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Personal learning environments: A Big Data perspective

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Abstract

Problem Statement: Traditional instructional learning based platforms (e.g., Learning Management Systems) and master – apprentice model is not sufficient for the companies and their human capital anymore. Employees should lead their vocational competence in a connected, fast changing world. It is a great challenge for enterprises and people to find relevant learning resources in an unstructured, scattered, distributed, and overwhelmingly large amount of information ocean and un-learn / learn continuously in this environment.
Purpose of Study: Personal Learning Environments enhanced with Big Data analysis opportunities and emerging technologies seem a solution for the aforementioned problem. This study aims to propose a preliminary Personal Learning Environment Architecture leveraging Big Data possibilities.
Methods: Systematic literature review method is used to review the literature reviews including the research of Big Data in education and personal learning environments.
Findings and Results: Based on the literature knowledge captured, a preliminary personal learning environment architecture is synthesized and proposed.
Conclusions and Recommendations: Proposed preliminary architecture seems to address basic usecases in the literature. However a detailed data gathering should be conducted in a large enterprise using more sophisticated technics such as field surveys, descriptive analytics and case studies. Although the architecture is promising for the personal learning environments, it needs systematic validation with more data both technologically and andragogically.

Keywords: big data in education, personal learning environment, personal learning assistant, personal learning mentor, learning analytics

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1. Introduction

The future of education has been expressed probably the best by Alvin Toffler. In his bestseller book *Future Shock*, he argued that, "Tomorrow's illiterate will not be the man who can't read; he will be the man who has not learned how to unlearn [1]." Salman Khan, the founder of Khan Academy, thinks we are on the eve of a huge paradigm shift that will transform traditional institution based classroom education [2]. It's obvious that in order to be illiterate of the future generations, a learner should lead his lifetime learning Journey.

However learners in corporate world still use pretty much traditional instructional learning based platforms. Although they converted majority of their courses from classrooms to the environments like MOOCs and Learning Management Systems, their approach to learners is from an institutional perspective and instructional in terms of educational theories. This need is addressed by proposing personal learning environments (PLE) by Van Harmelen [3]. In the last decade there have been hundreds of PLE studies yet it is still a very popular research topic. A PLE can be defined as an environment that enables the learner to lead his/her learning process.

Existing widespread tradition of education is defined as "dominant design of educational systems" in [4] and an alternative design based on personal learning environment is introduced. This design pattern emphasizes a symmetric connection rather than an asymmetric one. Links between PLE, social media and self-regulated learning is elaborated and a multi-level framework is proposed for leveraging social media in PLEs [5]. A relatively new framework in which a mobile personal learning environment and the institutional learning management platforms interact is implemented, and it's seen that the use of this solution increased students' motivation [6]. This study might be considered as a synthesis of instructional and self-regulated personal learning approaches. Another recent study proposed a design of personal learning environment for corporate self-regulated learners [7]. A Personal learning environment application using mobile technologies has been implemented for workplace learners with promising results [8]. On the other hand, some new technology tools and methods are emerging. Advanced machine learning and virtual and augmented reality are some of these new trends [9,10]. Generally, PLEs are linked with Web 2.0 era in the literature. However Web 3.0, 4.0 and 5.0 are new emerging technologies [11] and also connected with aforementioned technology trends such as conversational interfaces based on autonomous agents and advanced machine learning.

Big data analysis is considered to offer great opportunities for companies, academic world, government organizations and so on [12]. It also establishes a ground for inter-disciplinary research [13]. Big data is generally characterised by its Volume, Velocity, Variety, Veracity and Value [14]. Nowadays, this characteristics are in effect for the data created within learning ecosystems considering informal learning in social media [5] and the big volume of data circulating in these environments [15]. Formal and informal learning within the big enterprises is also a potential area to benefit from big data technologies. For example when a Software/Requirements Engineer is in question, his/her workplace learning environment is a big data use case. A big data review in software engineering domain can be found in [16]. A requirements engineering tool which has a potential extension for the real time learning platform for requirements engineers working in a large telecommunications company [17,18] has been designed by the researchers of this study previously. However there is a gap in the literature on PLE applications that utilize Big Data and emerging technologies. This study aims to address this gap.

In this study, we first conducted a systematic literature review (SLR) of reviews covering the intersection of Big data and Learning/Education discipline and PLE reviews. Second, a preliminary Personal Learning Environment Architecture is proposed. The rest of the paper is organized as follows: research method details are given in the second section. The third section discusses the results obtained from extracted data and is followed by the proposed PLE architecture and the conclusion.

2. Research Method

Systematic literature reviews (SLR) in software engineering field standardized by Kitchenham and Charters [19]. This methodology has been used in more than two thousand studies (Google Scholar's citation count) circa November 2016. We applied this standard in this study as well. The original method is inherited from evidence-based medicine. Kitchenham and Charters adapted the method for Software Engineering field [19]. There are three main phases of the SLR: planning, conducting and documenting the review. The review steps are, specifying the research questions, design of the search strings, conducting the search, selection of the studies, evaluating the quality, and consolidation of the data collected from literature.

2.1. Research Questions

We aimed to answer following questions:

Research Question 1: Are there review studies in which big data and learning or education are interacting? What are the main results of each review?

Research Question 2: Are there review studies for personal learning environments? What are the main results of each review?

2.2. Search Strategy

We designed a search string based on the two questions specified in previous section. To cover all relevant studies, keywords and terms related to learning and big data are composed in the search string.

Similar terms are included using OR Boolean operator to get a wider coverage. There are two search statements we generated:

allintitle: **(**"learning analytics" **OR** "academic analytics" **OR** "educational data mining" **OR** "personal learning" **OR** "personalised learning"**) AND (**"survey" **OR** "review" **OR** "meta analysis" **OR** "meta-analysis"**)**

allintitle: **(**"big data" **OR** "data mining"**) AND** "education" **AND** ("survey" **OR** "review " **OR** "meta analysis" **OR** "meta-analysis"**)**

2.3. Literature Resources

We used Google Scholar as the primary literature resource for three reasons. First, coverage of Google Scholar is very high (87 %) [20] for studies published in English. Second, the subject of the study is interdisciplinary and Google Scholar is a central convenient platform to find the relevant research under study. Third, the search strings needed to be customized to meet the specific needs of the different databases and this may be a very time consuming task for the researchers. On the other hand, Google Scholar has some important drawbacks as well [21]. For example, Google Scholar search interface has a 256 character limitation. That means, if the length of the search string is longer than 256, it truncates the string without warning [21].

Our search covers the studies published till October 2016 with no start date specified. We also added another filter on the content search. We conducted the search by using “allintitle” keyword to limit the keyword search within paper titles. In this manner we tried to increase relevancy and narrowed the search results.

2.4. Study Selection Process

We obtained 22 studies when executed aforementioned search strings. In the first filtration phase, we made a quick scan of the abstracts of all the resulting papers and made elimination based on the following inclusion and exclusion criteria:

Inclusion Criteria:

- Paper must contain review studies of big data in learning or education domain or review studies in PLE field. Literature surveys must have defined research questions and a formal review process. Study may not refer itself as a systematic literature review.

- Studies must be reviewed in peer reviewed workshop OR conference OR journal OR are reported in a technical report OR MS/Phd thesis.

Exclusion Criteria:

- Studies that are not in English

After the first filtration, 18 papers which are given in reference section [22–39] remained for the second phase. In the second phase remaining 18 papers' full content were read and assessed according to the quality criteria given in the next section. Finally, 11 papers with highest quality assessment scores were selected.

2.5. Study Quality Assessment

Each candidate review was evaluated using the questions specified in quality assessment section of systematic literature review of reviews survey [40]. These questions are as follows:

- **Q1:** Are the review's inclusion and exclusion criteria described and appropriate?
- **Q2:** Is the literature search likely to have covered all relevant studies?
- **Q3:** Did the reviewers assess the quality/validity of the included studies?
- **Q4:** Were the basic data/studies adequately described?" [40]

Each candidate paper was given a score using the assessment questions. Each question is 25 point. The highest score was 80 and the lowest score was 35. All review studies scored above 55 points were selected. Evaluated studies are shown in Table 1.

Table 1 Quality Evaluation Results

Study	Q1	Q2	Q3	Q4	Citation Count	Total Score	Year	Type	PLE/Big Data	Country
[22]	15	20	10	20	14	65	2015	Journal	Big Data	Malaysia, India
[23]	20	20	15	20	1	75	2016	Journal	Big Data	USA
[24]	10	15	10	20	717	55	2009	Journal	Big Data	USA, Australia
[25]	15	20	10	20	2	65	2011	Conference	PLE	South Korea
[26]	10	10	10	20	0	50	2015	Journal	Big Data	India
[27]	10	15	10	15	0	50	2015	Chapter	Big Data	India
[28]	20	20	20	20	9	80	2015	Conference	Big Data	Finland, Australia, USA, Canada, Spain, Lithuania, Sweden
[29]	15	20	10	20	4	65	2014	Journal	Big Data	UK
[30]	10	10	10	25	13	55	2014	Journal	Big Data	Spain
[31]	20	20	20	20	46	80	2014	Journal	Big Data	Greece
[32]	5	10	5	20	50	40	2012	Conference	Big Data	India
[33]	5	10	10	20	0	45	2013	Chapter	PLE	Ireland
[34]	10	10	10	20	23	50	2013	Journal	Big Data	India
[35]	15	20	10	25	756	70	2010	Journal	Big Data	Spain
[36]	15	15	15	20	104	65	2014	Journal	Big Data	Mexico
[37]	10	10	10	15	0	45	2015	Conference	Big Data	India
[38]	5	10	10	10	1	35	2015	Journal	Big Data	India
[39]	20	20	20	20	112	80	2011	Conference	PLE	Germany, UK, Spain

2.6. Data Extraction and Data Synthesis

To reach the data needed to answer our research questions and constitute some additional statistical data, we extracted following data from the papers: Title, Quality Criteria 1 Score, Quality Criteria 2 Score, Quality Criteria 3 Score, Quality Criteria 4 Score, Overall Quality Score, Year of Publication, Type, Country, Highlights. Extracted data is synthesized using tables presented in the following section.

3. Data Results

In this section, two research questions defined in section 2.1 will be discussed.

3.1. Research Question 1

Are there review studies in which big data and learning or education are interacting? What are the main results of each review? :

Yes. There are quite a few review studies in which big data related terms (Learning Analytics (LA), Educational Data Mining and Academic Analytics) and learning in Education. Main results of each review are given in Table 2 in chronological order.

3.2. Research Question 2

Are there review studies for personal learning environments? What are the main results of each review? :

Yes. There are only two review studies selected in this review concerning Personal Learning Environments. Main results of each review are given in Table 3 in chronological order.

Table 2. Learning Analytics and Educational Data Mining Review Studies

Study	Year	Title and Highlights
Baker and Yacef [24]	2009	The State of Educational Data Mining in 2009 : A Review and Future Visions This is the first review study we found in Educational Data Mining literature. It is also one of the most cited studies. It investigates the most cited papers between 1995 and 2005 and considers where the EDM come from and its future. Between 1995 and 2005, the dominant category has been relationship mining methods in EDM research. However, prediction was in the dominant position in 2008-2009. One of the most common applications of mining methods has been the student model improvements such as factors in predicting student failure or success. The other application areas have been improving models of a domain's knowledge structure, pedagogical support and search for empirical evidence to improve educational theories. From 2008 on, public data and tools also started to be used by researchers as well. In conclusion, EDM methods have had a valuable impact on education as of 2009. Although this impact is limited, it has a promising potential as in cognitive psychology and biology.
Romero and Ventura [35]	2010	Educational Data Mining : A Review of the State of the Art This is the most cited review we found. It first describes the stakeholders and objectives of EDM. It is used for personalizing e-learning, getting objective feedback regarding students' learning, evaluating courses, enhancing decisions and organising resources of education institutions. It notes that the number of publications about EDM increased dramatically in recent years. Previous research (during 1993-1999) had focused mainly on predicting student performance. DM is used in following educational tasks: analysis and visualisation of data, providing feedback for supporting instructors, recommendations for students, predicting student's performance, student modelling, detecting undesirable student behaviours, grouping students, social network analysis, developing concept maps, constructing courseware and planning and scheduling. EDM is still not a mature area but it's developing. More unified and collaborative studies are needed instead of individual isolated studies.

Cooper [29]	2014	Learning Analytics Interoperability - a survey of current literature and candidate standards The survey deals with existing data exchange standards between multiple systems. Existing standards with potential applicability to learning analytics is grouped into four categories: 1. Logging Standards: Extensible Event Stream (XES), PSLC DataShop Tutor Message Format (DataShop), Contextualized Attention Metadata (CAM) 2. General Web Standards: Atom Syndication Format (Atom), Friend of a Friend (FOAF), Semantically-Interlinked Online Communities (SIOC), Activity Streams (AS), Attention Profiling Markup Language (APML) 3. Educational Technology Standards: National Science Digital Library Paradata and Annotation Schema (NSDL), Mozilla Open Badge Initiative (OBI), Information Model for Learning Outcomes and Competences (InLOC), e-Portfolio Portability and Interoperability (Leap2A), IMS Question and Test Interoperability Results (QTI), ADL Experience API (XAPI), IMS Learner Information Services Outcomes (LIS), European Learner Mobility Achievement Information (EuroLMAI), Learning Analytics Toolkit (eLAT), InBloom 4. Standards from Governmental/ or Other Bodies: Argument Interchange Format (AIF)
Corbi and Burgos [30]	2014	Review of Current Student-Monitoring Techniques used in eLearning-Focused recommender Systems and Learning analytics. The Experience API and LIME model Case Study The Study analyses current learner-monitoring techniques to prepare for the eLearning recommenders systems, and investigates standardization attempts in this area. From 2008 on, there is a dramatic increase in the number of papers about recommender systems. Basic system-dependent monitoring techniques are classified as Web Services, Scrapping, and raw database access which is by far the most often used method in literature. There are also some standard specifications for monitoring: Resource Description Framework or RDF, The Caliper framework/Sensor API, IEEE 1484.11.1/IEEE 1484.11.2, JSON Activity Streams and Experince API (xAPI). After reviewing monitoring techniques, a recommender engine model is presented based on xAPI and LIME (Learning, Interaction, Mentoring, Evaluation) model cited in the study.
Papamitsiou, and Economides [31]	2014	Learning Analytics and Educational Data Mining in Practice: A Systematic Literature Review of Empirical Evidence This Study presents empirical evidence of LA/EDM in educational strategic planning. It covers the period from 2008 to 2013. The study presents its results in a format of a SWOT analysis which is constituted from a thorough systematic literature review. Strengths: Volumes of educational data, accuracy of experimental results, powerful and valid algorithmic methods, good visualisation supporting stakeholders, personalization, revealing critical learning knowledge, insight about learning strategies and behaviours. Weaknesses: Focus on reporting rather than decision, no standardization in data sources, mostly quantitative results, complex systems, Skilled stakeholders are required to interpret the results. Opportunities: Generalised platform development, chance for efficient learning and decision making, Self-reflection/ self-awareness/ self-learning, perceived usefulness. Threats: Ethical and privacy challenges, over-engineering, trust
Ayala [36]	2014	Educational data mining : A survey and a data mining-based analysis of recent works The study analyses recent EDM studies using data mining methods. It presents the result of the analysis of EDM field in a SWOT analysis format again. Strengths: Baseline of DM and educational fields are quite robust, positive perception among researchers, events and media are expanding quickly. Weaknesses: Newly developing field, few researchers, application of DM to explore Education rather than extending DM, student modelling dominating the approaches. Opportunities: Education is first priority for majority of the World, Society is open for non-traditional education methods, EDM is an enabler for student-centered education and personalisation, data is growing exponentially due to fast development of ICT technologies. Threats: the lack of particular theory for EDM, common terminology, reliable frameworks and architectures are demanded.
Sin and Muthu [22]	2015	Application of big data in education data mining and learning analytics-A literature review Learning systems have become accessible anywhere through the technological developments. Students' and institutions' activities during education process generate massive amount of data that cannot be processed via traditional data processing means. The

		primary topics of interest in EDM 2014 conference are listed as Behavior Detection, Skill Estimation, Game-based learning and Student Modeling, Performance Prediction, Q-Matrix, Adaptive Learning, Attrition Risk Prediction in the study. The EDM articles in review scope are categorised in following themes: Introductory, Student Performance, Data Mining, Pedagogy. On the other hand, there are three major trends considering the LA studies in review scope: introducing the concepts and developing LA field, technical development of LA framework and tools, LA usage in social learning. The coverage of the study should be extended by a systematic review.
Ihantola et al. [28]	2015	Educational Data Mining and Learning Analytics in Programming : Literature Review and Case Studies This study reviews the literature regarding EDM and LA work about programming education for the time period 2005 – 2015. It also replicates some studies to see their validity. In the last ten years, although there has been a dramatic rise of articles in the field, there is a lack of multi-institutional studies in EDM and LA in programming domain. Studies rarely made their data publicly available. Reproducibility of previous studies is an important challenge for the field. Researchers of this study replicated three previous studies and one of the replication failed. Three main categories are extracted from the research goals of the articles in the scope of the review via thematic analysis: Students: Ability and knowledge, Affective states, Behaviour, Difficulties, Drop-out risk and performance Environment: Algorithm analysis, (Automated) feedback/grading, IDE usage, Testing Programming: Behaviour, Errors, Patterns, Process, Progress, Strategies, Metrics, Testing behaviour
Avella et al. [23]	2016	Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review To narrow the gap between higher educaion stakeholders and LA , this review presents a summary of the technics, benefits, and challenges regarding the use of learning analytics in higher education. Review reveals following potential benefits for the higher education: Finding target courses, curriculum development, student learning results and behaviors, personalized learning, improved instructor performance, Post educational employment, Learning analytics practitioners and research community. It also reminds for some challenges: Data tracking, Data collection, Evaluation process, Data analysis, Learning sciences connection, Learning environment optimization, Emerging technology, Ethical and privacy issues.

Table 2. Personal Learning Environment Review Studies

Study	Year	Title and Highlights
Beuth et al. [39]	2011	Understanding Personal Learning Environments: Literature review and synthesis through the Activity Theory lens This study reviews the personal learning environment publications referencing over 100 articles published before 2011. The main research question in this review is: “What are the characteristic, distinguishing features of Personal Learning Environments?” PLEs in the literature are worked out using the Activity Theory framework to understand the key components of them. Overview of the study is given in terms of Activity Theory elements as follows: i. TOOLS: Mediate an activity to achieve a desired outcome a. Customisation b. Facilitation ii. SUBJECT: Primary actor/agent of PLE a. Ownership b. Control c. Literacy iii. OBJECT: Gives specific direction an activity a. Interest b. Participation c. Control iv. RULES: Norms, Conventions, Values

		a. Openness b. Distribution c. Connecting v. COMMUNITY: Larger group in which the subject participates, such as Personal Learning Network a. Social Support b. Boundary Crossing vi. DIVISION OF LABOUR: Organisation of the system a. Roles of Learners b. Roles of Teachers c. Roles of Peers d. Roles of Institutions
Liew and Kang [25]	2012	Personal Learning Environment for Education: A Review and Future Directions This study aims to review the research trends in the education discipline and its relation with PLEs. In summary, authors found that PLE studies mainly concentrate on development and evaluation of the PLEs. Previous literature can be classified into two broad categories: technology category, which focuses on the tools and applications of PLEs, and education category which studies the education theories. A new study type that would combine these two approaches is needed. Technologists and theorists should work together.

4. Proposed Personal Learning Environment Architecture

Our architecture proposal for Personal Learning Environments based on the literature covering PLE and Big Data in Education is depicted in Figure 1. The main components of the architecture is explained briefly as follows:

- **Internal Learning Environment:** This element comprises data generating systems within the enterprise. Learning Management Systems, Human Resources Management Systems, learners' on the job data (For example software code implemented by developers or requirements engineering artefact created by business analysts, in general software engineering big data) are some of the systems within this environment.

- **External Learning Environment:** This environment represents all the learning related data coming from outside of the enterprise. Social learning platforms in which learners shares their knowledge and learn from other participants' reflections are the first group for outside learning sources. Linkedin, Twitter, Facebook, Youtube, TED Talks are just some of these social learning platforms. Second resource group is MOOCs such as Coursera, Udemy and Udacity. Another learning source is research libraries. Google Scholar, Google, IEEE, ACM, Elseiver, University libraries, Wikipedia, etc. are a few examples for this category. External learning objects are not limited to mentioned examples and there are a myriad of learning related resources which may be added to the list.

- **Data Capture and Analysis:** This module functions as capturing and analysing all structured and unstructured data coming from inside and outside of the corporation.
- **Data Source Adaptors:** This submodule is responsible for exchanging data from learning resources using data integration technologies and standards.
- **Smoothing:** This submodule does data preparation operations (Cleaning, filtering, privacy and anonymization, etc.) before analysis.
- **Real time Learning Analysis:** All data accumulated into the system is analysed via this component. Metric measurements, goal readiness and prediction, recommendations, feedbacks for improvement areas, visualisations, information search, retrieval and reporting for the learner are some of the main functionalities provided by this element.
- **PLE Design:** This is the component, which enables self-regulated learners to design and maintain their personal learning environment by themselves.

- **Personal Learning Mentor:** Even self-regulated learners may need a mentor. Mentor may be a conversational interface connected to the intelligence provided by RT Learning Analysis Module. However it doesn't have to be software only. It may be a human mentor supporting the learner in his personal learning environment as well.
- **Channels:** Personal Learning Mentor should interact with the learner in a place, time, and channel agnostic manner. Learner should be able to continue his or her learning experience while switching contact points (For example switching from web to mobile or mobile to digital TV, etc.) with the system. Channels component provides with the learners this flexibility and continuity in their learning experience.

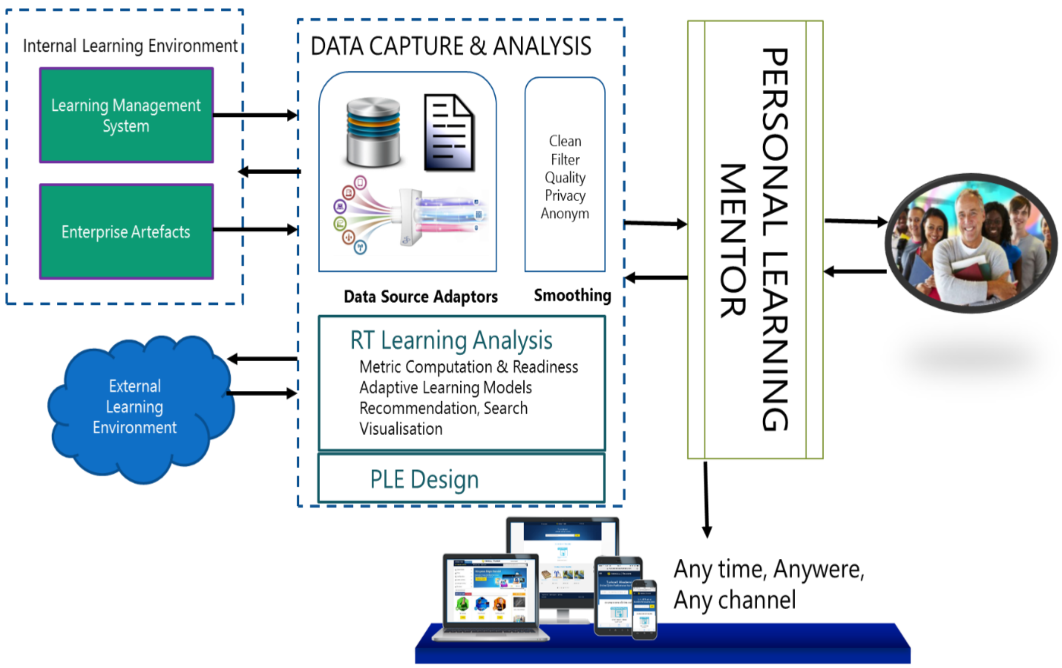

Figure 1 A Preliminary Architecture for PLE

5. Conclusion and Future Research

In this study, we conducted a systematic literature review research scanning all the review works concerning educational data mining, learning analytics and personal learning environment. We also proposed a preliminary PLE architecture based on the captured knowledge from the outcome of the review.

There are quite a few review studies regarding EDM and LA. It's observed that the impact of the EDM/LA research is limited until 2010. However research accelerated and started to become mature after 2010. The variety, distribution and monitoring of huge learning data in many systems brought us to new issues of data exchange standardisation and big data era in education. Big data usage in personal learning is highlighted in several reviews as one of the most promising future research areas.

On the other hand, only two reviews has been found regarding to PLEs and they're not very recent studies. Nevertheless, the review made in 2011 is of good quality and its results together with EDM and LA studies have been used in designing the preliminary PLE architecture. Proposed architecture covers basic Big Data and PLE requirements in the literature. However some areas stay unaddressed such as ethical issues and the reliability assessment of information accessed via Personal Learning Environment.

Following research will be done as the next step to this work in the future.

- A systematic literature review will be conducted on PLEs since there's no recent review studies in literature.

- A more detailed study in a large enterprise using more sophisticated and empirical technics such as field survey will be done.
- Enhancement and systematic validation of the preliminary architecture with more data coming from above two items will be done.

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