Exploring e-portfolios and Independent Open Learner Models: Toward Army Learning Concept 2015

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ABSTRACT

The Army Learning Concept (ALC) 2015 describes a learning model that leverages peer-based learning. According to ALC 2015 "the future learning model must offer opportunities for Soldiers to provide input into the learning system throughout their career" as well as account for Soldiers' prior knowledge and experiences (ALC 2015, p. 6). In order to accomplish this vision, learning systems such as game-based, adaptive or intelligent tutoring systems will need to leverage independent open learner models that are populated by systems, instructors, or the users themselves. Electronic or digital portfolios (a.k.a. e-portfolio) are a concept currently under review by the International Standards Organization (ISO) that enables users to monitor and share skills, educational goals, competencies, outcomes, and achievements. E-portfolios and independent open learner models are user managed and can aid decision making on career development as well as provide personal reflections beyond the abilities of most assessment systems and Learning Management Systems (LMS) representative of formal learning and training. This paper reports exploration that seeks to understand what implications for the ALC 2015 learning model can be gleaned from e-portfolios and independent open learner models. We address the following questions: What are the most salient components of e-portfolios and independent open learner models that taken together may be predictive of performance? How can e-portfolios and independent open learner models be used to create more effective learning environments? What additional data sources are needed to develop robust e-portfolios and learner models for training? What privacy protection should be considered? What ethical and accessibility issues should be considered? The challenges identified by this exploratory research are applicable to achieving the vision of ALC 2015.

ABOUT THE AUTHORS

Dr. Elaine Raybourn has a Ph.D. in Intercultural Communication with an emphasis in Human-Computer Interaction. She has led computer game research in multi-role experiential learning, social simulations, and designing training systems that stimulate intercultural communication competence, and adaptive thinking. Her team's work was identified by the Defense Science Board Summer Study on 21st Century Strategic Technology Vectors as "critical capabilities and enabling technologies for the 21st century that show promise." She is a former ERCIM (European Consortium for Research in Informatics and Mathematics) fellow, and is a National Laboratory Professor at the University of New Mexico's Department of Communication. Elaine is a recipient of the Department of the Army Award for Patriotic Civilian Service, awarded to her by the U.S. Army Special Forces. Currently Elaine is on extended assignment from Sandia National Labs to PEO STRI Games for Training, Advanced Distributed Learning Initiative, and Defense Acquisition University.

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INTRODUCTION

United States Army institutional training is primarily comprised of instructor-led courses that are difficult to modify to meet individual learner's needs (Bickley et. al., 2010). According to Army Learning Concept (ALC) 2015, "although the Army was an early adopter of distributed learning nearly 20 years ago, the program did not fully realize its intended goal of anytime, anywhere training" (ALC 2015, p. 3). However, the Army has not abandoned its goal of anytime, anywhere training. The ALC 2015 describes a learning model that leverages personalized, self-paced instruction, and opportunities for peer interactions. This vision incorporates learner education and assessment capability that at its best will empower learners to be fully engaged with their learning. "The future learning model must offer opportunities for Soldiers to provide input into the learning system throughout their career" as well as account for Soldiers' prior knowledge and experiences (ALC 2015, p. 6). In order to accomplish this vision, learning systems such as game-based, adaptive or intelligent tutoring systems will need to leverage historical and real-time learner data populated by systems, instructors, or the users themselves.

PROBLEM STATEMENT AND RATIONALE

Recent years have seen increased interest in educational technology that adapts and tracks users' performance. Many are turning to technologies such as intelligent tutoring systems and adaptive cognitive training to boost learner performance. These games, simulations, and adaptive or intelligent tutoring systems often utilize what is known as a *student model* to "provide knowledge that is used to determine the conditions for adjusting feedback" for purposes of description or prediction (Woolf, 2010, p. 49). These student models are usually local to the application—that is, they are often treated as a component of a standalone intelligent application, and not as an independent, life-long knowledge representation of learning history. Developing adaptive games, simulations, and intelligent tutoring systems is no easy task. Therefore it is not unexpected that most science and technology development has focused on developing systems with student models that are local to individual tutoring and adaptive systems, closed to learner inspection, and therefore limited in what they can know about a learner outside the training system. Advances in computing have made the aggregation and utilization of data gathered from disparate sources more accessible for the development of historical, independent open learner models.

RESEARCH OBJECTIVES AND METHODS

This concept paper reports a preliminary effort to understand some of the challenges associated with realizing the ALC 2015 learning model vision. The authors utilized a variation on thought experiment methodology (Clement, 2009) to hypothetically position independent open learner models and e-portfolios in the context of ALC 2015 for the purpose of better understanding implications and furthering theory exposition. Thought experiments can be used in computer science to reason through system design, implementation, theory, and interactions. Our thought experiment consisted of conducting a literature review and crafting a scenario based on ALC 2015. We also compared data fields collected during a study of game-based experiential learning (Raybourn, 2009, Raybourn et al., 2010) with data fields characteristic of e-portfolios and independent open learner models to better understand how these data could apply to our scenario. This helped us understand how these technologies might be useful for learner-system interactions particularly for adaptive training and intelligent tutoring. Our intention was to conduct preliminary research toward understanding if independent open learner models and e-portfolios are able to be used to inform lifelong learning and adaptive training systems that cross multiple applications and domains.

ALC 2015 Scenario

For our future scenario we considered the example of an Army Soldier in 2015 who trains anywhere, anytime. She trains in the field, with different simulators, on different platforms, in the classroom, and with her peers (both co-located and distributed). Her training is comprised of interacting with technology such as intelligent computer-based tutoring, mobile performance aids, virtual environments, augmented reality, and social media. Her learning is self-paced, collaborative, adaptive, and/or mediated by instructors, virtual mentors, and embodied agents. She creates content, tracks her own learning, and monitors her progress.

Subsequent sections outline our literature review of relevant models that we considered to be key enablers of the ALC 2015 "anytime, anywhere" training vision.

REVIEW OF LEARNER MODELS

To track learning across platforms and monitor progress as envisioned by ALC 2015 we propose that the training community draw upon ongoing research in computer science and education in open, independent, life-long learner models and e-portfolios. While e-portfolios are used to some degree in military education as portals to one's information, we propose that e-portfolios and independent open learner models could be used to inform student models found in standalone applications such as military adaptive training systems, games, assessment modules, and intelligent tutors. Currently we are not aware of the fielded use of open learner models or e-portfolios that hook to intelligent tutoring or adaptive systems to track Soldiers' learning or progress across military training technologies.

Open Learner Models

An adaptive system can provide higher quality feedback when it has a more accurate and complete understanding of the student. One approach to increasing this understanding of the learner is to use open learner models. Open learner models are defined as student models that are accessible to the learner being modeled or possibly to teachers, peers, or others who may be able to enhance the model (Bull & Kay, 2007). In addition to improved accuracy, open learner models are thought to enhance metacognition, motivation, and collaboration and/or competition. Learners may access data, add reflections, and edit, etc. which may ultimately enhance their trust in the system. Open learner models may be components of adaptive systems or web-based intelligent learning environments (ILE).

Negotiated Learner Models

Negotiated Learner Models is a type of open model that allows both system and learners to collaboratively agree on the contents of the model (Bull, 2004). Negotiated models can result in more accurate learner models and boost learner reflection. These models may be preferred by learners who want the system to initiate interaction and negotiation. If the learner and the system have differing beliefs about knowledge representation the negotiation process is initiated.

Independent Open Learner Models

An independent open learner model is an open learner model that is used independently of or external to a system (Bull, 2010). The purpose of an independent open learner model is to provide information to the learner about her knowledge and progress. This enables the learner to monitor understanding and plan future learning. Instructors or learning systems input questions and define misconceptions for each learner. Learners then choose how they want to apply the model information to further their learning (Bull et al., 2008). Independent open learner models have been used in courses where the models are assessed and in courses where the models are optional and in both cases learners seem to find them to be helpful (Bull et al., 2008).

Lifelong Learner Models

A lifelong learner model is a distributed technical framework that provides comprehensive management of personal learning data (Kay & Kummerfeld, in press). It enables learners to aggregate information about themselves from diverse sources, manage which applications have access to read and/or write information, directly input personal information, and share information with others. It is also expected to provide an open learner model to support self-directed learning and interpret learner information from various tools. Two key challenges are the user interface to large collections of information and the ontologies necessary for understanding information from diverse sources (Kay & Kummerfeld, in press).

e-portfolios

An electronic or digital portfolio (a.k.a. e-portfolio) is defined as a learner-driven collection of digital artifacts articulating experiences, achievements, and evidence of learning (Commonwealth of Australia, 2009). E-portfolios are being used internationally for lifelong learning initiatives and the International Organization for Standards (ISO) is developing an e-Portfolio reference model. E-portfolio key characteristics were developed from several use cases from different cultures and language communities including those from Australia, Canada, Korea, China, and France.

Like open learner models, e-portfolios are learner managed. E-portfolios can aid decision making on career development as well as provide personal reflections beyond the abilities of most assessment systems and Learning Management Systems (LMS) representative of formal learning and training.

Table 1 describes components that might be included in an e-portfolio and independent open learner model.

Table 1. Potential Learner Model Components

Components	Description
Profile	Basic information of the user (e.g., user identification, favorite subjects, hobbies, aspirations, goals)
Education & Training	Education and training history, grades, and feedback
Career	User's activities that demonstrate capabilities
Qualification	Official evidence data (e.g., academic transcripts, professional/vocational qualifications, certificates, licenses, and letters of recommendation)
Experience	Extra-curricular activities (e.g., clubs, internships, volunteer activities)
Outcome	Digital and non-digital artifacts that resulted from learning experience (e.g., documents, photos, animations, videos, audio files, images)
Feedback	Feedback from instructors, peers, and others from the learning process
Reflection	Personal descriptions (e.g., comments, explanations, etc.) about learning or teaching activities including perceived strengths and weaknesses

Various techniques to represent data in learner models and e-portfolios have been proposed. Representations range from simple (e.g., skill meters) to complex (e.g., exposing Bayesian networks). Interactive techniques initially began with proposals to allow learners to directly edit (Kay, 1995) learner model data. However, current techniques for interaction with learner models focus on addition (adding evidence to a model) and negotiation (Bull & Kay, 2007). Potential interactive approaches for adding evidence may be through conversational agents such as chatbots (Kerly, et al., 2006) or embodied conversational agents (e.g. Morel & Ach, 2010).

In summary, similarities exist among open, negotiated, independent open, and lifelong learner models, and e-portfolios. Independent open learner models and e-portfolios seem to satisfy the requirements of lifelong learner models that present opportunities to interact with external data repositories and learning systems. For these reasons we have chosen to advance the notion that independent open learner models and e-portfolios be considered by the training community as a means to advance the vision of ALC 2015.

A CLOSER LOOK AT LEARNER MODELS

Populating data fields

Notional e-portfolio and independent open learner model data fields were compared with data fields created from a game-based training experiment held in the summer of 2008 (Raybourn, 2009, Raybourn et al., 2010). Table 2 below indicates the data fields from Table 1 populated with typical game study data available for analysis.

Table 2. Game Study Data in e-Portfolio

Components	Description
Profile	Learner identification, gender, age, ethnicity, language communities
Education & Training	Quiz results
Career	Job title
Qualification	TAIS (Test of Attentional and Individual Style)
Experience	Military experience, Video game experience
Outcome	Game performance, videos of facial expressions while conducting peer evaluation, pre-test and posttests
Feedback	In-game feedback from peer Reflective Observer/Evaluators, Performance ranking by expert, performance ranking via Latent Semantic Analysis (LSA) and statistical analysis, visualizations
Reflection	AAR self debriefing, AAR debriefing from Reflective Observer/Evaluator

Game study data fields used to notionally populate the table included demographics, preferences, military experience, in-game reflection on peer performance, recall test, psychometric inventory, self-evaluation, SME evaluation, and pre-/posttest attitudes toward learning. The collection of these data is not unlike what can be expected from data collection opportunities in 2015. In a number of categories (such as Experience) the types of video games played, and extent of military experience is derived from open response, suggesting that if the learner has experience other than military, it can be made explicit in the model. In the category of Qualification, the results of the psychometric inventory are listed. A recommendation for military training e-portfolios would be to include a category on psychometric or other evaluations.

Taking these data categories into consideration we addressed the following high level questions:

What are the most salient components of e-portfolios and independent open learner models that taken together may be predictive of performance?

These technologies are likely to capture large volumes of data making it difficult to find the salient data necessary to act upon. We anticipate data serving as evidence for related prior knowledge, prior performance, current state of cognition and physiology, and being a good self-directed learner will contribute to predictions of performance.

Prior knowledge and performance on similar tasks is typically the best predictor for new performance. The ability to incorporate education and training history, qualification, and experience components from an e-portfolio or independent open learner model could provide key elements of prior knowledge and performance. Additionally, if these models are able to include information such as topics understood and current misconceptions, these elements could be useful predictors for performance in related domains.

If we broaden the concept of an e-portfolio and independent open learner model to serve where real-time data is captured, the current state of cognition and physiology could contribute to predictions of performance. If a learner is currently in a very stressful state, distracted, or unmotivated, that information is likely to predict poor performance.

As self-directed learning becomes increasingly important, knowing whether a learner is a good self-directed learner will likely serve as a predictor of future performance. While the notion of what constitutes a good learner may be largely subjective, metacognition, self-regulation, self-efficacy, and goal orientation are traits characteristic of a self-directed learner. An e-portfolio and independent open learner models ability to capture learner reflection, goals, and aspirations could also contribute to predictions of performance.

How can e-portfolios and independent open learner models be used to create more effective learning environments?

E-portfolios and independent open learner models offer opportunities to infer learner attributes through data mining and statistical analyses. These data can set the initial challenge level in intelligent tutoring systems or adaptive systems avoiding the cold start problem where the system initially knows nothing about the user (Bull & Kay, 2007) or where learner stereotypes are used (Woolf, 2009). We believe e-portfolios and independent open learner models can be used in military training to automatically populate student models for intelligent tutoring systems, simulations, games, and adaptive training environments. We propose that independent open learner technologies such as those explored in this paper are able to be used to inform lifelong learning and adaptive training systems that crosscut multiple applications and domains while continuing to track learners' progress.

E-portfolios and independent open learner models may also be used to provide better forms of adaptation. Durlach and Ray (in press) distinguish between local and model-based adaptation. Local adaption involves providing feedback to repair errors in understanding without taking explicit learner information into account whereas model-based adaptation takes the student model information into account to influence the sequence of instruction. Model-based adaptation that relies on rich information about student individual differences is considered to be more adaptive.

What additional data sources are needed to develop robust e-portfolios and independent open learner models for training?

In the previous two sections, we described various components of e-portfolios and independent open learner models that were likely to be used in productive ways. Adaptive training systems will likely be key generators of e-portfolio information. However, data will also need to come from external data sources to populate proposed components of e-portfolios.

Social media and health monitoring sites could be valuable external data sources. These sites typically expose machine interfaces, which can be used by an e-portfolio management system to populate data. Profile, career, education and training history, and qualifications may be captured from sites like Linked In. Detailed experience, feedback from peers or instructors, and sources of reflection could be captured from sites like Facebook. Health monitoring sites like Withings, which are sure to evolve, can capture consumer grade sensor information like blood pressure.

Other systems like previously used Learning Management Systems or even personal communication tools like Gmail may be used in the future. These external sources may not currently expose machine interfaces. Previously used LMSs or similar systems could provide past learning progress information to populate open learner models (e.g., topics, misconceptions). Personal communication systems like email or cell phones could be monitored to capture more accurate representations of context for learning.

What privacy protection should be considered?

E-portfolios and independent open learner models will contain highly personal information. Personally identifiable information (PII) is heavily regulated through OMB and DoD governance. While this information will be very beneficial for adaptive training opportunities, policies will need to be adhered to in order to protect it.

There is a natural tension between the need to protect privacy and the desire to use technical innovations that create new ways to share historically personal information in more public ways. We see this tension surrounding social media and location based services. Facebook, the popular social networking site, is one of the companies on the forefront of privacy debates which, together with Congress, is shaping the balance between the benefits of sharing personal data and the legislation necessary to protect it.

Central to this discussion is the consideration that social norms are changing. As Mark Zuckerberg, the Facebook CEO, is quoted in Kirkpatrick (2010), "People have really gotten comfortable not only sharing more information and different kinds, but more openly and with more people. That social norm is just something that has evolved over time. We view it as our role in the system to constantly be innovating and be updating what our system is to reflect what the current social norms are." As social norms evolve, so too does education and guidance on individual operational security associated with using social media[1]. This guidance will undoubtedly be a critical part of e-portfolio protection and access considerations.

At the present time, DoD 5400.11-R, "Department of Defense Privacy Program" serves as the core DoD policy on privacy. This regulation governs how personal information is collected, managed, accessed, and disclosed. E-portfolio and independent open learner models privacy protections will fall under this existing privacy guidance. A mechanism for discovering system-specific privacy considerations is through a privacy impact assessment (PIA). It is DoD policy that PIAs be completed on DoD information systems and electronic collections that collect, maintain, use, or disseminate PII. We are not aware of any DoD sponsored PIA for e-portfolios or independent open learner models. However, the Australian Government's national training system developed one in 2010 that captures e-portfolio specific considerations.

The Australian PIA for e-portfolios found three key risk factors related to the handling of e-portfolio personal information: 1) the extent of learner-generated content, 2) learner control of access to e-portfolio content by third parties, and 3) the dynamic and online nature of e-portfolio systems. To address these risks, the report concluded that training organizations responsible for managing e-portfolios should 1) ensure that learners are aware of potential privacy risks and are properly educated and supported to manage those privacy risks, 2) scaffold the right educative framework around the generation of e-portfolio content, 3) manage access to e-portfolio content, including fine grained access controls, and 4) keep e-portfolio personal information secure.

What ethical and accessibility issues should be considered?

As e-portfolio and independent open learner model management guidelines are further developed, they will need to consider, with the involvement of learners, two core questions:

Who owns the data? The concept of an e-portfolio or independent open learner models assumes that it is owned by the learner. However, typically an institution will serve as a steward for the responsible management of data. In that role, core considerations concerning the management of data focus on the retention of data, the ability for a learner to pack up and move his or her e-portfolio or independent open learner model to a new system, the ability for different roles (learner, teacher, intelligent tutor, mentor, etc.) to add data, and limits on data that may be added for quality control or legal purposes.

Who has access to the data? The Australian Government's Draft e-Portfolio Guidelines suggest organizations create an access matrix with rows representing the content areas of the e-portfolio, columns representing roles with access, and the content of cells showing the means by which access is made available. This is a good way for service providers to make the answer to this access question clear and explicit. Learners will also need to be provided with

[1] http://www.defense.gov/socialmedia/education-and-training.aspx

education and guidance (similar to social media guidance) that informs them of the risks of giving wide access permissions to sensitive personal data.

LIMITATIONS AND FUTURE RESEARCH

The goal of this research was to report a preliminary effort to understand some of the learner modeling challenges associated with realizing the ALC 2015 vision. Our effort was limited in exploration to a survey of the literature, comparing notional data fields with actual data fields that are commonly generated from experimentation, and applying what we learned to the ALC 2015 learning model vision. Further investigation regarding the feasibility of learner models for military training is needed. Future research could focus on models that are independent and applicable to multiple adaptive training systems, open to learner inspection and manipulation, and responsibly unlimited in what they could know about learners (relationships, training on diverse platforms, historical learning, culture, region, accessibility, mood, daily activities, etc.). Natural representations of cognition for use in a variety of intelligent and adaptive systems for training and education should also be a focus of future research (Hutchinson, 1995).

Such an exploration may further include understanding how data can be harvested from sensors and social media such as LinkedIn and Facebook for automated population of e-portfolios and independent open learner models. We plan to conduct such investigations in the context of ADL's evolving research to define a next generation SCORM learning environment. A candidate open source tool for large-scale data analysis called the Titan Informatics Toolkit, may also be used for ingestion, processing, and display of informatics data (McLendon et al., 2010).

CONCLUSION

In order to accomplish ALC 2015, learning systems such as game-based, adaptive or intelligent tutoring systems will need to leverage historical and real-time learner data populated by systems, instructors, or the users themselves. E-portfolios and independent open learner models could be used to inform the student models found in standalone applications such as military adaptive training systems, games, assessment modules, and intelligent tutors.

The present paper described how e-portfolios and independent open learner models could be among the enabling technologies key to bringing the ALC 2015 "anytime, anywhere" training vision to fruition. The concepts presented in this paper are applicable to tracking career or lifelong learning. Advances in computing have made the aggregation and utilization of data gathered from disparate sources more accessible for the development of historical, independent open learner models that can make key contributions to student models used in game-based training, and adaptive, intelligent tutors.

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