# Exploring the role of experience API in supporting new trends in Educational Technology: A literature review

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# ABSTRACT

Exploring the role of experience API in supporting new trends in Educational Technology: A literature review

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Despite its growth in the area of educational technology, Experience API (xAPI) continues to be under-used as a solution across the different platforms in institutions and organizations. There is a lack of any detailed summary in the literature about the potential and the limitation of using xAPI in conjunction with learning platforms and technologies. This thesis examines the role of xAPI in promoting, shaping and supporting learning in organizational contexts. This discussion is developed by using cases reported in the literature and new cases from contemporary educational technologies. The thesis illustrates the role the standard plays within current major trends in digital learning and within the context of a broader ecosystem of learning platforms and technologies. It provides a useful and thorough account of xAPI and its potential to an audience of individuals responsible for implementing xAPI within organizations. xAPI provides to some extent a promise of improved impact to Performance Evaluation and Evaluating training Effectiveness. However, xAPI lacks concrete cases and examples to support its utilization in the fields of Learning Analytics, Performance Management, Predictive Learning and Workforce Planning.

Keywords: Experience API (xAPI), Learning Management Systems, Learning Record Store, Learning Analytics, Microlearning, Evaluation Effectiveness, Predictive Learning, Adaptive Learning, Workforce Planning.

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## DEDICATION

I dedicate this study to my parents Mohesn and Eman, to my husband Ali and my kids Sami and Adam, who have been supportive and for believing in me.

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| xAPI | Experience Application |
| LMS | Learning Management System |
| LRS | Learning Record Store |
| CMS | Content Management System |
| AICC | Aviation Industry Computer Based Training Committee |
| SCORM | Sharable Content Object Reference Model |
| HTML | HyperText Markup Language |
| H5P | HTML 5 Package |
| RSS Feeds | Really Simple Syndication |

# Introduction

The number of e-Learning tools in play has increased with the increased use of computers, mobile apps, social media, YouTube, and collaborative learning tools such as Google drive (Tan, 2019). Many of these technologies use learning analytics and Experience API (xAPI) to track informal learning that takes place outside the traditional classroom setting (Rabelo, Lama, Vidal, & Amorim, 2017). In the workplace environment, the organizational learning paradigm is also shifting from formal training initiatives to diverse learning experiences; this is evident as more learners use informal learning and online technologies and platforms to acquire new skills (Tan, 2019).

There is a need to be able to track and analyse the learning experience that happens outside the norm of the formal learning scenario. Informal learning occurs more often than we realize, especially in the workplace, and plays an important role in the employee's learning and development (Cofer, 2000). To address this phenomenon, a directive from the Department of Defence (DoD) in the United States issued on October 5, 2017 requires that all of its learning solutions comply with DoD 5124.02, which, "[a]uthorizes the recording, analysis, portability, and management of learning experience data".

Creating an individualized learning experience in the workplace can be challenging, given the diverse needs of the learner and the myriad accessible learning and training tools. Understanding the evolution of xAPI and its role in workplace learning is a first step toward meeting this challenge.

## Problem Statement and Thesis Purpose

Presnall and Radivojevic (2018) mention that despite its growth in the area of educational technology, xAPI continues to be under-used as a solution across the different platforms in institutions and organizations. In addition, Berg, Scheffel, Drachsler, Ternier, and Specht (2016) indicate that there is a lack of shared understanding and information about xAPI applications among the stakeholders within educational communities. This thesis will provide a synthesis of current trends in learning technologies and an exploration of how xAPI can facilitate or limit these trends. Furthermore, it will address the lack of such a summary in the literature.

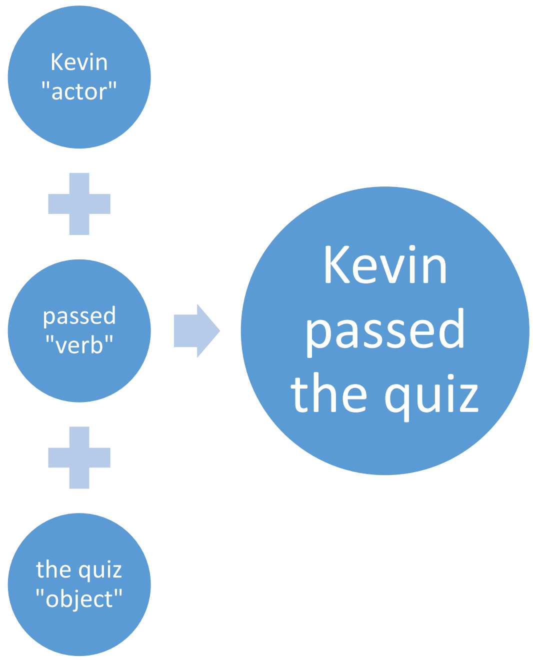
The goal of this thesis is to clarify the potentials, limitations and actual uses of xAPI in workplace learning in respect to emerging trends in eLearning and educational technology, such as: learning analytics, predictive learning, adaptive learning, microlearning, and measuring learning effectiveness paradigms. By providing a clear explanation of the potentials, limitations and actual uses of xAPI, it aims to support stakeholders in the IT industry, and the Learning and Development and Human Resources fields, as they make decisions about implementing xAPI and exploiting the data subsequently compiled in the associated Learning Record Systems.

## An Overview of Experience API

The Experience API (Application Programming Interface), also known as xAPI and Tin Can API, is a monitoring specification for eLearning and learning technologies. It was created by the Advanced Distributed Learning Co-libraries (ADL) as one of four components of their Training and Learning Architecture (TLA). ADL (2012) defines xAPI as “a service that allows for a statement of experience to be delivered to and stored securely in a Learning Record Store.” It is an open source eLearning specification that collects data when a learner interacts with learning content – for example, watching an instructional YouTube video clip -- whether online or offline and in any possible situation (Corbi & Solans, 2014). These interactions are collected as statements with simple English syntax, making it easy to read and understand. These syntaxes include three main components: “actor”, “verb” and “object”. However, they can also include information that provides context such as, e.g., “test results”.

**Figure 1**

*xAPI statement*




Adapted from *US DoD xAPI profile server recommendations*. M. Bowe., & A. E. Silvers, 2018, Data Interoperablity Standards Consortium (DISC). Copyright 2018 DISC. Adapted with permission.

To illustrate further, Figure 1 displays an example of a xAPI statement created and saved in the learning record store when a learner passes a quiz. These statements are transmitted between tools and systems such as Learning Management Systems and Learning Record Stores. These specifications were developed to standardize data gathering for both formal and informal learning. Additionally, they are created in a way that supports the continuous development of data collection techniques (Kevan & Ryan, 2016).

## Theoretical Framework

### *Informal Learning*

Formal learning is recognised as a teacher-centered vertical learning experience. It has clear learning objectives, which are defined and explained in courses and training sessions.

Formal learning in these courses takes place in a structured educational setting; usually, the outcomes of these formal learning experiences are measured. In today's world, however, learning experience mostly occurs unplanned. For example, the learner searches for information when an issue needs to be addressed at the workplace. Or the learner merely wants to fulfil an interest in a new knowledge or a skill. This type of learning experience is referred to as an informal learning event. Informal learning is defined as an unstructured, self-directed form of learning. Lohman (2005) explains that informal learning happens when employees participate in learning activities involving cognitive, emotional or physical effort, and results in the development of professional knowledge and skills. Marsick and Volpe (1999) regard informal learning as

- a learning experience that is prompted by external or internal interest,
- a learning experience that is unintentional,
- a learning experience that is interconnected with the learning of others, and
- a learning experience that is incorporated with the daily routine of the learner.

Cofer (2000) estimates (surely conservatively) that 70 percent of the learners' knowledge in the workplace is gained from informal learning. Informal learning can happen when the learner views a YouTube video on how to use a Pivot Table to analyse data at work. It can also occur when the learner interacts with H5P (abbreviation for HTML5 Package) content to learn about an application used in the workplace. It can also happen when a learner engages with social media such as Facebook or Instagram. These types of informal learning cannot be identified by the same tools used in the formal training setting. This requires us to explore other tools that can capture and track these informal learning activities or experiences. Hence, Experience API is mentioned most prominently as one of the tools that could be used in tracking informal learning. These types of informal learning are influential since they are less managed and controlled than the traditional in-class learning experiences. Informal learning provides the learner with opportunities to react or to control his/her own situational and social learning environments and learning experiences. As a result, the data from informal learning is powerful and it is important to track in all its different forms.

**Organizational Learning**

According to Liboni, Cezarino, Jabbour, Oliveira, and Stefanelli (2019) the learning environment in the workplace is evolving to address the challenges of the digitized workforce. In addition, this evolving environment is pushing towards a learning culture that is compatible with Industry 4.0. The fourth industrial revolution, also known as Industry 4.0, refers to the contemporary movement towards the computerization of manufacturing industries. The World Economic Forum (2016) describes Industry 4.0 as "a fusion of technologies that is blurring the lines between the physical, digital, and biological spheres" that will change drastically how we live and work and how these two aspects relate to each other. This industrial revolution is characterised by being exponential in its velocity, impacting the way we work and the way we develop skills and careers. Hermann, Pentek, and Otto (2016) explain that Industry 4.0 "enables the communication between people, machines, and resources" (p. 3928). They state that comprehending the complex work environment and providing a tactical delivery for the learners is an important aspect in this trend.

In addition, learners apply adaptive activities as a way of social learning. Chia (2017, p.8) states that such "adaptive action is undertaken in response to environmental demands. In this way, a community learns, grows and knows 'as it goes'". Consequently, learning is no longer based primarily on in-class formal learning. Learners are using just-in-time performance support systems to complete tasks they are struggling with. They view online videos and search the internet to learn how to perform a work-related task. It requires a revolution in learning and educational technologies to keep up with this latest industrial revolution, and hence the introduction of Education 4.0. Education 4.0 encompasses adaptability, lifelong learning, and the socialization and individualization of learning (Demartini & Benussi, 2017). As more learners use online technologies and platforms to learn new skills, organizational learning shifts from training to learning (Tan, 2019). New technologies, organizational change, competition and regulatory developments result in constant fast-paced change in the workplace that forces employees to continuously engage in learning, whether it is of the formal or informal variety (Marsick & Watkins, 2015).

**Connectivism as a Learning Theory**

Connectivism as a learning theory, initially proposed by George Siemens (2005), addresses learning needs in the current digital age. It states that learning occurs when learners connect with other learners across networks through the use of various information technologies (Kop & Hill, 2008). It acknowledges that information is stored, manipulated and used through information technology and that, as a result, knowledge itself is fundamentally distributed in nature. Connectivism also builds on the elements of social constructivism, which was formulated by Vygotsky (1978). According to Vygotsky (1978), the learning experience is developed through a learner's situated and social interactions with other learners. He argues that interactions among the learners promote the construction of specific learning. Dunaway (2011) indicates that one of the essential concepts in Connectivism is constructing continuous connections among learners through the development of learning. Learners regularly use different forms of informal learning such as social media, eLearning videos and just-in-time help to develop their skills and knowledge. In the era of digital information and the vast usage of internet and social media, the evolution of digital learning is evident (Dunaway, 2011). This requires new ways of learning, especially when using online platforms and applications. Therefore, xAPI specifications and standards play an important role when applied in the areas of connected learning. In various ways elaborated in this thesis, xAPI supports the enhancement of the learning experience in this digital age.

## Research Approach

In developing this thesis, I used the following search terms to identify my sources:

- xAPI and learning analytics,
- xAPI and predictive learning,
- xAPI and adaptive learning,
- xAPI and microlearning,
- xAPI and measuring learning effectiveness,
- xAPI and workforce planning, and
- xAPI and performance Evaluation.

The following databases were used to apply the search terms mentioned above:

- professional and business journals such as Emerald, Springer, Industrial and Commercial Training, Journal of Business Logistics, FACTIVA and *International Journal of Training and Development*;
- learning technologies centred sources such as ERIC, *Canadian Journal of Learning and Technology* and EdITLib Digital Library;
- technology-oriented journals and magazines such as *MERLOT*, *International Journal of Engineering & Technology* and *IEEE Xplore*;
- publications from organizations, conferences and professional associations such as United States Department of Defence, Association for Talent Development and International Association for Performance Improvement;
- Gartner Research Library; and
- blogs, such as ATD's Science of Learning and Human Capital blog and Learning Solution's Magazine

## The Evolution of Learning Standards and Specifications

### Exploring the History of e-Learning Standards

The first specification ever released for tracking learner's interactions with a Learning Management System was AICC, an acronym for Aviation Industry Computer Based Training Committee -- the group that created these specifications in 1988. The AICC specification uses simple HTML forms and text to define how a learning object located in a course content package communicates with a Learning Management System. According to Singh and Reed (2002), AICC was created for the purpose of regulating the training material for aircraft manufacturers. It was widely adopted and used before it was officially recommended as the standard for Computer-Based training (Singh & Reed, 2002). Eventually a new standard was required as AICC was limited in its ability to track and report course progress. In 2014 the Aviation Industry Computer Based Training Committee was dissolved and AICC support was discontinued.

SCORM was created in 2000 to address the limitations of AICC. SCORM is an acronym for Sharable Content Object Reference Model. It was created by the Advanced Distributed Learning Initiative as part of a research project for the U.S. government. SCORM is still the most widely used standard in eLearning. It can be easily integrated within Learning Management Systems, which are almost universally compliant with the SCORM standard and feature extensive tracking and reporting capabilities. Learning Management Systems are systems designed primarily to track and report users' interactions with formal online courseware (e.g., completion percentages, exam scores, time on task, certifications, curriculum or learning paths) though they may also keep track of, and report, other data such as classroom training events (e.g., registrations, instructor and classroom scheduling, etc.) or training budgets. Using SCORM standards in eLearning introduced many different possibilities in tracking interactions, gathering quiz data and reporting course progress.

With advances in educational technologies, SCORM standards came to be seen as limited or even inadequate. For instance, SCORM standards are not functional if an internet connection is not available. As a result, the SCORM standard is limited in its ability to address issues where tracking off-line learning experiences is required. Similarly, if the connection is lost during an online training session, the reporting for this session will be lost. Secondly, SCORM standards-related data can only be tracked in a Learning Management System that conforms to the SCORM standard and in combination with courseware that is packaged according to the SCORM requirements (with a SCORM 'manifest"). Many learners view YouTube videos or interact on social media when learning something new. As these types of media are not identified to Learning Management Systems, SCORM standards cannot track those eLearning experiences. Finally, SCORM standards are compatible mainly with Flash-based content, which is currently being replaced with HTML5 in eLearning technologies. In order to track HTML5 files, they must be exported to a SCORM standard format, which affects the quality of the eLearning content, imposing limits on the functionality of the material. It is more effective to create the content directly as HTML5 output.

HTML5 output is also preferred because, within an adaptive HTML5 framework, the content can be automatically adjusted and formatted to the constraints of different display devices (e.g., a Smart Phone vs. a tablet vs. a computer screen). Finally, SCORM has limited capability to support and track branching content. Collectively, these limitations make SCORM standards ill adapted to the current and continuously evolving eLearning solutions.

In 2013, Advanced Distributed Learning in the US government and Rustic software worked together to introduce the Experience API standard (pe xAPI), known as “Project Tin Can”. These standards were created to address the limitations of SCORM. According to Bowe and Silvers (2018) “the goals of xAPI were to address a myriad of challenges leveraging SCORM in modern technical architectures”. Experience API tracks learners’ interaction by creating sentences consisting of:

- **Noun** to identify the learner.
- **Verb** to explain the learning action.
- **Object** to identify the learning object with which the learner interacted.

These sentences are captured in the Learning Management System (LMS) and stored securely in a database called a Learning Record Store (LRS). The LRS can then aggregate the tracked information to produce reports. These reports can be used to update the instructional material and enhance the learning experience, especially when the tracked learning is informal, offline and outside the Learning Management System. For example, xAPI is able to support and track learning experiences that take place in platforms such as social media, mobile learning, performance management systems and many more. It is able to gather richer data such as learning gained from gaming, simulations and job performance.

Use cases from the U.S Coast Guard (USCG) (the U.S. Department of Homeland Security) provide insight into the context of how xAPI is used. USCG faced the challenge of connecting and communicating learning information across the different platforms deployed by different Coast Guard units. There was a limited compatibility between the distributed information systems. With the use of xAPI, USCG was able to capture and share any learning the members experienced and accomplished. Steve Flowers (2012) provides the following use case to demonstrate how xAPI is being used in the USCG setting:

- In the first use case USCG used xAPI to track perform activities and tests from members deployed at sea. Members use mobile devices to enter and store the data offline. When the members are within range or on board a ship, they transmit this data to a data store. Consequently, the data is transmitted to a regional Learning Management System. Additional information is entered by the unit heads to provide a comprehensive representation of the member's progress and accomplishments. By using xAPI, units were able to track the members' advancements towards the development of their expertise.

xAPI has promising capabilities, but how can these capabilities be utilized in the context of current eLearning trends? In this thesis, we will explore how xAPI can be used as a tool to support and enhance learning analytics, predictive learning, adaptive learning and measuring the learning effectiveness for the different eLearning tools used in workplace training. The role of xAPI within these contexts is not well understood. Many organizations have adapted xAPI but are still looking for guidance regarding how exactly the data accumulated in an LRS can be used productively, and to what purpose.

## xAPI and Educational Technology

### Learning Analytics

#### *How Can xAPI Contribute to Learning Analytics in Training and Learning?*

Based on the 1st International Conference on Learning Analytics (2011), learning analytics is defined as: "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs".

Consequently, learning analytics is characterised by the data collection and the analysis concluded from the learner's interactions with the learning environment, whether formal or informal. These interactions include the learner's interactions with the content, with other learners, and with the instructors (Elias, 2011). Shum and Ferguson (2012) explain that learning analytics is not focused on the learning process but rather on understanding the gathered data and its effect on the learner's experience. Ifenthalr (2017) specifics that the methodology of learning analytics is focused on the pool of both active and static data gathered about the learners and their learning environment. This data is used to analyse, evaluate and produce "real-time modeling" to forecast and augment the learning process.

This learning data has always been available in enormous volume; it is what created the interest in gathering and tracking it to shed light on learning activities (Lang et. al, 2017;

Siemens, 2013; Ferguson, 2012). Learning activities in the learning analytics context include learning opportunities, self-evaluations, learning suggestions and feedback, peer evaluations, group exchanges or additional links and resources (Ifenthalr, 2017). Learning data could also include descriptive information, such as the time spent to complete a certain learning activity, access to online resources and progress towards completing a learning component. Another important component is descriptive information about the learners. This descriptive data might include learners' characteristics such as prior experience and knowledge, socio-demographic information, and prior performance.

Learning analytics has the potential to offer many advantages, such as the ability to provide aggregated data, instantaneous data and predictive data, which can be leveraged for future learning opportunities. To explain further, the aggregated data can include comparison of different learning paths, information about learning habits and learning preferences, and learning outcomes based on learning episodes. In addition, it tracks progress towards completion of a learning objective. The instantaneous data can provide insight into the assessments that are completed by the learners. Furthermore, it can provide information about the feedback the learners received. Finally, learning analytics can provide many opportunities for predictive learning modules; for instance, it can optimize learning paths based on patterns of success and failure. Based on the recommendations gathered from the learning analytics, possible learning risks can be identified that will inform the developers of alternate learning interventions that will improve learners' interactions with the learning content and increase the success rate among learners.

How is this information being gathered? Learning analytics relies on web-based applications that can gather the information, whether through content management or learning management systems. According to Yupangco (2017), there are three types of data that can be gathered in learning analytics: engagement data on how the learner is engaged with the learning content; performance data, which is related to learner's assessments and evaluations; and finally, support data, which is gathered from sources that are not related to the LMS (Learning Management System) or CMS (Content Management System). Examples of data sources are

- information gathered through logs from a learning site,
- information such as IP address of the device the learner is using,

- the time the learner spent on a learning activity or a resource,
- login information such as date and time of login,
- information about the enrolment of the learner in learning courses,
- the frequency of accessing the learning content,
- information about participation in learning activities (such assessments, discussion forums and posting learning journals),
- information about viewing online learning resources,
- the feedback the learner is receiving from the instructor and other learners,
- information about tracking learning completion, and
- information about comparing the learning logs with external information such as the frequently opened support tickets.

Understanding the methodology used in gathering data for learning analytics will help us understand the impact of using xAPI in augmenting the collected information. As mentioned in the “Exploring xAPI” section, the methodologies of gathering information for both learning analytics and xAPI are similar and possibly overlapping. However, it is challenging to know which information sources are the most effective. In order to identify the best resources and efficiently gather the essential data, it is necessary to know the purpose of gathering data for learning analytics (whether it’s for learning forecast, personalization, learning interventions, or information conceptualization) and where this data is needed. xAPI can be utilized to increase the possibilities of the data gathered, specifically when the platform used to deliver and manage learning doesn’t itself support the use of learning analytics tools.

Analysing xAPI learning data for the purpose of enhancing the learning experience is intriguing but can be very challenging for many reasons. One of the main reasons is that the various Learning Management Systems and other learning platforms lack consistencies in tracking xAPI data, thus making it difficult to combine and analyse data gathered from these platforms, even for the case of similar learning interactions occurring across the platforms (Chiang, Tseng, Chiang, & Hung, 2015).

With the help of xAPI, learning analytics can provide an important foundation for other trends in educational technology. xAPI can be used to collect and aggregate the data and learning analytics can be used to compile. analyze, interpret and understand this data. The combination of tools can provide a foundation for aligning learning analytics with learning theories. To clarify, based on studies by Schumacher and Ifenthaler (2018), learners anticipate that learning analytics can play an important role in supporting their “self-regulated” learning. This supportive role takes place through the aid of personalized and adaptable learning. This is linked to motivational theories.

To illustrate, a process theory of motivation such as the Goal Setting Theory indicates that the goal is an aim of an action. This theory explains that learner’s goals are possible predictors of their achievements. Learning goals can be motivational because they direct learner’s efforts and lead to the development of learning strategies that help those learners reach their goals. However, the learning goals must encompass specific characteristics to be motivational. For example, they must be clear, specific and have a time frame. They must be challenging to be motivational and there must be feedback available for the learners to know how well they are learning.

Learning analytics can provide information about how well the learners did in previous learning. This information can be used then to structure a personalized and adaptable learning for the learners. Using this information to set up a well-defined learning goal can affect the progress of self-regulated learning because it will provide a learning environment that is highly motivating. Learning analytics with the help of xAPI, can provide more information on learning areas that require improvements, identify areas of risks and struggles the learner is encountering, and inform adoption rates of the learners for the newly learned skill or knowledge.

On a larger scale, this information can be helpful in improving the level of competencies across the learners while reducing cost and increasing profits, resulting in increased organizational efficiency. For that reason, there could be a positive connection between xAPI and learning analytics and the possibility of each one feeding the other one with data. Using them collaboratively can enhance the learner’s experience, specifically if the benefits are reflected in the users’ personalized learning journeys.

However, there are many challenges facing learning analytics according to Ferguson (2012). One of the challenges is constructing a strong connection between learning analytics and learning science. There are many systems used to track learner interactions with the learning content such as learning management systems and virtual learning systems which, as a result, creates a large amount of data that needs to be analysed and aggregated. These learning systems can generate massive amounts of data; however, they are basic when it comes to analysing and interpreting data (Ferguson, 2012; Dawson, 2009). Therefore, these data are basic and mechanical, and they lack connection (interpretation or meaning) with the learning sciences.

Learning analytics focuses mainly on the quantitative data that are generated from learning behavior with the use of quantitative metrics analysis but it does not take into consideration the social data. To explain further, this data includes static information about the leaner such as age and previous education. In addition, it includes dynamic data about the learner's engagement with the learning content. However, Shum and Ferguson (2012) indicate that learning analytics may lack social data such as preferences, learner's reflections of the learning process, discussion of resources between the learners, and agreement or challenging opinions about learning. Social interactions between the learner and the content, the instructor and the other leaners is an essential part of the learning process.

Shum and Ferguson (2012) emphasise the importance of considering how the learning happens and how it can be reinforced and maintained while taking into consideration social analytics aspects such as "identity". Shum and Ferguson (2012) refer to identity in analytics as the data related to pre-inherent learning qualities, learner's individuality and the learner's personal desires. For example, this can be related to the individual learning preferences – whether, e.g., the learner prefers to acquire the new knowledge through watching a video or reading step-by-step instructions. Dawson (2009) states identity can be augmented by the usages of social network learning. If this challenge is addressed, it can create an environment where the learner's "self-awareness" can be increased. Learners can access, produce or obtain reports with details about their research over time and include information about the where the results of the research are coming from. This provides the learners with information about how much time and effort is spent in these directions. In addition, the learners can get information about which sources and channels have been the most successful.

Dawson (2009) also mentions the challenging task of developing different approaches of working with a broad set of databases with the intention of optimizing the "learning environments". To explain further, data gathered about the learner's interaction and movement within and across different learning environments can be captured and analysed for the purposes of making strategic interventions in the learning of individuals who are at risk. This can be evident when managing data outside the virtual learning environment or any learning system, such as informal learning or data from mobile learning.

Ferguson (2012) adds that is not easy to focus on the viewpoint of the learner. It is important to take into consideration all types of data gathered from assessments, whether quantitative or qualitative. For example, rather than gathering data on scores alone, the data should also include information about the learner's engagement, satisfaction and motivation. For example, the gathered data can include information about the learner's engagement with the learning content through attempts and participations. Data can also include information about the learner's engagement with their peers through their interactions in forums, peer reviews, and engagement in collaborative social learning environment. To illustrate more, learner A posts a message and subsequently learner B posts a reply message. This data can be captured and used to analyse learners' engagements. In addition, learners can provide input about their satisfaction and motivation through questionnaires and surveys. xAPI can be used in these examples to gather data about the learners.

The wide-ranging scope of data collection that is implicated in learning analytics raises some issues. Developing and applying strong "ethical guidelines" can be difficult in learning analytics. For instance, what rights do the learners have towards their gathered data, and what are their responsibilities with regards to recommendation and personalization provided as a result of learning analytics. All these challenges, if addressed, can provide lessons learned for the application of xAPI when used in combination with the different learning trends in Educational Technologies.

Although the above-mentioned examples may be promising, there is a lack of evidence in the literature -- an absence of practical cases demonstrating whether xAPI can indeed add value to the learning analytics. In addition, there is no evidence in the literature to inform whether the work associated with integrating xAPI Learning Record Store with learning analytics system will yield the advantages included in the above-mentioned examples, and whether it is possible. The return on investment of such integration needs to be investigated in order to provide an informed recommendation.

Furthermore, there is a struggle with managing the enormous amount of data produced by learning analytics (Reyes, 2015). This big data requires an infrastructure and storage capabilities for supporting learning analytics. The question here is, would the addition of xAPI data yield a measurable outcome that learning analytics is not able to achieve on its own? Again, there is a lack of evidence in the literature and in practical examples. As a conclusion, there is a lack of results and the existing ones are not convincing when it comes to demonstrating advantages or benefits of using xAPI with learning analytics.

**Predictive Learning**

***What Could Be the Role of xAPI in Predictive Learning?***

Predictive analytics has been used successfully in many areas such as marketing, social media, and medicine for many years (Hazen, Boone, Ezell, & Jones-Farmer, 2014). It uses contemporary and historical data and aggregates these data to predict future habits and behaviours. For example, tracking tools and complex algorithms are used to predict the purchasing behaviour of the customers, which is then used to target those customers with marketing offers. Analogously, in the Predictive Learning paradigm, we can track the learners' interests and their learning habits to present them with content that could enhance their learning experience, specifically in the topics they are interested in.

Sin and Muthu (2015) explain that Predictive Analytics in learning "enables predication of the student's behaviour, skills and performance by analyzing various activities performed by the student while interacting with the Learning Management System or with fellow students" (p. 1036, 2015). It uses mathematical calculations and statistical analyses of data which are gathered from historical and current learning experiences to deliver an outcome when a learning action is triggered. Predictive learning is based on the utilization of predictive modeling use cases. This necessitates predictive modeling with a clear and appropriate set of justifications and requirements. For example, a learner shows continuous interest in using MS Teams to schedule online meetings.

By using xAPI, search engines can gather information about the employee's interest about this topic and the various searches performed by the learner across the different search engines and search sites. Data about the performed searches is collected and then gathered in the form of xAPI statements. Consequently, this information is used to anticipate the relevant learning content related to Microsoft Teams functionalities and feature. This predicted relevant learning content is presented to the learner in the format of RSS feeds (Really Simple Syndication) or via meta data associated to content in a content management system or the semantic web or a video feed.

For it to work, Predictive Analytics requires a large amount of data. Both historical and current data is needed to provide the appropriate prediction for the outcome. It also requires gathering data related to learning trends and patterns. This data is general and not personal to a learner. Once this data is gathered for the appropriate predictors, a linear statistical formulation is created to process this data. A revised calculation model is created with the addition of new data. Learning specialists can use predictive modeling from the learner's historical learning data, run a predictive algorithm to determine what type of content and learning experience the learner might be interested in and the kind of learning path they are likely to choose. However, it can be limited in understanding human behaviour because its prediction relies solely on data that is previously recorded and gathered, and not on real time data.

By gathering this data, Predictive Learning can be used to facilitate the

- prediction of a learner's performance,
- prediction of learning behaviours,
- learning and performance related risks detection,
- learner skill consideration, and
- learning path recommendation.

It is important to note that Predictive Learning depends on the relevance and value of the gathered data. So how effective is xAPI as a tracking tool for Predictive Learning? And how well can the collected data be aggregated to predict future learning?

Predictive Learning models are used to help struggling learners who require assistance based on the information gathered about their learning behaviour in a given learning episode. These predictive models track the learners' behaviour in online environments and provide a forecast about their learning success. The predictive model tracking data includes learning completion, presence, participation and any form of social learning.

However, it's important to note that predictive data tracking should be learner-centred in order to provide the appropriate learning intervention. Kruse and Pongsajapan (2012) explain that a learner-centered approach considers the learner as an active agent in the learning processes. The gathered data is based on the learner's experience, acquired knowledge and skills, therefore, the focus in this approach is on the activities performed by the learners. Because this data is personal the learning intervention will be tailored to the needs of the learner. For example, a learner is struggling with completing a task in a software application and tries to find information online. With predictive analytics, this learner-centered approach to data gathering can then be used to evaluate the topics the learner is pulling and pushes the appropriate learning topics to assist this struggling learner.

On the other hand, a content-centered approach relies heavily on the learning content rather than the learner. In this case, the gathered data is pushed to the learner based mainly on the sequencing of learning and pushing learning topics to the learner regardless of what the learner needs or is struggling with. For example, the learner is trying to complete a task in a new application. The information will be pushed to learner based on the curriculum and the planned learning sequence – which is common to all learners, and not individualized. The approach cannot predict the needs of the learner because the data does not represent the learner's personal learning.

There are several complications in using xAPI in Predictive Learning. The continuous increase in the amount of data and the diversity of the platforms involved make the task of managing it challenging (Waller & Fawcett, 2013). Furthermore, Virtual Learning Environments (VLEs) must be able to work with xAPI to optimize the quality of the gathered data, yet few VLEs are compatible with the different data stores. Baneres and Serra (2016) explain that in the case of Predictive Learning, xAPI is required as an interface layer in transferring inputs from the VLEs into a Predictive Analytics System. Furthermore, according to Cooper (2014), interoperability between predictive learning systems, Learning Management Systems and xAPI is important to creating a successful learning experience, but is currently problematic because it is hard to pull data from different systems and integrate it, especially when the data is spread out across theses systems.

On the other hand, Friedman and Popescu (2008) indicate that in order to predict the quality of the outcome a comprehensive knowledge of the variable inputs is required. They also state that not all inputs could be captured or reflected easily. In the xAPI case, even though the system could track the learning experience that takes place at a certain moment during a certain interaction, it cannot track e.g., the emotional and the psychological data of the learner, which they regard as critical. As a result, xAPI cannot be utilized on its own as a comprehensive predictive learning tool. However, the leaners can be asked to provide their emotional or motivational states as input optionally with the use of xAPI and Learning record stores.

This is another educational technology trend that lacks practical and convincing examples of the usage of xAPI data. In addition, there is a lack of substantial research in the literature about the effect of using xAPI in combination with predictive learning. As mentioned by Waller and Fawcett (2013), there is currently a challenge accommodating multiple platforms and multiple sources of data when working with Predictive learning. According to Attaran and Attaran (2019) this large amount of unprocessed data doesn't provide any value for predictive analytics. For example, it should include clear and precise data about the historical learning experiences and learning patterns to provide a suitable learning forecast. In addition, they indicate that there are technical challenges in integrating predictive analytics into the organizational infrastructure. This includes the different data types gathered from different platform and systems. Therefore, incorporating xAPI data as an additional source is questionable, as a solution. Finally, there is a lack of real-life examples and studies in the literature on whether the addition of xAPI data would add a value to an already challenging infrastructure in Predictive Learning.

## Adaptive Learning

### *What Could Be the Role of xAPI Data in Designing and Creating Adaptive Learning Environments?*

Adaptive learning is the utilization of machine algorithms to manage and then coordinate the interactions between the learner and the learning environment to provide a personalized learning experience. The processes are constructed with the application of the first interactions with the learning material. Later, the machine algorithm will adapt the learning material according to the learners' needs based on their reactions to tasks, quizzes or learning experiences.

To explain more, based on the learning path the user takes, a learning sequence will be presented with learning topics and learning objectives. This adaptive content will include learning examples, explanations and demonstrations specific to the leaner's needs. The sequencing and the level of difficulty (e.g., introductory, intermediate or advanced) are based on the learner's previous interactions. Adaptive learning then presents the learner with the appropriate media files, text, simulations etc. based on the leaner learning needs. In other words, adaptive learning is defined by real time automated changes in the learning material based on the learner's interactions and performance. This type of learning can provide a safe environment for the user to learn and practice real work-related knowledge and skills, for example, in medicine and aviation.

There are other advantages to using this type of adaptable content. For example, it can be used by many learners who display different characteristics. It also helps in reducing the effort and time spent on unnecessary learning activities. In addition, it can address the different learning needs, knowledge and skills backgrounds, attention spans, abilities and interest that characterize learners.

Adaptive Learning has a long history in educational technology. It was introduced by B.F Skinner (1950). He created a teaching machine for introducing novel concepts rather than supporting memorization. According to the learner's response an adaptive path is presented to the learner. If the response was accurate the leaner would receive feedback and positive reinforcement. If the answer is incorrect the learner would be presented with little hints towards getting the correct answer. However, through the years Adaptive Learning continued to be applied in education with limited success. It was re-introduced a few years ago by Former US Secretary of Education Arne Duncan (2013), who envisioned learning to be more personalised in the future.

Kerr (2015) defines personalized learning as the variation of content delivery method and pace according to the learner's needs. In addition, he states that Adaptive Learning is a form of personalized eLearning experience. It is based on the collection of previous interactions between the learner and the online content and, subsequently, using this information to lead the learner into personalized learning paths in an eLearning environment. He explains that in the Adaptive Learning environment the interactions, learning objectives, content and the pace of learning vary for each learner.

Therefore, in order to create an adaptive learning environment, we need to utilize the data and the appropriate algorithms in the eLearning environment in order to adapt it to learner's interests and preferences (Maseleno, Sabani, Huda, Ahmad, Jasmi, & Basiron, 2018, p. 1125). Gavrilovic, Arsic, Domazet, and Mishra (2018) applied an algorithm using JAVA programming language to create effective adaptive learning. They explain that the algorithm depends on data gathered from the learning objects for each learner, the results of applied tasks by the learner using the Java grader and the learning management system. It then directs the learner to the adapted learning materials that allow improving the confirmed knowledge.

Tseng, Chu, Hwang, and Tsai (2008) explain that the personalized information that is gathered for the development of adaptive learning should revolve around the "learning style" and the "learning behavior" of the learners rather than relying merely on "learning performance". By following this approach, they were able to conclude that taking into consideration the learning styles and behaviours of the learners resulted in an increased sense of learning accomplishments and learning effectiveness. To reach this conclusion they analyzed the results from three groups of students using different adaptive learning approaches (two-source adaptive course, single source adaptive course, and Non-Adaptive course). They used a questionnaire based on James Keefe's four-fold framework (Keefe, 1987) to identify the initial learning styles of the students. They define learning style as mediating among learner characteristics, the content, and the instructional method: "the characteristics of the content of a learning experience are a critical factor affecting the relationships that exist between student characteristics and instructional methods" (Tseng, Chu, Hwang, & Tsai, 2008, p. 778). In addition, they indicate the learning behaviour of the participants as their online behaviour such as "idle time, response time, effective learning time, ineffective learning time, and login time" (Tseng, Chu, Hwang, & Tsai, 2008, p. 778). They used parameters for learning styles and learning behaviour to determine the "difficulty levels" and "presentation styles" of learning content for each learner. Based on the result of this study Tseng, Chu, Hwang, and Tsai (2008) propose an effective adaptive learning application that takes several sources of personalized data into account, with individual learning behaviors and learning styles.

The two examples above illustrate the circumstance that "adaptive learning" varies as an approach depending on the selection of characteristics which are the basis for adaptation. In the second example, "learning styles" play a critical role, though this is a controversial construct in the education literature, with a strong following among practitioners, but very little support in the academic research literature (Pashler, McDaniel, Rohrer & Bjork, 2008; Coffield, Moseley, Hall & Ecclestone, 2004; Tobias, 1989).

Adaptive learning has been used in the workplace to accelerate learners' onboarding process. It provides the new employee with an engaging learning environment that enhances the adaption of new skills and knowledge (Lavoué, Monterrat, Desmarais, & George, 2018). Adaptive learning provides the employee with a recommended learning path that is specific to his or her needs. This adaptive training technology allows organizations to provide the learners with only the essential learning that focuses on the needed skill or missing knowledge. It helps the developers and mangers to zoom in on the learners who are struggling with the learning content as well as learners who are inactive or, alternatively, interacting continuously with the learning content. It's also beneficial because it provides reports and analytics about strengths and weaknesses of the learners with regards to the learning material.

Understanding the development of the Adaptive Learning content is important in exploring the effect of xAPI. In addition, it can help in knowing whether xAPI standards can support this type of adaptive content development. According to Lee and Park (2008) there are different approaches for developing adaptive instruction. Therefore, an "adaptive" instructional approach refers to the specific educational approach that uses instructional strategies and built-in resources to allow each learner to take the learning path that is based on their learning needs, at their own pace. These approaches include Macro-adaptive instructions, Micro-adaptive instructions, Adaptive Hyper Media Systems and Aptitude-treatment instructions. Each approach will be described in turn.

The macro-adaptive instruction is dependent on creating a few main instructional objectives with general content and specific delivery methods. xAPI can track and gather data about the learner's achievements in relation to the instructional objectives and construct a personalized learning path across the different contents and delivery methods. xAPI can be an excellent tool for facilitating the adaptation of the learning content on a macro-level, specifically when the learner is moving from one learning episode to another.

The third approach, which is the micro-adaptive approach, focuses on the specific learning needs for the individual to provide suitable instructional treatment for this learning need. This type of approach guides the learner through the learning experience through the continuous process of analysing and diagnosing the learner's needs, performance and abilities. It uses this data to recommend and adapt the instruction to suit the individual needs of the learner *within* a given learning episode.

Pearson's Platform for Adaptive Learning (https://mlm.pearson.com/northamerica/educators/features/adaptive-learning/index.html) is a real example. Pearson invested heavily in transforming their approach and business model from textbook publishing to Adaptive Learning recently. They conducted extensive research for 40 different Adaptive Learning tools to compare with their Adaptive Learning platform. The research indicates that Adaptive Learning tools must be able to gather detailed information about individual learner's behaviors. This takes place by tracking how learners interact with the learning content. They indicate that "tools that don't collect data in real-time are not adaptive" (EdSurge, 2018, p. 16). The first stage in their adaptive platform is collection of data. This collected data should have three main characteristics. The first one is data type such as learner's interest, number of attempts, test scores or the resources visited for help. The second one is data granularity and difficulty level such as the level of the acquired skill or knowledge by the learner. The last type is the learner's history and whether the tool can track learner's previous performance. This example provides another justification for the potential use of xAPI at the micro-level to gather this information and use it for the creation of the adaptive learning experience that is recommended for the learner.

Therefore, regardless of the instructional approach for adaptive learning, xAPI can serve as an instrumental tool in gathering the required data in order to tailor the instruction and adapt the learning experience to the learner's characteristics and needs.

Learning behaviours and learning performance can be captured using xAPI. xAPI can be used to augment the data gathered from these learning experiences. However, this requires a technical infrastructure (Kevan & Ryan, 2016) that is able to collect this data with xAPI and then use it to create adaptive learning. In other words, Adaptive Learning Management systems cannot operate without the help of a Learning Management System to collect xAPI data gathered from the learners' interactions. With the use of xAPI statements, alternative paths and algorithms can respond to the gathered data and make learning decisions.

According to Qazdar, Cherkaoui, Er-Raha, and Mammass (2015, p. 3) there is a continuous increase in the use of learning management systems in organizations and educational institutions. Yet, there is a dearth in the application of adaptive learning, even though it is compatible with a learning management system. One of the reasons for the lack of Adaptive Learning is the limitation in the basic tracking tools in the learning management system: they are unable to support the creation of personalised adaptive learning. For example, even though Learning Management Systems can provide data about learner's interactions, they are unequipped with the ability to provide detailed data from an integrated Adaptive Learning system which is embedded within the Learning Management System. In addition, therefore, Qazdar et al. (2015, p. 3) state that eLearning standards such as xAPI are required to incorporate adaptive learning systems into learning management systems. xAPI can act as a bridge that connects the two systems in providing the required data.

The role of xAPI is important in adaptive learning. It can be applied to the aggregated data from a learning management system tracking data via xAPI, including the learner's interactions, interest and searching habits, to aid in the delivery of personalized eLearning resources. Consequently, a learning path would be recommended to the learner which is also characterized through xAPI statements in Adaptive learning.

Sottilare, Long, and Goldberg (2017) examined the utilization of xAPI in Adaptive Learning. In their study they evaluated the possibilities to improve the learner's "competency assessment capabilities of the Generalized Intelligent Framework for Tutoring (GIFT)" (Sottilare et al. 2017, p. 266). GIFT is a computer-based system that was used in this study to improve the adaption and the effectiveness of an Intelligent Tutoring System. GIFT was used to create fine grained xAPI statements for successes accomplished in GIFT-based tutors. In addition, GIFT was enabled to utilize the generated xAPI statements and use them to adapt the learning instructions. They explain that different levels of learning experiences should be considered when selecting the appropriate adaptive learning instructions. They claim that Adaptive Learning did improve by using the xAPI statements. They concluded that modifying xAPI statements to include fine-grained details resulted in improved Adaptive Learning in the Intelligent Tutoring System. They identified five xAPI statements refinements which include:

1. Tracking learning achievements which will aid the flow of learning. For example, augmenting the learning experience by strategizing the selection of the next learning topic or providing an option to skip a topic.

2. Tracking the duration of learning across different learning events. This will improve the understanding of learning consumption and type of contact the learner has with the content. This information can be then used to aid the adaption of the next learning topic. For example, using this information to establish the aptitude for the next learning topic if it should be high, low or moderate based on the time the learner spent on the previous topic.
3. Tracking the source of the learning to determine the quality. They indicate that xAPI statements should include rating based on the efficiency of the learning curriculum (Sottilare et al. 2017). This type of information will provide a mechanism for evaluating the quality of the learning experience such as informal learning.
4. xAPI statements should including both learning and forgetting. Sottilare et al. (2017) indicate that memory of newly learned knowledge and skills is strengthened when learning begins. However, they also indicate that when the learning is completed, learning decay begins. They argue that learning decay (forgetting) levels are different for each learner depending on when the actual learning occurred and the quality of learning. Tracking this information will help in understanding the rate of the learning decay and to help in identifying when a refresher or a learning intervention might be useful for each learner.
5. Tracking assessment of domain competency, whether this is quantifiable, such as a quiz score, or an immeasurable activity, such reading. Quiz score are already used in xAPI implementations. What Sottilare et al. (2017) recommend for less measurable activities or experiences, is using general rules in xAPI statements concerning learning data, based on the effect of these immeasurable activities on the learners' leading them into future evaluated learning experiences when possible.

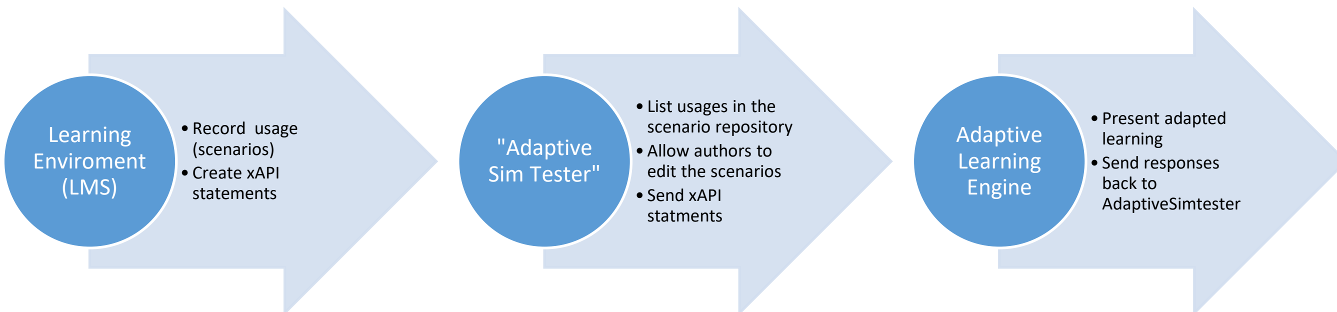
Tracking xAPI interactions is important in determining the next eLearning path the learner will take in the Adaptive Learning environment. However, according to Qazdar et al. (2015) learning interactions that take place in a Learning Management System very often do not support Adaptive Learning. This is due to the lack of interoperability between the two systems and the inability of Learning Management Systems to provide an algorithm for Adaptive Learning. A design intervention based on the utilization of xAPI and then producing adaptive content provides the possibility of including adaptivity in Learning Management System. This case demonstrates an approach for using xAPI to create a connection between Adaptive Learning systems and Learning Management System, if they are used together.

On the other hand, Rosen et al. (2018) explain that the design of an Adaptive Learning environment requires other elements, such as assessments, to demonstrate the learner's competency in the subject. In addition, this design relies on active learning which requires persistence from the learner. Therefore, it is important to take into consideration all design elements for a successful Adaptive Learning environment rather than relying only on the gathered xAPI statements.

Streicher, Bach and Rolle (2019) tested the use of xAPI data to improve Adaptive Learning experience. Based on their study, they concluded that xAPI statements improved the outcome of adaptive learning. In their study, they tested combining xAPI statements' streaming capability with the visualization of the content usage to aid the development of the test cases for adaptive learning. To clarify further, they gathered sequenced xAPI data about the learner's usage and interactions. Later, they attached those xAPI statements to "AdaptiveSimTester" which is a software architecture they created that has the capability to input those xAPI statements. The "AdaptiveSimTester" includes a scenario repository that lists usages (scenarios) from the learning environment described through xAPI statements. The "AdaptiveSimTester" allows the authors to edit and randomize those usages (scenarios) and then sends them to an adaptive learning engine via xAPI statements. According to Streicher, Bach and Rolle (2019) using xAPI data in this case was successful in validating and improving an already applied adaptivity logic. This example demonstrates the interoperability of xAPI statements and the feasibility of integrating xAPI data or statements with an adaptive engine.

**Figure 2**

*Software Architecture*




Adapted from "Usage simulation and testing with xAPI for adaptive e-Learning" by A., Streicher, L. Bach, & W. Roller, in M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Iannou, & J. Schneider (Eds.), *European Conference on Technology Enhanced Learning* (pp. 692-695), 2019, Switzerland: Springer. Copyright 2019 Springer Nature. Adapted with permission.

In conclusion, the addition of xAPI data to an Adaptive Learning software architecture is another possible implementation. However, it is another ambitious possibility that does not have an adequate pool of research studies that prove strongly its effectiveness. With the long history of adapting learning in education, there is still a lack of information on how to improve challenges of interoperability between adaptive learning and other systems such as learning management systems and learning record stores.

According to Sleeman and Brown (1982) computerized assisted instruction using Intelligent Tutoring Systems (ITS) was introduced in the 1970's in classrooms and research labs. Intelligent Tutoring Systems (ITS) have a long history in adaptive learning (Kulik &

Fletcher, 2016 ). Design innovations in Adaptive Intelligent Tutoring Systems are evident in areas of language education, mathematics, science, and medicine (Erumit & Cetin 2020; Oxman & Wong, 2014). Oxman and Wong (2014) also indicate that there is an increase in the usage of Adaptive Learning in corporate training and higher education. Evidence of successful Adaptive Learning is apparent with Pearson's MyLabs products. They are successfully and widely used in higher education (Johnson & Samora, 2016), but results do fall well short of the original promise of ITS and adaptive learning.

The original impetus for ITS research was to find a way to bridge Bloom's "2-sigma" divide – the difference in learning outcomes from individualized tutoring as compared with large group (classroom) instruction, which is about two standard deviations. VanLehn (2011), in a more recent and comprehensive review of the ITS literature, concluded that ITS are effective because of features such as feedback, scaffolding, learner control, but also found that the 2-sigma difference is due to the fact that individual tutoring in most studies was mastery learning based, and the large proportion of the variance over classroom instruction was due to this feature, alone. Looking at past ITS studies through this lens, Vanlehn concluded that simple adaptive tutors which provide answer evaluation of learners' inputs have a mean effect size of 0.31, while those that are step-based (can evaluate each step in the solution path or reasoning generated by a student) plateau at about a 0.76 sd effect size.

## Microlearning

### *How Could We Use xAPI in Supporting the Use of Microlearning?*

The integration of YouTube and social media platforms in day-to-day interactions with different technologies has influenced the way learners search and view learning content. In the age of Web 2.0, there is a move towards the consumption of small nuggets of information (Emerson & Berge, 2018). There is also a demand for up-to-date and just-in-time training in the workplace to access or provide effective learning outcomes in a timely manner when they are most needed; these short learning pieces can be interactive and used across multiple devices to address specific learning needs, whether personal or work related.

Microlearning is defined as the process of delivering eLearning in small pieces, where the content is focused on one or two objectives, and the duration of the content is only a few minutes. This allows the learners to absorb, and possibly apply, the newly attained knowledge before moving on to the next learning nugget. These "bite-sized" learning activities can be delivered through a short video, a mobile application, just-in-time performance support, or infographics. Microlearning can also be used to supplement or reinforce formal learning. This can happen when Microlearning is provided as a preparation for training or as a post training support. YouTube and H5P already provide learning developers with ways that they can integrate xAPI enabled content in their Microlearning activities. This allows learning experiences to be tracked and measured.

Emerson and Berge (2018) explain that employees can benefit from the integration of Microlearning into the organization's Knowledge Management System. Knowledge Management Systems are systems used to create, share, use and manage knowledge within the organization (Girard & Girard, 2015). Knowledge Management Systems could consist of several components in one system or integrated systems comprising, typically, elements such as a content repository, frequently-asked questions database, best practices database or expertise database.

Emerson and Berge (2018) state that Microlearning can engage and motivate the learners. However, they do not provide any evidence to support their claim. In addition, it can facilitate workplace training if applied strategically within the employees' daily work tasks. Implementing Microlearning training can lead to performance improvement in the workplace. According to a survey conducted by Chang (2004) employees' performance improved with use of an electronic s performance support system (EPSS) including hypermedia features such as microlearning. They concluded that the use of EPSS in the organizations they surveyed resulted in improved performance (as demonstrate by an overall mean of 3.5–4.5, where the qualitative interpretation of the number ($n$) used following breakout: $n < 1.5$ is None, $1.5 \leq n < 2.5$ is Little, $2.5 \leq n < 3.5$ is Some, $3.5 \leq n < 4.5$ is Much and $4.5 \leq n$ is Very Much. This measures the overall performance based on various components, which includes online help/reference, data/information base, productivity software, learning/training support.

Fox (2016) argues that a successful performance improvement is aimed at targeting ineffective tasks and providing the employee with on-going help and support to improve task performance and EPSS are specifically intended to address just this aim.

Microlearning modules also contain a small amount of content, which makes the content potentially mobile, easy to update, and interchangeable. The advantage that Microlearning offers is that it makes training in the present-day workplace accessible, inventive and pertinent (Fox, 2016; Emerson & Berge 2018). Injecting training into an employee's hectic workday can be difficult. However, providing employees with small informational nuggets can provide the needed learning in a time frame that can easily fit into the employee's workday, or that fits into and facilitates their regular workflow, consequently, improving the employee's performance and work productivity (Emerson & Berge, 2018).

Using xAPI in Microlearning is beneficial for the success of these mini learning modules as they might be viewed as an informal learning. Learners' interactions and actions with content will not be captured and tracked if they are not hosted in a learning management system. Relying on simply tagging Microlearning is not enough in this case. Because tagging this content will not provide any additional information about the learning experience except that the content was accessed by the learner. Data such as the time the learner spent to view the content of microlearning, data, about the learner's interaction with the content and data about the number of times the content was viewed by an individual learner is important in evaluating the effectiveness of the viewed Microlearning content. xAPI can be used to address this issue. On the other hand, these Microlearning episodes and modules can be tagged and indexed for on-demand training. This way the learners will be able to easily search for them and find them. Finally, they can be requested and used by the employees at a time that is convenient for them. They can easily be provided to the learners on any mobile device. By tracking xAPI data we can identify and use the appropriate content with the best form of modality. In addition, most importantly, xAPI will allow us to track the learner's interactivities.

The successful application of Microlearning as contextualized, targeted, bite-size learnings relies on the ability of the eLearning standards to support it. Behringer (2013) claims that xAPI can address the different requirements of a successful Microlearning approach. Behringer's study focused on the capabilities of mobile devices such as the touch screen, speech recognition, multi cameras and multi-sensing options. In addition, there are the advanced network technologies such as the $4^{th}$ and the $5^{th}$ generation connections. These advanced features require xAPI as a standard for tracking learner's interactions during microlearning experience.

These requirements also include the ability to allocate and store the Microlearning content on multiple servers, share and collaborate across the multiple devices, and gather data about feedback and learner's interactions. He explains that the "learning objectives" and "learning outcomes" which are to be achieved by the learner in a Microlearning module should be outlined.

In addition, xAPI improves Microlearning interoperability by gathering data related to the learner's location, context and engagement with the content, especially with regards to mobile Microlearning. The advantage of using Microlearning is that it does not require a Learning Management System for it to exist since it can be available anywhere. However, a search engine is required to operate on theses distributed sources. Behringer (2013) does not provide any explanations about the issues and the systems involved when it comes to the search engines related to microlearning contents. For example, he does not clarify if the Microlearning content is hosted on a distributed content management system, or if categorization of content is used. It is important to know how the learner will be able to find this content and how is this content being searched and retrieved.

The instructional implementation of Microlearning with the use of xAPI is important to the success of Microlearning in workplace training. It is a misconception to think that Microlearning can be used as the sole approach for addressing every learning need. In cases where the task requires complex and long processing steps, Microlearning is not a feasible solution. Therefore, Microlearning cannot be used as a substitute for formal training. Formal learning is also essential for acquiring fundamental knowledge and skills sets. Fox (2016) argues that Microlearning might not be effective when used for learning complex tasks or for a novice learning a skill. He explains that it works best as a refresher or for reinforcing a learned skill. It can be best used for ongoing personal and professional learning. Therefore, it is critical this type of learning content, in small "nuggets", should be easily found by the employees through a computational search when they need it, and in many cases this can be a challenge. There is extensive literature on "Learning Objects" and "Learning Object Repositories" dating back two decades. Wiley (2002) explains how creating and managing computational searches for "learning objects" and "learning repositories" failed in the past. He states LOR initiatives failed because of many reasons such as lack of "Learning objects" classification or metadata enabling effective search and retrieval, lack of content standardization (lack of consistent technical standards, and lack of standard formatting standards) across the "Learning Object Repositories", and lack of quality control assurance.

There could be a potential in using xAPI data to extract more learning data for the purpose of enhancing the learning experience when the learner is using Microlearning. Nevertheless, it is another trend with limited practical examples on the benefits of implementing xAPI data with Microlearning. The evidence provided by Behringer (2013) does not take into consideration issues related to search engines for distributed content management systems such as categorization. In addition, there is no evidence in the literature on whether xAPI data could improve these limitations. As mentioned in the preceding paragraph, there is a history of failed learning objects approaches and learning repository initiatives. Hence, there is still a need for real-life cases to inform the impact the xAPI data when incorporated with Microlearning.

## Measuring Learning Effectiveness

In this section, I will explore the role of xAPI in measuring "effectiveness". Specifically, I will explore how xAPI could be used to support measuring learning effectiveness in informal learning environments.

In the world of learning evaluation, the Kirkpatrick evaluation model identifies training effectiveness in four distinctive levels. These four levels are reaction, learning, behaviour, and return on investment. To illustrate more, table 1 includes a comprehensive explanation about the level of evaluation, the purpose of the specific level and the method used to assess each level. The Kirkpatrick evaluation model includes the following:

**TABLE 1**

*KIRKPATRICK FOUR LEVELS OF EVALUATION*

| Kirkpatrick Level of Evaluation | Purpose | Method |
| --- | --- | --- |
| Level 1 - Reaction | • Assess the reaction of the end users to the training | • End-users evaluation survey using Likert scale from 1 to 5 |

| | | |
|---|---|---|
| | • Assess the effectiveness of a particular instructional strategy<br>• Assess the effectiveness of the training | • Trainers evaluation survey with short close ended questions |
| Level 2 - Learning | • Assess the extent to which end users achieved a designated learning objective<br>• Assess a specific content the end user needs to focus on | • Learning tests and quizzes<br>• Simulations |
| Level 3 - Behaviour | • Assess the extent to which the end users apply the learned content<br>• Assess if the learned content is transferred into on-the-job behavior after a specific period is passed | • Interviews with Managers<br>• Focus groups<br>• Observation of on the job performance based on training objectives |
| Level 4 – ROI (Return on Investment) | • Assess the impact of the learned content or skill | • Monetary value<br>• Business impact |

Traditional analysis and evaluation tools, such as Kirkpatrick's evaluation model, are mainly used for tracking and evaluating learning in formal workplace training. They are utilised to understand the outcome of the training experience; however, these tools can be inadequate when evaluating informal learning. As mentioned earlier, informal learning of professional skills and knowledge involves activities that require cognitive, emotional, or physical effort (Lohman, 2005). Such learning experiences cannot be tracked or measured using the traditional tools already discussed. Carliner (2012, p. 176) explains some of the challenges in assessing informal learning in general using Kirkpatrick's four level evaluation approach. Two of the main levels for evaluation are measuring efficiency of the training activity and determining the degree of knowledge the learner acquired during the learning process. These two levels can be measured by the learner's reaction (Level 1) and the degree of learning (Level 2). Caliner (2012) indicates that the challenges with evaluating these two levels is that most of the learning is happing unintentionally and there are no clear learning objectives which we can evaluate against. So how can xAPI evaluate these two levels?

xAPI data can be used to evaluate learner engagement in an informal eLearning setting by providing interaction statements. In addition, one of xAPI's data strengths is that it can capture test results and scores in these statements. These scores can be used as a tool for evaluating the knowledge and skills the learner gained from the informal learning experience. However, the real importance in measuring training effectiveness relies on level 3 (i.e., change in behaviour) and level 4 (i.e., return) which is a challenge to measure. More recently, a fifth level (i.e., return on investment) has been added to the model. Therefore, incorporating xAPI standards in level 1 (i.e., reaction) and 2 (i.e., learning) evaluation might not be crucial. One positive aspect of the xAPI standard is that it can be used to track performance improvement.

Performance improvement is represented in the change of behaviour (Level 3) and can be measured by observing the application of the new skills or knowledge on the job. xAPI can gather information about task completion and the rate of completion. An Activity Provider is anything that has the capability to create and send xAPI statements. These xAPI statements are generated based on actions the user performs while in that system. Activity providers[1] can be anything from an email program such as MS Outlook, a customer relationship system or even a device used when preforming a task at work. These activity providers can be programmed as an in-app experience and performance tracker. They can send xAPI statements about an employee's performance to a LRS. As such, activity providers do not capture learning but rather the actual work that is done in real life.

Another example of an activity provider is a digital adoption application. They are used to measure and track the learner's adoption of the newly acquired knowledge and skills. This digital adoption application overlays on top of the software systems used to provide an in-app experience and to track the learner's adoption by collecting data about the clicks and the completed tasks. This gathered data then used to compare with the performance baseline that

[1] https://xapi.com/activity-provider/

was initially recorded by the instructional designer. Finally, the most important levels in the Kirkpatrick levels of evaluations are level 3 and 4. xAPI can provide some help when measuring and tracking level 3. As for level 4 which is return, meaning largely whether programs have met the expectations of stakeholders, measuring the success at this level is already difficult as it is. Level 4 requires complex analysis of financial, operational, sales and marketing data and competitive intelligence, and complex assumptions about markets, as well as quantified or operationalized statements of stakeholder expectations. xAPI can provide little for level 4 for now.

Murphy, Hannigan, Hruska, Medford, and Diaz (2016) explain how xAPI fits with the Kirkpatrick evaluation model and show how it can be effective in measuring learning efficiency with an example from the U.S. Army. The U.S. Army uses xAPI to assess combatants' performance and to gather information about their qualification scores. Previously, they had been relying on final qualifications for their evaluations. Being dependant on final scores made it impossible to gather information about experiential activity when evaluating training effectiveness. As a result, they couldn't figure out the main source of the mistakes the combatants were making during their training. By using xAPI statements, they were able to gather information that wasn't originally available to them. This information included learning experiences the combatants had, whether it was formal or informal, in a classroom setting or out in the practice fields. In particular, xAPIs from simulations provided information about the skills and knowledge of the learners.

Simulations are considered one of the main methods for army training and learning. Murphy et al. (2016) explain that in comparison with real operations, controlled simulations provide the learners with a safe environment where they can stop, resume and replay any training or learning challenge. Additionally, they can be tailored to provide a customized learning experience for individual learners. Due to these circumstances and the need for an effective assessment tool, the U.S. Army incorporated xAPI in the process of evaluating the training and learning provided for their soldiers. This user-case provides an excellent example of how xAPI can be utilized. In addition to test scores, xAPI can gather information related to quizzes attempted by the soldiers in the simulations. Data from xAPI also provided information on the value of these specific simulations for training and learning. The researchers conclude a combination of xAPI and learning simulations can furnish an effective delivery tool.

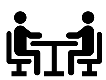
Understanding the reason behind the need for this type of evaluation is essential in identifying whether training or learning is effective or not. According to Kirkpatrick's model of training evaluation (Kirkpatrick & Kirkpatrick, 2006), level one evaluation is used to evaluate the reaction of the learner and to the learning experience. In this example, the U.S. Army wanted to evaluate their simulation training by using the Training Effectiveness Assessments (TEAs) provided by the Department of Defence. TEAs emphasize the learners and measure the level of learning and the application of the newly acquired skill. TEAs were used to evaluate training effectiveness based on the 4 levels of Kirkpatrick's evaluation method; however, in the case of war fighters training it was difficult to evaluate level 3 and 4. Level 1 (reaction) and 2 (learning) were easy to asses by using questionnaires and quizzes. As for level 3 (behavior) the US Army would rely on data gathered from evaluating the degree to which performance transfers from one level to the next in a simulated training event. But this was hard to track and only contained the results from the last level. In addition, level 4 (ROI - (Return on Investment) was almost impossible to evaluate because the data should come from the battle field such as the combat outcome and accuracy. Therefore, the measurements of both level 3 and 4 rely on the capability of evaluating the degree of the transferred knowledge and skills which were gained during the training in operational settings.

To be able to track this data in this scenario a curriculum was developed based on the performance of the trainees in their individual training. The content based on the training was fast-tracked based on the training achievement and the settings where the trainee's aptitudes are demonstrated to track performance (level 3). This was all done while leveraging the use of xAPI in this case. The aim was to evaluate if this adaptive curriculum with the use of xAPI could improve training effectiveness in a measureable way. Murphy et al. (2016) found that the use of xAPI was effective in evaluating performance and, in addition, it was easier to communicate the xAPI data inputs across the different performance simulators. Finally, it is impossible to evaluate level 4 (Return on Investment) since the evaluation relies on the outcome of a real combat. As a result, with the available data and the help of xAPI, the US Army was able to evaluate better the TEAs.

The US Army example shows how xAPI can be used at the different levels of training effectiveness evaluation. In Kirkpatrick's level two evaluation, "learning" is used to assess the acquired knowledge and skills as a result of learning. The following data can be used to measure how efficiently the learner attained information from training:

Figure 3

*Types of Gathered Data*

| | |
|---|---|
|  | Reviews |
|  | Before and after training tests and quizzes |
|  | Interviews |

Adapted from "Leveraging interoperable data to improve training effectiveness using the Experience APA (xAPI)," by J. Murphy, F. Hannigan, M. Hruska, A. Medford, & G. Diaz, 2016. Paper presented at *the International Conference on Augmented Cognition, AC2016: Foundations of Augmented Cognition* (pp. 46-54). doi.org/10.1007/978-3-319-39952-2_5 Copyright 2016 Springer International Publishing Switzerland. Adapted with permission.

As mentioned in the above scenario with the US Army, xAPI can be implemented to assess “behaviour”, which is the third level of evaluation in Kirkpatrick’s model. This level of evaluation focuses on the application of the newly acquired knowledge, skills or attitudes, the degree to which these skills are used when performing an actual work task. The information for this level is gathered from observing the work done by the learner. It can be also based on information about whether the leaner is using the new skill on a daily basis, and if there a noticeable change in the performance after doing the training. xAPI can gather data for third level Kirkpatrick evaluation by focusing on performance. In addition, activity providers[2] are used to create xAPI statements from work applications such as email client application, relationship management systems, work-flow systems or any work-related systems. In this use case, the information gathered from the US Army simulators is used to compare with the actual performance of the soldiers in operations.

Kirkpatrick’s level 4 evaluation assesses the overall productivity of the institution or the organization. This is done ideally through the measurement of return on investment of training. However, assessing level four evaluation “results” is challenging and often difficult to attain. In the case of the U.S. Army trainings, gathering this type of information is not possible, even with the aid of the xAPI. This is because the process of defining the worth of training in the case of soldiers is hard to achieve, especially in live environments (Murphy et al. 2016).

The research conducted by Murphy et al. (2016) concludes that xAPI plays an important role in measuring training effectiveness. They found that by using xAPI they were able to improve the effectiveness of their Army training when using simulations and as a result it improved the results related to performance measurements. The findings of this research indicated all trainees performed very well. With the data gathered from xAPI across performance simulators the group with adaptive curriculum completed the training in nearly 40% less time than the usual span. Using xAPI certainly helped them to better evaluate the training effectiveness and to addresses the basic TEA evaluation shortcomings. However, while it appears to be a potential solution for the long-standing issue with measuring effectiveness of the

[2] https://xapi.com/activity-provider/

informal learning, oddly it is still widely unutilized in conjunction with informal workplace learning.

The xAPI data standard was introduced by Advanced Distributed Learning, which is part of the US government. The examples mentioned in this section are related to US Army and how they were able to apply xAPI standards to collected valuable information they needed to evaluate their training specially in situations where the application of the new skills and knowledge and return on investment is very challenging to measure such as a real battle field. Compared to the other educational trends mentioned in this thesis, the application of xAPI standards to measure training effectiveness at the US Army has proven to be successful. This example could be used to provide an insight on the application of xAPI standards for training evaluations. However, more empirical evidence is required to fully understand the implications and the advantages of utilizing xAPI data to enhance the measurement of training effectiveness in different contexts and scenarios.

## Workforce Planning

### *What Could be the Role of xAPI in Workforce Planning?*

Workforce planning focuses on synchronizing the human resources with the organization's objectives through skills and knowledge development. Workforce planning involves forecasting the volume and structure of employment over a future period. It is vital for the organization to anticipate the projected gap between the demand for talented human resources and its ability to fill this demand. Addressing this gap is critical to ensure the capability and the capacity of the organization to meet goals, scale, grow and survive. In addition, workforce planning is important because of the cost involved in bridging the gap between the projected workforce demand and the ability to address it. The organization then needs to construct an action plan concerning training, development, recruitment, succession (in contemporary terms, this is "talent management"), in order to achieve optimal results. Workforce planning is considered an essential tool for predicting future staffing needs, ensuring access to talent and building an effective workforce.

However, workforce planning relies on different models that depend on the information gathered from different human resource sources. These sources include external and contextual information such as educational statistics, labour market reports, employment figures and business intelligence data concerning trends, competition, markets. In addition, the human resources data include internal information within the organization such as job descriptions, employee records and labor relations, training, skills, employee's competencies, qualifications and job requirements.

According to Wiles (2020), human resource professionals find it hard to close the skills gap between the planned workforce and the projected one. Having the right tools are essential for addressing this challenge and supporting the elimination of this gap. These tools should be data driven to help identify the gap and provide a basis for recommendations for future requirements for workforce planning. People-related analytics data such as resources, expertise and skills are essential to creating a workforce map. This map, along with workforce data and activity, should be parallel to the organizational strategy. If workforce planning is conducted strategically, it will add value to the organizational strategy. In order to gather this data, the organization needs to know the supply and demand, the services the organization provides and the competition in the market. This will set the starting point for identifying the goals for workforce planning. In addition, the organization will need to know where it wants to head in the next few years. Information about the current situation with regards to recruitment and performance management can help in identifying employees who are at risk and employees who have a potential to be high performers.

Training can improve the employee's performance and as a result it can greatly affect the process of workforce planning. This falls under the talent management category. New hires join the organization with the minimum base talent but as they learn more, they are able to perform their job better and this can play a significant role in increasing the productivity and value of the organization. With the correct learning path, these new employees will become the future stars and with the right retention strategies, the organization will be able to retain them.

Cotten sums it up by (2007) stating that successful and strategic workforce planning can result in having "the right people with the right skills in the right job at the right time performing their assignments efficiently and effectively" (2007, p. 6). However, she explains that one of the major challenges of strategic workforce planning is the scarcity of complete and reliable data about the existing workforce; in other words, the employees' skills and knowledge. Information about employee knowledge and skills might be available to the organization through a robust human resource management system. In cases where the information about the employee's knowledge and skills is not available, human resource management should investigate pulling this information from other sources such as reaching out to the employees to get information about any training or certifications they completed outside their work. Human resource management can also get information from sources such as reports about the employee's interaction with the electronic employee support system or the knowledge base at the organization. This kind of data can potentially be collected via xAPI

An important tool for successful workforce planning is workforce analytics. Workforce analytics is defined by Huselid (2018) as the method of comprehending, aggregating and overseeing workforce metrics (workforce measurement criteria) in combination with analytics to understand how to improve workforce planning and, as a result, improve business success related metrics. In addition, it is used to predict the organizational workforce needs and improve strategy implementation (Levenson, 2018). Workforce analytics functions differently from learning analytics since it focuses mainly on behavioral data. Behavioral data includes staffing information, promotions and turnover patterns.

Levenson (2018) explains that there are two methods that can be used when conducting workforce analytics: "competitive analytics" and "enterprise analytics". Workforce analytics is mainly used to improve employment, training, workforce planning, performance management and employee commitment. If the data gathered is well defined, workforce analytics can provide a clear path for employee improvement based on candidate profiles, training progress and performance feedback. So how can xAPI be used as an effective tool for on-going data gathering for the existing workforce within the organization?

xAPI follows the same concept of capturing the learner's or the employee's interactions with the system. In terms of employee training, xAPI can be easily integrated into the learning management system. xAPI can also be implemented to track employees' interactions and engagement with the work and day to day tasks. For example, xAPI can be used to see if the employee was able to successfully access a work-related policy located on a knowledge base to perform a required task. This type of action is not an example of formal learning, but it can be tracked as part of the xAPI statement. In addition, xAPI can track all the information related to the new employee onboarding program. This information can be included in the employee profile and can be used to inform workforce planning and the requirements of filling the gap between the current work state and projected business needs.

As explained earlier, workforce analytics focuses mostly on employees' attributes such as

- Characteristics: this includes gender, physical metrics and work history; and
- Facts: this includes data about employees or learners where this data changes with time such as training level, years spent in a position and age.

On the other hand, workforce analytics can also be used to compare performance across the different departments. According to Levenson (2018), using workforce analytics is critical to understanding performance problems at an organizational level rather than the individual user level. He emphasises the importance of following a holistic approach when identifying the criteria for workforce analytics. One of the main challenges in workforce analytics is lack of data related to employees' individual learning experiences with details such as training performance, learning process and learning interest. For example, workforce analytics cannot capture data about an employee who is trying to use Pivot Tables in MS Excel to provide newly requested reports. This employee might be facing challenges in finding the resources or the support to perform the assigned task. xAPI can be used in this case to capture this data about the employee's learning attempts and searches which can be included in the workforce analytics. This information can then be used to support workforce decision-making. In this case, for example, the supplemental information from xAPI can support the assignment of a coach to provide the required support. Therefore, if xAPI is utilized when possible and in combination with workforce analytics, then performance issues can be addressed in a granular way. This can help the learners by providing them with support and coaching when they require it.

Castells, Monge and Contractor (2011), state that by applying relational analytics, workforce analytics will provide the organization and the stakeholders with more insightful data. When gathered on its own, characteristic or attribute data is not adequate because it provides one dimensional information. However, if used in combination with relational data, it will provide analysts with multidimensional information. xAPI provides both attribute data, such as "Kevin completed the assigned task", and relational data, such "Kevin replied to Sara's discussion form". If workforce analytics incorporates xAPI data, it can add a value to workforce related decision making. In the following section I will focus on the workforce identification criteria offered by Leonardi and Contractor (2018) in their recent article in *Harvard Business Review* to go deeper with the analysis of xAPI with examples from these criteria. They propose the application of six elements in relational workforce analytics:

- "Ideation": The organization gathers information about the employee's educational information, work experience, personality to identify their skills and profiles.
- "Influence": The organization gathers information about the employee's connection to other employees.
- "Efficiency": Creating a team with efficient members who have relevant skills to complete a task can be improved if the organization has a good analytical workforce system.
- "Innovation": The organization gathers data about the employees' attributes to identify those who are high performers and skilled.
- "Silos": Organizations consist of functional units, departments, divisions and groups. These groups might have very limited interactions and communications with one other.

(Perlich & Provost, 2006) explain that using relational learning analytics is important in addressing complex networks; however, it requires a rich collection of data. This rich data can be used to predict the impact of relations on changing behaviour within a work environment. xAPI is available in network and learning platforms such as LinkedIn learning. It can also be used in an internal network system. This will allow the organization to find and aggregate this rational network analytics to easily identify those influencers in the organization with the help of xAPI. Other social platforms are available in organizations such as Microsoft Teams and SharePoint. However, these platforms do not support xAPI for the time being. Currently, other communications and collaboration platforms such as Slack are also increasingly popular in the workplace. Slack and some other platforms are capable of doing network analysis, that records and reports on the patterns and types of communications across the workplace. This data could also be fed into workplace analytics tools via xAPI connections. Most organizations do not use the network analysis feature, but this is likely due to lack of perception concerning how the resulting data and reports could be used.

Gathering attributes data such as skills and knowledge is essential but not enough for creating an efficient team that can complete a task in a timely manner. Guenole, Ferrar and

Feinzig (2017), explain that using relational workforce analytics is essential in predicting efficient team structure with a positive outcome in relation to a task or a project. For example, this means that organizations need to gather information about the interconnection between the employees and, for the purpose of this thesis, the learners. In addition, gathered data should include information about the employees' extra-organizational network, as those employees can reach out to external expertise for more information and support. Such data can help predict the proficiency of the team and their ability to complete an assigned task or a project successfully. As mentioned earlier, when it comes to xAPI, gathered information such as xAPI from LinkedIn Learning can be very beneficial, however, unfortunately it is limited when it comes to other social platforms.

Furthermore, this data could contain information from performance evaluation reports, work experience and educational level. Leonardi and Contractor (2018) and Guenole, Ferrar and Feinzig (2017) provide an interpretation about the structure that could create an effective team and that could be identified through relational workplace analytics. xAPI can gather data related to participation in discussion forms, especially when they take place in a learning management system. Therefore, there is an opportunity of using xAPI in combination with data gathered from relational workforce analytics to augment the benefits of staffing a highly innovative team that can provide a competitive advantage for the department and the organization as a whole.

The higher the level of connection, the more effective it is for the organization, generally, and this can lead to a competitive advantage in the market (Guenole, Ferrar & Feinzig 2017). Organizations with this advantage can share valuable information across their departments and groups and as a result use this information to improve their services and products. With relation to xAPI, this information can be easily gathered from a learning management system when the employee participates in discussion forums. For example, xAPI statements can be used to track the frequency of the employee's participation and whether the employees are participating with the same group or if they reach out to other groups. Again, if the organization uses collaboration and communication tools that would permit xAPI connectors, then a more fulsome picture of the connections across organizational boundaries would be available with the right analysis of the data.

Another area where the organization can benefit from having relational workforce analytics is by identifying the high-valued employees and their relationships to the other employees. Missing important data about those employees can create a possible weakness for the organization. This can happen from reliance of the organization on those valuable employees, and not understanding their relation and connection within the workforce. Identifying those invaluable staff is very important for the organization to ensure a backup is always available and therefore there is no effect on the overall performance.

Often, an organization does not keep clear and essential attributes-related information about those employees. In addition, the management are not aware of their value until they lose them. Therefore, attribute data in addition to relational analytics in workforce planning is applied to identify those employees and as consequence create a backup or a succession plan. In sum, if xAPI supplied data is used in those different relational workforce analytics then the data must be gathered with a focus not only on the general data such as employees' attributes and states, but it also on the employee's interactions and interconnections. Those interactions should be between the employees and the systems and among the employees as well.

In conclusion, xAPI can gather static data including attributes such as physical data and factual data such level of education, but for improved analytics with higher impact on workforce planning, xAPI should be used to gather relational data. This rational data could then enhance staffing planning to bridge the gap between the available skilled workforce and the organizational demand. However, more research and real cases must be conducted to support this hypothesis. At the moment, there are no specific cases demonstrating the feasibility and effectiveness of using xAPI to gather data that, fed into workforce analytics processes and the related tools would lead to enhanced workforce planning.

It must be acknowledged that there is also a challenge with managing and analysing the huge amount of data that would be implicated in the application of xAPI we are considering here (Reyes, 2015). We must take into consideration the limitations of the platforms that are compatible with xAPI or that are not capable of producing xAPI statements. One of the main issues with the utilization of xAPI is the ability to analyze and understand the large volume of data that xAPI can collect in the LRS, making sense of it, and knowing what to do with it. Furthermore, this large amount of gathered data requires an infrastructure and storage that is capable of hosting and supporting this data. Therefore, it is important to conduct further research and development to know if the integration of xAPI standards would produce an improved outcome for bridging the gaps in Workforce Planning.

## Performance Evaluation

### *What Could Be the Role of xAPI in Performance Evaluation?*

Performance evaluation is known also as performance appraisal. Both terminologies can be used interchangeably. They are defined by the observation and evaluation of the job performance in order to develop plans to meet performance objectives. More specifically, Neely, Gregory, and Platts (2005) define performance measurement as "a metric used to quantify the efficiency and/or effectiveness of an action" (Neely et al. 2005, p. 1229). These performance metrics are captured by performance measurement systems. Performance measurements are strategically required because they influence how the learners must perform in the context of their work. Hence, the criteria used in performance measurement systems should be derived from organizational objectives. Each of these criteria must be clear, comprehensible and easily quantifiable (Sahl, 1990). Subsequently, these criteria must be linked to learners' positive developmental activities. This link is required to reinforce the learned skills and knowledge and to rectify any performance-related weaknesses.

The use of xAPI could enhance the data gathered by the performance measurement systems. For example, xAPI data could track data about the learner's performance on their job and compare how well they completed a task against a certain performance criteria or performance measurement. The data might include the completion of a task, the rate of the completion, or customer feedback. When all this information is gathered by xAPI and used in combination with the typical data entered into the performance measurement system the result can be more impactful (Poeppelman et al., 2014). Concrete examples and real cases will be illustrated below.

Another aspect of performance evaluation is measuring key performance indicators (KPIs). These are used to describe and quantify the level of performance required at different levels in the organization. It is difficult for learning specialists and instructional designers to identify performance gaps in order to design and develop learning content that enables the desired performance (Bourne, 2008; Perrini &Tencati, 2006). When it comes to eLearning content, the focus is typically simply whether the learners or employees completed their learning activities. However, this should not be the main KPI. Learning specialists and instructional designers should be concentrating on designing learning content that is impactful and improves the application of the newly learned skills. Therefore, it is important to understand how the organizations are measuring their KPIs and to understand whether xAPI can play a positive role in gathering the needed information.

Organizations and institutions use business objectives and financial goals as the basis for measuring KPIs (Bourne, 2008; Pecori, Suraci, & Ducange, 2019). Organizations use this information to improve and ensure the overall progress towards achieving the desired business objectives. These business objectives and the financial goals include work efficiency, timelines, quality, employee's performance that is needed to fulfill the overall strategy, and employee's skills. xAPI potentially can gather information related to employees' performance and skills, their work efficiency and any information related to timelines.

The KPIs can be an effective tool if the business objectives are captured during the training needs analysis and then implemented effectively in the training design and content. Capturing and constructing the proper business objectives early on can make them one of the main resources for successful KPIs measurements in learning. Learning KPIs are used to measure learner engagement with the training content. They can also be used to track learner attendance in training sessions. Furthermore, they can be used to measure learner progress and completion of training activities.

xAPI can be used for KPIs that are related specifically to learner engagement. Learning management systems (LMS) provide a wealth of data about the learner's interactions with the learning content. They can also track the learner's participation in discussion forums and the degree of involvement the learner has with his or her assigned learning course. This information can be communicated and stored in a LRS through an xAPI connector. Additionally, xAPI can track the learner's participation in other online activities and consequentially further inform KPIs matrices which are related to the learner's engagement. For example, it can track activity completion, the time it took to complete a learning activity, the passing rate of an activity and test scores for activities that occur within other applications that are not integrated with, or connected with, the LMS. All these instances are indictors of the learner's progress and performance in learning.

In the literature there are a few examples reported that illustrate the application of xAPI in gathering information about performance evaluation. xAPI is used by the U.S. Army to gather and enhance the measurements used in encoding and evaluating the contextual performance of learners. This approach was used in conjunction with an adapted learning methodology across the different systems and environment to monitor the learner's performance which was "observed, assessed, evaluated, or asserted by systems or observers" as stated by Poeppelman, Hruska, Long, and Amburn (2014, p. 2). This was accomplished by using interoperable systems for tracking the location of the learner, the learning event, the personalized learning content. They used xAPI, as well as the Human Performance Measurement Language (HPML,) to code performance measures, across the different U.S. Army simulators.

HPML is developed by the Simulation Interoperability Standards Organization (SISO) and is based on Extensible Markup Language (XML) representation. The purpose of this language is to provide a human and machine-readable language to express the performance measures carried out by the learner. It also allows for clear grouping of performance data in the form of performance capacities and the evaluation of these capacities. In this research, the combination of xAPI and HPML provided the trainers, the developers, the management and the researchers with easy-to-understand data. Later, they were able to track and aggregate the data for macro-adaptation of the learning content based on the learners' performance. This demonstrates the capability of xAPI to work effectively with other systems and languages to track learner's data, in addition to helping the other systems to leverage the processing of this data in order to assess, measure and provide performance improvement learning content.

It is important to note that other systems are a pre-requisite for the success of this technical architecture for using xAPI for performance evaluation. For example, the utilization of a Learning Record Store and Soldier Performance Planner (SP2) made the combination of HPML and xAPI codes possible. This demonstrates the ease of using xAPI across the different systems and its interoperability. As a result, encoding the performance information provided a foundation for the adaption of the individualistic and personalized training episodes. Therefore, xAPI can play an important role in performance evaluation since it can be easily and efficiently integrated into performance related systems and simulators.

## Conclusion

More research should be conducted to understand how xAPI could be used in conjunction with other educational technologies to improve the learning experience. There are many limitations in using xAPI in educational technology. Even though xAPI consists of simple sentences to track training, the e-learning applications and mobile apps which utilize these sentences require a third-party Learning Record Store (LRS). Furthermore, LRS work independently of the learning management systems. Technical expertise is required to set up the connection between the learning management system and the learning record repository

One of the main obstacles in implementing a wider usage of xAPI in the learning environment is the lack of technical skills. Even though the elements and structure of xAPI are relatively simple, adoption of this technology continues to be challenging because it requires technical skills and knowledge which many Learning and Development or HR personnel do not possess.

There is also a limitation when dealing with the large amount of data that can be generated. xAPI can create too much data about learning experiences. With this large amount of data, it's hard to analyse and know which data is relevant and which is not. In addition, many times an xAPI activity statement is not put into a context and does not describe performance. Further improvements are required to align xAPI data with the learner's performance. By doing so, the gathered data can provide a deeper understanding of the learning experience and its effect on improving performance.

The other two limitations that could affect the role of xAPI in conjunction with these new educational trends are security and data privacy. There are many apprehensions today with collecting information and data, and the way it's used. There are issues of confidentiality, ownership, consent, purpose of use, and reliability and trustworthiness of data, as well as of algorithms and those using the data. Therefore, there are concerns about the security of the xAPI data, given that the LMS, or any other application implicated in the technical architecture, and LRS work independently. The concern with data privacy is evident in recent issues between

Google, Amazon and Facebook and the General Data Protection Regulation (GDPR) rules. It is also evident in the strict regulations of the Data Protection Law in the European Union. This could have an effect on data privacy when it is related to tracking xAPI data on eLearning systems such as LMS and LRS. The purpose of xAPI is to record, gather and then aggregate these data to improve the learning experience for the learner or provide insights to the learner's organization but possible privacy related implications can have a major effect on the usage of xAPI in learning in general.

A comprehensive account of the role of xAPI in promoting, shaping and supporting learning (mostly, in organizational contexts) was produced in this thesis document. This was achieved by showing the role the standard plays within current major trends in digital learning and within the context of a broader ecosystem of learning platforms and technologies. The account was developed by using cases reported in the literature and new cases from contemporary educational technologies where I felt they were missing.

The thesis provides a useful and thorough account of xAPI and its potential to an audience of individuals responsible for implementing xAPI within organizations. In addition, the thesis provides information for configuring reports that will leverage the data collected in a learning record store.

After analyzing and documenting the contributions that xAPI may enable, I have also described the challenges and critical issues it faces. These include the usual concerns with "big data", namely, concerns for data quality (much of the data in an LRS may be "self-report" data with questionable validity), lack of context to make proper sense of the data and confusion of correlation with causation, and also the issues mentioned above concerning data privacy and protection. As reported in this thesis, many promises have been made for xAPI in relation to Adaptive Learning, Microlearning, and Measuring Learning Effectiveness, but there is still a serious lack of adequate evidence in case studies or reports and we need a larger pool of concrete instances.

Cases and examples have been identified that support the notion of xAPI's positive impact, though they tended to lack specific details or clear accounts of evidence for the claims made. But most of the literature on the subject is speculative or merely highlights the potential. More real examples are needed to evaluate the return on investment and the outcomes of incorporating xAPI standards into those educational technology trends. Based on the literature identified in this thesis, xAPI only provides, to some extent, a promise of improved impacts to Performance Evaluation and Evaluating Training Effectiveness. However, xAPI still lacks concrete cases and real examples to support its utility, especially in the fields of Learning Analytics, Performance Management, Predictive Learning and Workforce Planning.

Given the lack of firm evidence and the dearth of detailed case studies that illustrate the utility of xAPI in relation to learning and performance in organizations, the main contribution of this thesis is the identification of the various current educational technology trends where xAPI might play a role, and other areas of potential application, and the exploration of how this might look.

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