Personal Learning Environment (PLE): A Learner and Data Centric Approach

Schawn E. Thropp

Concurrent Technologies Corporation

Johnstown, PA

thropps@ctc.com

Mark Friedman, CKMP

Concurrent Technologies Corporation

Suffolk, VA

friedmam@ctc.com

Matthew Elliott

Concurrent Technologies Corporation

Johnstown, PA

elliottm@ctc.com

ABSTRACT

Researchers, instructors and designers continue to look for the right balance of learner control within learning experiences. Some believe this personal, learner-centric approach will drive the best learning outcomes. But what makes a learning experience personal? Is a personal learning experience driven and controlled solely by a learner or can another entity (e.g., instructor, teacher and system/application) contribute? How can the evolving field of learning analytics support the evolution of these personal learning ecosystems?

Members of the learning, education and training community have been researching and experimenting with a variety of "personal learning environments" (PLEs) as a way of giving a learner more control. PLEs can give the learner the ability to curate an adaptable means of aggregating content, people, applications and tools. This ecosystem helps make the learning experience more personal and also more useful to the person's specific needs and interests.

One often overlooked aspect of driving towards a more personal learning ecosystem is the evolving discipline of learning analytics. Learning analytics can be viewed as the use of a variety of data and analytic techniques to support the analysis and study of the "learning process." Some define learning analytics as the science behind turning data into action, enabling new developments in curriculum mapping, personalization and adaptation, prediction, intervention and competency determination.

This paper examines the characteristics and components of PLEs and looks at the ways PLEs can create more friction-free environments in which learning feels more open and autonomous. It then examines the impacts learning analytics could have in creating a future in which PLEs can help learners leverage the lifelong learning experiences they encounter.

ABOUT THE AUTHORS

Mr. Schawn Thropp: Mr. Thropp is a Technology Advisor within the Learning and Human Performance Solution (L&HPS) organization at Concurrent Technologies Corporation (*CTC*). He is responsible for research, development and advisement of advanced technologies within the learning, education, training and performance support domain. Mr. Thropp brings over 11 years of technical expertise within the learning and human performance domain. Mr. Thropp has a Masters in Computer Science from Johns Hopkins University.

Mr. Mark Friedman: Mr. Friedman is a Principal Technical Analyst for the L&HPS organization at *CTC*. He is responsible for development, testing and fielding of advanced technology training and instructional technology projects for Government clients. Mr. Friedman brings over 25 years of education and training, instructional technology development and project management experience to his assignments. Mr. Friedman has an MBA in Strategic Management from the College of William and Mary and a Certified Knowledge Management Professional certificate from the KM Pro Society.

Mr. Mathew Elliott: Mr. Elliott is a Software Engineer for *CTC*. For the past four years Mr. Elliott has worked on social computing and data driven systems for the intelligence community and other Government clients. His interests include data science, machine learning, social computing and visualization. Mr. Elliott has an M.S. in Engineering Management from Robert Morris University.

Personal Learning Environment (PLE): A Learner and Data Centric Approach

Schawn E. Thropp

Concurrent Technologies Corporation

Johnstown, PA
thropps@ctc.com

Mark Friedman, CKMP

Concurrent Technologies Corporation

Suffolk, VA
friedmam@ctc.com

Matthew Elliott

Concurrent Technologies Corporation

Johnstown, PA
elliottm@ctc.com

INTRODUCTION

One highly significant question/challenge we face in the e-learning industry is how to make the learning experience more personal and engaging—so personal and engaging that maybe the learners do not even know they are taking part in a learning experience. The goal is learning that "just happens"—the learning experience is integrated within our daily lives and our personal day-to-day workflow. For example, one aspect of being personal and engaging is the loneliness factor, which learning theorists sometimes explore as a question of social presence (Picciano, 2002) (Anderson, Rourke, Garrison, Archer 2001). How many times have you experienced a typical "online learning activity" where you felt lonely—no one to talk to, no one to ask questions of, no one to praise you when you do something well or tap you on the shoulder and offer help when you are not doing so well? Learning management systems and other niche learning solutions provide capabilities such as discussion forums, wikis, and blogs to assist with the feeling of less isolation during a learning experience. But do such tools really help? Or are these just advancements in technology that are finally being used and/or making their way into a learning experience?

Advancements in intelligent agents, intelligent tutoring systems, semantics and learning analytics are promising to bring a set of solutions that could be tailored together to make a true personal learning environment. A conceptual environment:

1. in which the learner is in control,
2. that is personalized based on a variety of facets to stimulate the learning process; and
3. driven by the intelligent analysis of a variety of data sources.

The intersection of these concepts begins to define the traits, characteristics, requirements and needs to build a sustainable framework for a personal learning ecosystem.

A key sustainable and adaptable feature of this ecosystem is the personal learning assistant. These personal learning assistants are transparent to the learner and work on behalf of the learner within the ecosystem. They gather bits of information left behind by the learner in everyday activities – regardless of whether those activities are traditionally considered to be learning activities. This would include information about usage of tools and systems such as, but not limited to:

- discussion forum participation
- social media activity
- application or operational system usage patterns
- usage patterns of job performance aides/applications
- search history.

In order to define a personal learning ecosystem, as pictured in Figure 1, in which facets of personal learning, personalized learning and learning analytics are integrated to form a series of thriving, adaptable and intelligent personal learning assistant(s), we believe two very important topics have to be researched and studied: the learner (learner-centric) and learning analytics (data centric). This paper focuses on these two topics to begin to lay a foundation for a flexible and adaptable personal learning ecosystem managed and maintained by a series of transparent personal learning assistants.
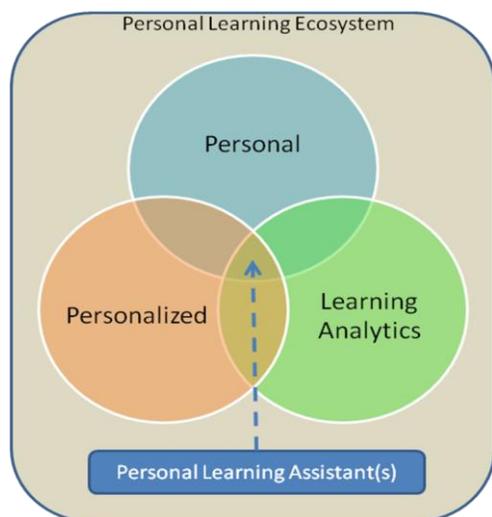
Figure 1: Conceptual Personal Learning Assistant Traits Intersection

THE LEARNER

"We are by nature observers, and thereby learners. That is our permanent state." – Ralph Waldo Emerson

What is a learner-centric approach? Researchers and theorists have described a learner-centric approach as one in which:

- The focus is on student learning rather than what the teacher is doing (Blumberg, 2008).
- The role of the trainer changes from being the source of all knowledge, instead the trainer is seen as a facilitator or guide to the learning process (McDaniel, Brown, 2001).

Why put the learner first? There are obvious answers to that question. If we put the learner first–or in the center–they will be more engaged with the material, understand the meaning of the material vs. just memorizing the material and apply concepts learnt more effectively (Blumberg, 2008).

Blumberg (2004) goes on to describe that when using a learner-centric approach, students tend to:

- Know why they need to learn and how to learn
- Have self awareness of their learning abilities and their processes of gaining it
- Are responsible and are prepared to become informed citizens
- Can retrieve and evaluate information
- Use knowledge to solve problems

- Can communicate their knowledge in real settings.

A learner-centric approach ultimately leads to a more personal or personalized learning experience. However which one is it? Personal or personalized, or is it both?

Personal vs. Personalized

What is the difference between personal learning and personalized learning? One of the best distinctions our research found was by University of Florida professor Wendy Drexler. Drexler basically argues that the distinction is as follows:

- Personal learning is learning in which the learner controls the learning process, environment, resource and people they interact with (Drexler, 2010).
- Personalized learning is learning in which the learning process, environment, resources and people the learner interacts with are controlled (or makes decisions for the learner based on his/her past choices or experiences) by some other entity (teacher, tutor, software application) for the learner (Drexler, 2010).

Taking a deeper look at each of these terms begins to reveal some differences. Personalized learning is probably the most often used of the terms. Personalized can mean many things to many people and in most cases these distinct meanings are correct – that is what makes something personalized. For example:

- During the learning process, a system or application determines that content should be tailored to meet the learner's progress. If a topic is determined to be challenging to the learner, perhaps additional ancillary content is provided (e.g., based on a pre-test, introductory knowledge check, or even an advanced learning analytics capability).
- Options are presented to the learner to change the modality in which the content is presented (e.g., video, all text, immersive, game play, etc), enabling the learner to choose how they would prefer to see the content.

In a personal learning model, the learner is in the center and controls the process, environment, resources and people they interact with. In these cases there are still instructional aspects (e.g., learning objectives, teacher) to the process; however, these tend to be more in a facilitation or guiding manner. For example:

- During the learning process, the learner is presented with a set of suggested readings to review around a given topic. The learner chooses which resource or resources they will review.
- The learner is introduced to a set of peers and they elect which peers they gravitate towards. For example, the learner may decided to interact with another learner (or peer) because of a common research interest or a recommendation by their personal learning assistant.

In both cases, personalized and personal, each has facets that are important in building a richer learner experience. More importantly, these facets can be modeled within a set of personal learning assistants.

Current Research and Applicability

One form of a personal learning environment that is rapidly gaining traction (both in the research community and in operational use) is the concept of a massively open online course (MOOC). In MOOCs students choose their preferred mode of learning. Some prefer using a traditional approach based on reading assignments, while others utilize RSS readers and others still prefer synchronous dialogue time with the instructors (usually entering their own commentary into the dialogue via text chat). Most often, MOOCs are operated without cost to the student, so as to remain as open as possible; however now there are least a half-dozen of these well publicized experiments (see Table 1) and in the future, there could easily be more traditional, pay-to-participate, graded-type MOOCs available.

Table 1: Sample MOOCs

MOOC
Connectivism and Connective Knowledge 2011   http://bit.ly/jJaTp5
MobiMOOC   http://bit.ly/evc7WZ
Personal Learning Environments Networks and Knowledge 2010   http://bit.ly/mH2S4t
Personal Learning Environments for Inquiry in K12   http://bit.ly/k2xXJB
eduMOOC: Online Learning Today… and Tomorrow   http://bit.ly/itKUd7
Learning and Knowledge Analytics   http://bit.ly/li7dil

Allowing each learner to utilize their preferred channel of communication is very interesting and appears to be the most open and collaborative example of an online course. This focus on the learner's preferred communication channel places a personal touch on the learning experience, enabling the learner to choose many aspects of the experience.

In conclusion, based on our research and findings, we believe that both aspects of personalized learning and personal learning need to be utilized in a personal learning ecosystem. These facets will form the foundation of making the learning experience personal, which then can be designed and modeled into a personal learning assistant. More research is needed in defining the characteristics and facets of both personalized and personal learning experiences. As researchers we need to understand what works and is effective so that we can build a better understanding of a richer personal experience for the learner.

LEARNING ANALYTICS

Learning analytics is a fast and growing field of study. Interest continues to rise in how to measure and account for training and knowledge acquisition. We believe that learning analytics is the key enabler of a truly personal learning ecosystem in which facets of personal and personalized learning come together and create a variety of personal learning assistants. A learning ecosystem that uses the data and information "bread crumbs" that people leave behind in their everyday activities can help them take advantage of the variety of learning experiences they encounter throughout their lifetimes.

So what is learning analytics? Two of the best definitions we could find are:

1. "Learning analytics refers to the interpretation of a wide range of data produced by and gathered on behalf of students in order to assess academic progress, predict future performance and spot potential issues" (Johnson, Smith, Willis, Levine, Haywood, 2011).
2. "Learning analytics is the use of intelligent data, learner-produced data, and analysis models to discover information and social connects, and to predict and advise on learning" (Siemens, 2010).

As you can see, these two definitions are quite similar (so were others that we found during our research). Most definitions focus on these key characteristics:

- Use of a wide set of data (known and unknown)
- Use of new and emerging analysis models
- Primarily used for predictions, course of action correction and advanced progression measurements.

In the years past, arguably most of the attention on any form of learning analytics has been focused on assessment data (e.g., end-of-course surveys, knowledge checks, pre-test/post test). However, there are endless other sources that are not being tapped and analyzed. Before we take a look at these sources, let us first go back to the roots and take a look at data analytics in general.

Data Analytics & Data Science – Brief Introduction

"Data is the next Intel Inside" – Tim O'Reilly.

Data is ubiquitous; it resides on servers, computers, mobile devices, in data warehouses, databases, fileservers and on paper. Because of computing constraints, data access and other issues, a wealth of actionable data has been overlooked in the past. Data Analytics and Data Science is the science behind turning this data into useful and actionable data.

Data driven applications are everywhere and wildly popular. Here are some examples.

- **Netflix** – Netflix uses data collected from their users to make recommendations on what movies a user might like to watch. Movies are categorized, and users vote on movies they watch (1 to 5 stars). The Netflix recommendation engine learns and is able to predict what movie a subscriber might want to watch next.
- **Google** – PageRank is probably one of the most successful uses of data ever. PageRank uses the number of links pointing to a particular web page to determine its rank in Google's search results.
- **Pandora** – The Music Genome Project, similar to Netflix, uses user-generated input to refine recommendations for their users. Similar to Netflix, Pandora uses categorized music and user input (likes and dislikes) to select what type of song to play for that user's selected station.

These are just a few large-scale examples; there have been lots of smaller scale data mash ups as well. One to note was performed by a blogger from the San Francisco Bay area (Singh, 2011). The blogger was interested in ranking San Francisco Bay area high schools by measuring outcomes such as job titles and colleges their students attended, instead of how their current rankings are calculated (standardized test scores, class size, student teacher ratio, etc.). Without this information publically available from the school districts, the blogger turned to LinkedIn. Using LinkedIn data the blogger looked at the top eight high schools in the Bay area and accumulated statistics on colleges they graduated from, companies they worked for, their job titles and what industries they worked in. Results of the analysis can be found here: http://bit.ly/kJgBGO.

The Data Analysis Process

Now that we have looked at some examples of data analytics, we now shift our focus onto a brief explanation of the data analysis process. The data analysis process typically follows these steps: Obtain – Scrub – Explore – Model – Interpret (Mason, Wiggins, 2010).

Obtain – The first part of any data analysis effort is obtaining the data. As mentioned before, data is everywhere, you just have to find it. Recent Open Data initiatives have opened the door to previously unobtainable data sets. Data marketplaces like InfoChimps are providing infrastructure where people/companies can buy, share and sell formatted data.

Scrub – Scrubbing is the most important step of the data analysis process. Scrubbing or cleaning data will pay dividends in the long haul. It is much easier and more productive to work with clean, formatted data than something that looks like a series of poorly formed HTML tags. Information comes in a variety of forms that need to be sorted out. For example, consider how you might address the presence of the following term in your data: tank (water container) vs. tank (M1 Abrams). Each of these terms might all appear in a dataset. It will save time and money to differentiate, combine and consolidate the data. Semantic technologies have advanced to a point where they can provide a great deal of assistance in making this distinction and classifying data. Regular expressions are your friend during this critical step.

Explore – Once the data is clean it is time to explore the possibilities. During this step, data can be visualized using a variety of techniques. This visualization process will help drive the creation of hypotheses that can be tested in future steps. Data can be visualized on maps, charted in histograms, or clustered together in a dendrogram using K-means or hierarchical clustering. Open source tools such as Google Maps and Tableau have made it easy to start visualizing data with little learning curve.

Model – This is the hypothesis step, used to help predict and interpret. Selecting the right model will directly impact the outcome of the analysis.

Interpret – Let us go back to our Netflix example, the interpretation step in Netflix's recommendation engine is the recommendation itself. The algorithm or model has done what it is meant to do, predict an outcome. At this point, knowledge of a domain can help to determine if the model is accurate.

Learning Analytics – What the Future Holds

The 2011 Horizon Report predicts that the time for adoption of learning analytics is four to five years out. The report concludes that "learning analytics promises to harness the power of advances in data mining, interpretation, and modeling to improve understandings of teaching and learning and to tailor education to individual students more effectively." Although the report focuses in on the education market (K-12, higher education), the fundamental concepts described in the report apply across all learning domains.

Current Research & Development Efforts

There are several examples of research and development efforts underway that are looking at leveraging data and data analytics in their solutions. Most of these cases deal with a single data source in the sense that it is data collected within their own environments. These examples are only provided here to get an understanding of what some in the industry are building in regards to learning analytics.

Purdue University has developed a program called Signals (Purdue University, 2011). The Signals program is a campus-wide program that is integrated within its Blackboard Vista environment. The Signals program is used to detect early warning signs and identify the need for potential intervention actions for those students who may not be performing to the best of their abilities. The program utilizes common data analysis techniques, such

as data mining and predictive modeling to assess a risk level and signal the learners at the appropriate time.

The University of Wollongong has developed an application called Social Networks Adapting Pedagogical Practice (SNAPP). SNAPP is an application that allows users to visualize the network of interactions resulting from discussion forum posts and replies (University of Wollongong, 2009). SNAPP can be used to identify patterns of behaviors such as:

- Who is posting to the forums more frequently – key information brokers
- Who is replying to posts
- Which learners are interacting with which learners the most
- Which learners are "disconnected."

Knewton is an organization that is building a learning engine that is described as a continuous adaptive learning platform that assists students in preparing for Graduate Management Admission Test (GMAT), Law School Admission Test (LSAT) and Scholastic Aptitude Test (SAT) tests. Knewton advertises that it is "developing the most powerful adaptive learning engine. It is the only platform that offers continued adaptivity – the ability to customize educational content to meet the needs of each student on a daily basis (Knewton, 2011)." Knewton captures data within its own environment. This data is used to customize content and paths the student may take within the application.

The Kahn Academy has produced a website that hosts over 2100 educational videos in the fields of math, science, humanities and test preparation (Kahn Academy, 2011). Part of the solution set that the Kahn Academy offers is a rich set of data based on self-paced exercises performed by the learner. This data is then maintained and exploited to help a learner through a specific knowledge map. Information and data collected is available to show proficiencies in a particular subject, time spent viewing videos, time spent on exercises and achievements obtains. The Kahn Academy is another example of a solution that is focused on data that is collected within its own environment.

BRINGING IT ALL TOGETHER

On one hand we have a shift of focus happening towards learner-centric approaches, personalization and enabling a more personal approach to learning. On the other hand we have the emergence and maturation of

data analytics within the learning, education and training domains. We believe there is a perfect storm brewing at the intersection of these fields of study; something that will truly put the learner front and center and enable the provision of solutions in which the learners:

- Are more engaged,
- Experience an increase in long term retention,
- Have a self-awareness of their learning capability, and
- Have the ability to understand their processes for obtaining knowledge and skills.

So, what are the next steps? What has to be done to control this perfect storm in order to obtain value out of the emergence of these fields of study? Based on our research, we believe that the study and development of a personal learning ecosystem along with the definition and understanding of personal learning assistants are needed.

Personal Learning Ecosystem Framework

Because of the variety of "learning environments" that exist today, it is hard to define a single learning framework. Arguments can be made that we learn in variety of ways and in a variety of contexts (peer-to-peer conversations, LMSs, gaming environments, use of social media applications, etc). Each of these contexts, however, fit into an overall ecosystem. In this ecosystem there is:

- A mixture of media and content that can be leveraged,
- A significant number of applications that learners can be engaged with,
- A rich set of untapped data sources to assist with personalizing and engaging the learner, and
- A fundamental infrastructure to deal with communication, security and data storage.

This ecosystem has to define a set of parameters, conditions of use, policies and practices for content/media, learners, solutions providers, data and a rich set of applications.

We believe that the following components of the ecosystem will need to continue to be studied, researched and developed:

- **Open Application Programming Interfaces (APIs)** – continued development of open APIs

enabling open communication across applications and accessing the rich data that exists in these applications
- **Data Storage** – techniques for easily storing, maintaining and accessing portable data storage (e.g., private data clouds)
- **Anytime Access** – ability to gain access to data, applications and information in the ecosystem anytime through any means (e.g., PC, mobile device, Internet of Things)
- **Communication Protocols** – with the identification and definition of open APIs, one also needs to utilize communication protocols that are transparent and easy to use
- **Data Framework** – with the rich set of data being left behind, do we need to look at defining data sets or data definitions? Or should we look at more self-describing data sets where the entity accessing the data understands ahead of time the types of information they are gaining access to?
- **Variability of Content and Context** – support for the variability of content and media in use today and the future needs to be supported along with the variety of contexts in which this content is used.

One thing that must be done within this ecosystem is to utilize advancements in these components that are taking place in other domains. There is no need to reinvent the wheel and focus should be on leveraging the advancements already made.

Personal Learning Assistants

The concept of a personal learning assistant is not new. Even the activities that one might imagine a personal learning assistant would perform are not new. Solutions that utilize personalization techniques and intelligent tutors exist today. So what is different? What has changed? We believe the driving factor for what is causing this change is the abundance of data and, more importantly, the use of this data.

In its simplest form a typical intelligent tutoring system (ITS) contains three primary components: an expert model, a student model and a tutor model. These models interact with each other to help guide or tutor the learner throughout a learning experience. The challenge in any ITS solution is building these models up front. What if the models were built on the fly, using the information and data gathered through the lifetime of the learner used to assist the learner through any and all experiences? We believe that is the difference.

Then what is a personal learning assistant? What characteristics does one have? What are its roles and responsibilities? These are the types of questions that need to continue to be researched and developed. We believe that ultimately a set of characteristics or traits can be identified. These characteristics and traits will then lead to the development of a set of personal learning assistants, eventually leading to a taxonomy of personal learning assistants that can be intermixed and used collaboratively within a personal learning ecosystem.

In order to be successful and ultimately usable, these personal learning assistants should focus on one and only one role or responsibility. This is the keep it small and focused philosophy – do not define monolithic and huge assistants that do everything. In this manner the personal learning assistants then can be easily reused in other contexts. Roles and responsibilities might include things like:

- Monitor and gather data from a variety of sources
- Clean data that has been gathered and provide the ability to supply that data in a variety of formats
- Model data that is gathered to assist in the development of prediction models, course correction models, recommendation models, etc.
- Assist in answering questions throughout the learning process
- Provide alternative paths or adapt the path during a learning experience to challenge and engage the learner's sense making skills
- Coach, mentor and provide positive feedback to the learner throughout learning experience.

The vision here is that your personal learning ecosystem would have multiple personal learning assistants all working in harmony with each other to deliver a true engaging and personal experience.

CONCLUSIONS

As seen throughout this paper, the learning, education and training domain continues to make strides toward learner-centric approaches. In the mean time, instructors and designers are beginning to have the opportunity to access and think about how to use a growing set of learner data. As these fields of study continue to mature and transition research into

solutions, more and more benefits come to the light for the learner.

Finally, with the emergence, research and application of data analytics within the learning and human performance domain, more and more opportunities exist to really drive a learner-centric approach to learning, education and training. The ability to track the massive amounts of data "bread crumbs" left behind by learners in many of their online activities is growing exponentially. Turning that rich and deep digital footprint into actionable data is the cornerstone of building a true personal learning ecosystem filled with a variety of personal learning assistants facilitating a true immersive, personal and personalized learning experience.

REFERENCES

Siemens, George (25 August 2010). What are Learning Analytics? Retrieved from http://www.elearnspace.org/blog/2010/08/25/what-are-learning-analytics/

Blumberg, P. (2009) Developing Learner-Centered Teachers: A Practical Guide for Faculty. San Francisco, CA. Jossey-Bass

Blumberg, P. (2004) Beginning journey toward a culture of learning centered teaching. Journal of Student Centered Learning. Volume 2, Issue 1. Pgs 68-80.

Singh, Vik. (2011, April 18). Ranking High Schools Based on Outcomes. Retrieved from http://zooie.wordpress.com/2011/04/18/ranking-high-schools-on-outcomes/

Purdue University. (2011). Signals – Stoplights for student success. Retrieved from http://www.itap.purdue.edu/tlt/signals/

University of Wollongong. (2009, December 4). About SNAPP. Retrieved from http://research.uow.edu.au/learningnetworks/seeing/snapp/index.html

Knewton. (2011, June 28). About Knewton. Retrieved from http://www.knewton.com/about/

Johnson, L., Smith, R., Willis, H., Levine, A., and Haywood, K., (2011). *The 2011 Horizon Report*. Austin, Texas: The New Media Consortium

Kahn Academy. (2011, June 28). About Kahn Academy. Retrieved from http://www.khanacademy.org/about

Picciano, G. A. (2002). Beyond student perceptions: Issues of interaction, presence, and performance in an online course. *Journal of Asynchronous Learning Networks*, Volume 6, Issue 1. July 2002. Retrieved from http://sloanconsortium.org/sites/default/files/v6n1_picciano_1.pdf

Anderson, T., Rourke, L., Garrison, R., Archer, W., (2001). Assessing teaching presence in a computer conferencing context. *Journal of Asynchronous Learning Networks* Volume 5, Issue 2. September 2001. Retrieved from http://sloanconsortium.org/sites/default/files/v5n2_anderson_1.pdf

Drexler, Wendy. (2010, August 5). Personal vs Personalized Learning. Retrieved from http://teachweb2.blogspot.com/2010/08/personal-vs-personalized-learning.html

Mason, Hilary, Wiggins, Chris. (2010, September 25). A Taxonomy of Data Science. Retrieved from http://www.dataists.com/2010/09/a-taxonomy-of-data-science/