills and are often a matter of cutting and pasting from one site to another. Personalized start pages, which are individualized assemblages of feeds and widgets, fall into this category.
- *Mashups by integration* create more complex applications that integrate different application programming interfaces (APIs) in order to combine data from different sources. Unlike mashups by aggregation, the development of mashups by integration needs considerable programming expertise.

Thus, there is a need for mashup PLE systems that leverages the mashup concept to help learners plug learning components from multiple sources into a self-controlled space. These systems need to support both types of mashups. This ranges from simply juxtaposing content from different sources (e.g. feeds, widgets, media) into a single interface (mashup by aggregation), to a more complex remixing of different APIs into an integrated application, in order to create entirely different views or uses of the original data (mashup by integration).

Social Software-mediated Knowledge Ecologies

Social software has been opening new doors for personalized connectivity, freeform knowledge networking, and dynamic knowledge ecology building. The social software networking model is based on personal knowledge networks, loosely joined, thus providing a powerful realization of the knowledge ecology concept, which builds the cornerstone of the participation element in the 3P learning model. Chatti & Jarke (2009) explore how social software technologies, such as blogs, Web feeds, wikis, podcasts, social tagging, and social networking services can support the building and maintaining of knowledge ecologies. The authors note that social software mediated knowledge ecologies are organized from the bottom up. They emerge naturally and are derived from the overlapping of different personal knowledge networks.

Leveraging Social Software to get Knowledge to People

Web 2.0 and social software also provide powerful mechanisms that would allow learners to cope with the knowledge overload problem caused by a knowledge-pull learning model. Harnessing collective intelligence has become the driving force behind Web 2.0. In Web 2.0, collective intelligence decides what is valuable through filtering, rating, feedback, reviews, criticisms, and recommendations. Amazon’s review and recommendation system, YouTube's rating scheme, Google's PageRank algorithm, eBay's feedback, Digg's voting are successful attempts to harness user's collective intelligence on the Web. Social bookmarking, social tagging, and folksonomies are also successful examples of the collective intelligence in action, as users share, organize, filter interesting information for each other, browse related topics, subscribe to an interesting tag and receive new content labelled with that tag via Web feeds, and discover unexpected resources that otherwise they would never know existing (Chatti & Jarke, 2009). Based on these concepts, we can develop knowledge filters that can harness the collective intelligence and leverage social filtering methods to rank and recommend learning entities. Learners act as guides individually when they interact with learning entities on the Web (e.g. bookmark web pages, tag resources, recommend items, review books, comment on blogposts, trackback sites, share videos, vote on news). The idea is to aggregate this distributed local filtering behavior to improve the search for and recommendation of relevant learning entities.

Conclusion

In this paper, we addressed how the growing complexity and constant change of knowledge require a new approach to learning. We mainly discussed the 3P learning model, characterized by the convergence of lifelong, informal, and personalized learning within a social context. The 3P learning model reflects the nature of learning and knowledge as being personal, social, distributed, ubiquitous, flexible, dynamic, and complex in nature. It represents a fundamental shift toward a more personalized, social, open, dynamic, emergent and knowledge-pull model for learning, as opposed to the one-size-fits-all, centralized, static, top-down, and knowledge-push models of traditional learning models. The 3P learning model includes three major elements: Personalization, Participation and Knowledge-Pull. Finally, we set out a framework that illustrates the 3P learning model in action, by implementing the main ideas underpinning the 3P learning model, based on Web 2.0 concepts and social software technologies.

References

Anderson C. (2006). *The Long Tail*. New York, NY: Hyperion.

Aroyo, L. et al. (2005). Learner Models for Web-based Personalised Adaptive Learning: Current Solutions and Open Issues. Deliverable 1.3 of the Prolearn EU/FP6 Network of Excellence.

Attwell, G. (2007). The personal learning environments - the future of elearning? *eLearning Papers*, 2(1).

Beck, J., Stern, M., & Haugsjaa, E. (1996). Applications of AI in Education. *ACM Crossroads*, 3(1), 11–15.

Brown, J. S. & Adler, R. P. (2008). Minds on fire: Open education, the long tail, and learning 2.0. *EDUCAUSE Review*, 43(1), 16–32.

Brusilovsky, P. (1996). Methods and Techniques of adaptive hypermedia. *User modelling and User-Adopted Interaction*, 6(2/3), 87–129.

Burgos, D. et al. (2007). Integration of adaptive learning processes with IMS Learning Design considering corporate requirements. Deliverable 1.11 of the Prolearn EU/FP6 Network of Excellence.

Chatti, M. A. & Jarke (2009). Social Software for Bottom-up Knowledge Networking and Community Building. In Lytras, M. D., Tennyson, R. & Ordonez de Pablos, P. (Eds.) *Knowledge Networks: The Social Software Perspective* (pp. 17-27). Hershey, PA, USA: IDEA Group Publishing.

Chatti, M. A., Jarke, M. & Frosch-Wilke, D. (2007). The future of elearning: a shift to knowledge networking and social software. *International Journal of Knowledge and Learning*, 3(4/5), 404–420.

Chatti, M. A., Jarke, M. & Specht S. (2009). PLEF: A Conceptual Framework for Mashup Personal Learning Environments. *IEEE Technical Committee on Learning Technology (TCLT)*, 11(3).

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.

De Bra, P. (2002). Adaptive educational hypermedia on the Web. *Communications of the ACM*, 45(5), 60–61.

Downes, S. (2005). E-learning 2.0. *ACM eLearn Magazine*. Retrieved March 15, 2010, from http://www.elearnmag.org/subpage.cfm? article=29-1&section=articles.

Downes, S. (2006). *Learning Networks and Connective Knowledge*. Retrieved January 4, 2010, from http://it.coe.uga.edu/itforum/paper92/DownesPaper92.pdf

Engeström, Y., Engeström, R. & Vähäaho, T. (1999). When the Center Does not Hold: the Importance of Knotworking. In Chaiklin, S., Hedegaard, M. & Jensen, U.J. (Eds.) *Activity Theory and Social Practice: Cultural-Historical Approaches* (pp. 345–374*)*. Aarhus: Aarhus University.

Hafner, K. (2004, September 16). Software tutors offer help and customized hints. *The New York Times*.

Holland, J. H. (1998). *Emergence: From Chaos to Order*. MA: Addison-Wesley.

Husband, J. (1999). *Wirearchy is emerging*. Retrieved January 4, 2010, from http://wirearchy.com/

Jonassen, D. H. (1991). Objectivism versus constructivism: do we need a new philosophical paradigm? *Educational Technology Research and Development,* 39(3), 5–14.

Kravcik, et al. (2005). Interoperability of Adaptive Learning Components . Deliverable 1.1 of the Prolearn EU/FP6 Network of Excellence.

Lubensky, R. (2006). *The present and future of Personal Learning Environments (PLE)*. Retrieved January 4, 2010, from http://members.optusnet.com.au/rlubensky/2006/12/present-and- future-of-personal-learning.html

Mejias, U. (2005). A Nomad's Guide to Learning and Social Software. *The Knowledge Tree: An e-Journal of Learning Innovation*, Edition 7, Oct 2005, ISSN 1448-2673.

Mergel, B. (1998). *Instructional Design and Learning Theory*. Retrieved January 4, 2010, from http://www.usask.ca/education/coursework/802papers/mergel/brenda.htm

Nardi, B., Whittaker, S., & Schwarz, H. (2002). NetWORKers and their Activity in Intensional Networks. *Computer Supported Cooperative Work,* 11(1/2), 205–242.

Ohlsson, S. (1994). Constraint-based Student Modeling. In: Greer, J.E. & McCalla, G.I. (Eds.) *Student Modeling: the Key to Individualized Knowledge-based Instruction* (pp. 167–189). Berlin: Springer Verlag.

Polanyi, M. (1967). *The Tacit Dimension*, New York: Anchor books.

Reigeluth, C. M. (Ed.) (1999). *Instructional Design Theories and Models: A New Paradigm of Instructional Theory (Vol. II).* Mahwah, NJ: Lawrence Erlbaum Associates.

Siemens, G. (2006). *Knowing Knowledge*, Lulu.com.

Specht, M., & Burgos, D. (2007). Modeling Adaptive Educational Methods with IMS Learning Design. *Journal of Interactive Media in Education*. Special Issue Adaptation and IMS Learning Design.

Surowiecki, J. (2004). *The wisdom of crowds: Why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations.* New York: Doubleday.

Tam, M. (2000). Constructivism, Instructional Design, and Technology: Implications for Transforming Distance Learning. *Educational Technology & Society*, 3(2), 50-60.

Tobin, D. R. (2000). *All Learning is Self-Directed: How Organizations Can Support and Encourage Independent Learning.* Alexandria, VA: ASTD Press.

van Harmelen, M. (2006). Personal learning environments. Retrieved January 4, 2010, from http://octette.cs.man.ac.uk/jitt/index.php/Personal_Learning_Environments.

Wenger, E. (1998). *Communities of practice: Learning, meaning and identity*. Cambridge, UK: Cambridge University Press.

Wenger, E., McDermott, R. & Snyder, W. M. (2002). *Cultivating Communities of Practice*. Boston, MA: Harvard Business School Press.

Wild, F., Mödritscher, F. & Sigurdarson, S. (2008). Designing for Change: Mash-Up Personal Learning Environments. *eLearning Papers*, 9.

Wilson, S., Liber, O., Johnson, M., Beauvoir, P., Sharples, P. & Milligan, C. (2007). Personal learning environments: Challenging the dominant design of educational systems. *Journal of e-Learning and Knowledge Society*, 3(2), 27-38.