Collaborative Mobile Learning: A Systematic Literature Review

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2 authors:

Nor Fadzleen Binti Sa'don
Malaysia-Japan International Institute of Technology (MJIIT)

Noorminshah Iahad
Universiti Teknologi Malaysia

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Nor Fadzleen Binti Sa'don
Universiti Teknologi Malaysia, Malaysia
n.fadzleen@gmail.com

Noorminshah Binti A. Iahad
Universiti Teknologi Malaysia, Malaysia
minshah@utm.my

ABSTRACT

21st century learning has given impetus to the exponential growth of mobile learning (ML). It fosters engaging personalized learning where students can optimize their understanding and learning gratification via wireless mobile devices. Hence, this indicates the importance of gauging the trends in ML in and its vast potential for the learners in multitude stages of educational realms. Although there are studies conducted on the research trends on ML, is not much studies conducted on the cutting-edge researches pertaining to Collaborative ML. Hence, this paper aims to study and analyze the state-of-the-art research conducted in the span of five years (2010-2014) in identifying the trends and focuses in ML that leads to synthesis of literature on collaborative ML. Collaborative ML is significant because it promotes active learning, cooperative skills and personalized learning. The systematic literature review is conducted based on Knowledge Discovery Database model developed by Marban et. al. (2008), capitalizing data mining as the main research methodology. Findings were based on top ten Impact Factor Journals on Educational Technology certified by ISI Web of Knowledge. Based from the findings, 991 papers were retrieved on ML trends using data mining and from these papers, collaborative ML is the top focus in all of the ten journals. Further rectification on Collaborative ML is studied to identify the patterns. The findings will propagate future studies on development on collaborative ML in multitude of perspectives.

Keywords: Augmented Reality, Collaborative; Gamification Mobile Learning; Research Trends; Systematic Literature Review; ; Impact Factor Journals; Wearable Computing.

INTRODUCTION

The emergence of a post-industrial information age and the explosive growth give impetus to the evolution of harnessing information and knowledge. Exponential growth of technological gadget and influx of mobile technologies provide expansive platform for researchers to look at their potentials in optimizing teaching and learning productivity, effectiveness and gratification. The robust development of mobile technologies has led to incorporation of mobile devices in learning ecosystems worldwide (Ariffin, 2011). As opined by Sharples (2010), one of the potential approaches is Mobile Learning (ML) where it is defined as utilization of “advanced mobile technologies, such as high bandwidth infrastructure, wireless technologies, smart devices,wearable and handheld devices.” To frame it in the context of learning paradigm, ML is interweaving the learning transitions in daily life sans formalized learning setting and scaffold learning process via portable tools, beyond the classroom boundaries. Due to the widening body of knowledge on ML, there is a need to refine and offer updated reviews on state-of-the-art researches on ML by conducting meta-analysis on empirical studies conducted on ML, especially in reputable and significantly cited Impact Factor Journals on Education Technology.

The convergence of the mobile devices with existing educational technologies provides learners with greater flexibility by making homogenous learning activities available and accessible by heterogeneous mobile devices (smart devices). The term M-learning is coined to describe the convergence of mobile technologies with E-learning and we can achieve this by utilizing wireless connectivity. In business, for example, the importance of m-learning has been raised as many companies look into mobile technologies to support mobility of their Knowledge Management (KM) activities. The advent of M-Learning created an environment of anywhere, anytime learning. With the advancement of hardware technologies now users could have wearable computing. Which actually support the concept of internet of things and inventually brings learning to everywhere with gadgets like (Smart Watches, optical head-mounted display (OHMD),Mobile ECG , Biometrics wrist bands, etc.

Mobile learning (M-Learning) is novel in that it facilitates delivery of learning to the right person, at the right time, in the right place using portable electronic devices.(Ally, Schafer, Cheung, McGreal, Tin, 2007).

With key features like portability, ubiquity, and customization of these mobile technologies enables us to put the power of knowledge literally in the hands of today’s society, by enabling them to have 24/7 access to acquire and ascertain study materials via a mobile device, takes away the constraints of always having to be in a “classroom environment” for learning to be effective.

M-learning is E-learning where different mobile devices are used for educational purposes. In this chapter we consider M-learning is extension of E-learning.

LITERATURE REVIEW

- *Definition of ML*

The concept of Mobile Learning derived from the mobile revolution of the late 1990s which changed the distance student from a citizen who chooses not to go to campus but within the parameter of the premise (Sharples, 2012). ML is akin to mobile devices optimizes for learning purposes where it is a device that has ubiquitous features which can be utilized in any places, sans physical constraints yet have a communication systems. It is about using the massive growth of mobile technologies to benefit learning and learners. Parallel with the development of computer technology, mobile phone goes one step further and it is remarked as a new organ in evolutionary of time line because it have directly integrates with the brain.ML refers to the use of mobile or wireless devices for the purpose of learning while on the move (Sharples & Vogel, 2011). Typical examples of the devices used for mobile learning include cell phones, smart phones, palmtops, and handheld computers; tablet PCs, laptops, and personal media players can also fall within this scope (Kukulsa-Hulme, 2010).The incorporation of mobile learning has been extensively studied and comparative studies on the instrumental values on education have been analyzed in order to increase the engagement and learner's gratification. In the context of collaborative learning, the learners engaged most with learning that they could do together, either by sharing phones or by passing things between phones.

- *Past reviews on ML*

There are many methods chosen in analyzing past empirical studies via meta-analysis, data mining, abstract mining, code analysis and SLR. For this research, SLR is chosen as the research methodology for this paper. It is defined as "a systematic, explicit, comprehensive" (Fink, 2007) and retrievable technique in identifying and synthesizing existing body of completed and recorded work produced by researchers and scholars. SLR was conducted on top ten Impact Factor journals on Educational Technology (Scimago, 2014) in order to analyze the research conducted on the aforementioned topic. By conducting SLR, it may offer extensive perspective for educators and researchers into state-of-the-art trends on ML.

Prior to this research, there were several significant reviews conducted on ML. Wu et. al. (2012) carried out an SLR on trends of ML and discovered that past empirical studies on ML predominantly studied two aspects in literature review; gauging the effectiveness of ML and developing ML framework, tool or system. From these two aspects, a review on seamless ML was carried out by Wong and Looi (2011) where parameters and constraints of ML were studied and analyzed. A review conducted by Hwang and Tsai (2011) utilized text mining to analyze six major education technology journals and reviewed the factors contributing to the success of ML in various countries. Despite myriad of research conducted on ML, it is discovered from empirical studies that majority of the reviews conducted were generally focusing on the overview of ML and SLR is not widely optimized to analyze state-of-the-art researches on current trends of ML. Due to the burgeoning importance imposed on the influence of highly cited researches in Impact Factor journals, there is a need to upgrade and review the latest research on ML and identify the trends that researchers and educators need to pay attention pertaining to ML.

OBJECTIVES

This chapter aims to carry out a Systematic Literature Review of empirical researches pertaining to ML. Other objectives comprise to:

1. identify the patterns and trends of ML from top Educational Technologies journals.
2. find out the methodologies and results of the studies on ML.
3. identify and suggest future works for Collaborative ML.

SCOPE AND LIMITATION OF STUDY

The SLR conducted on collaborative ML is limited to the parameter of five years span of published researches. The parameter is chosen in order to select the state of the art research conducted from reputable accredited publications which are the top ten Impact Factor Journals on Educational Technology. The literatures are selected from Impact Factor Journals due to its credibility and the research is then refined to focusing on the top topic of trends on ML.

RESEARCH DESIGN

The method chosen is Systematic Literature Review (SLR). SLR "aggregates all existing evidence on a research question" (Kitchenham et. al., 2009) and provides the state-of-the-art findings and evident-based guidelines for researches. In the context of this study, SLR is conducted on prior empirical researches, models and theoretical frameworks on existing literature on ML from the span of five years (2010-2014). The reason for choosing SLR is apart from helping researcher to find solutions, it gives practitioners the guidelines in developing pragmatic and appropriate tangible solutions in a specific context. In the context of this research, Knowledge Discovery in Database (KDD) Process (Marban et. al., 2008) is implemented to retrieve the required data on VLE management. KDD refers to the overall process of discovering useful knowledge from data, and data mining refers to a particular step in this process.(Fayyad, Piatetsky-Shapiro, Symth, 2006) It involves five steps: (1) data selection, (2) pre-processing, (3) data transformation, (4) data mining and (5) results analysis.

Figure 1 illustrates the stages conducted by the research in identifying the research patterns conducted on ML.

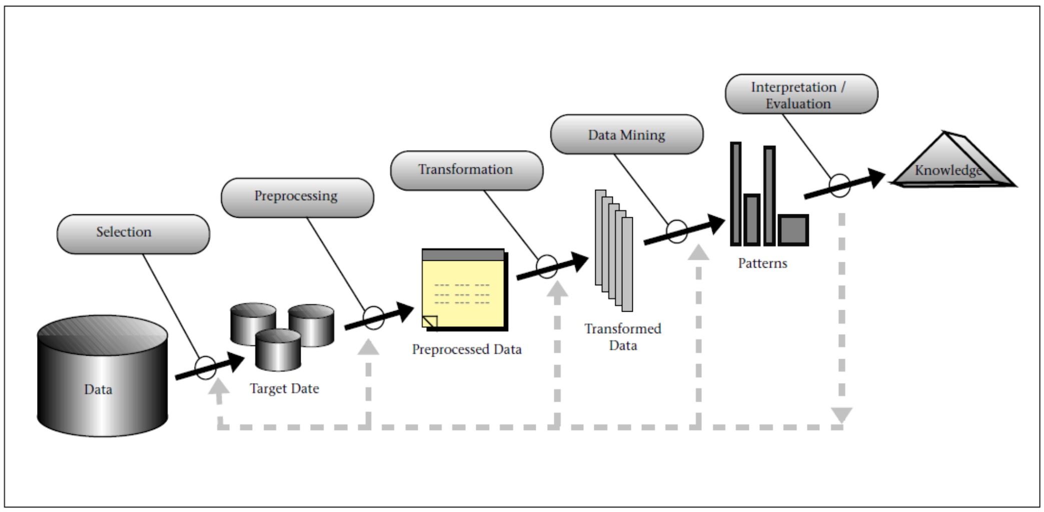

Figure 1: Stages of the Knowledge Discovery in Database

(i) Data Selection

The SLR was conducted based from top ten ISI Journals of Educational Technology. The journals were chosen based on indexed ranking on ISI Web of Knowledge. The journals chosen were Computer and Education, Journal of Computer Assisted Learning, International Journal of Computer-Supported Collaborative Learning, British Journal of Educational Technology, Interactive Learning Environments, Educational Technology and Society and Educational Technology Research and Development. All of the journals used in this research is tabulated in Table 1. Within the parameter of this research, the journals are identified as database and each journal is labeled from D1-D10 based on the latest ranking (Scimago, 2014). This is to ensure the credibility of the literature and higher impact on this research.

Table 1. Top 10 Impact Factor Journals for Educational Technology

ID	DATABASE	PUBLISHER	IMPACT FACTOR
D1	Computer & Education	Elsevier	3.720
D2	The Internet and Higher Education	Elsevier	3.257
D3	International Journal of Computer-Supported Collaborative Learning	Springer	1.717
D4	Journal of Computer Assisted Learning	Wiley	1.632
D5	Australasian Journal of Educational Technology	Australasian Society for Computers in Learning in Tertiary Education	1.363
D6	British Journal of Educational Technology	Wiley	1.313
D7	Interactive Learning Environments	Taylor & Francis Online	1.302
D8	Educational Technology and Society	International Forum of Educational Technology & Society	1.171
D9	Educational Technology Research and Development	Springer	1.155
D10	Learning, Media and Technology	Taylor & Francis Online	0.644

(ii) Pre-processing

At this stage, it involves collecting only necessary data and eliminating noise or unrelated data. Pertaining to selection parameter, the articles are filtered chronologically where only the ones published from the span of the last five years (2010-2014) are selected for the state-of-the-art element and validity to the current educational settings. From this process, 991 papers are selected specifically based on the topics pertaining to ML trends, in order to identify the main focus and issues extracted by myriad of scholars and researchers.

(iii) Data transformation

This stage refers to having a unified logical view of the wide variety of data and databases from the references gathered. In the context of this research, it involves mapping of the chunks and clusters of data and organizing them to a single naming convention. This research is based from the data collected from the literature. Based from the 991 publications, keywords were identified in order to identify research patterns conducted on ML. From the publications, collaborative ML tops the focus of research and it was featured in all of the top ten publications.

(iv) Data mining

At this stage, a particular data-mining method is chosen in order to further analyze and refine the respective factors. Based on KDD model (Fayyad, Piatetsky-Shapiro, and Smyth, 1996), the method can be: summarization, classification, regression or clustering. For this research, summarization is chosen as it is seen as the most suitable method in identifying further patterns in collaborative ML. Summarization is conducted by extracting the data from the abstract and body of literature. This is to analyze the gist of the research that leads to dispersion of theories and suggested models, framework and studies done on collaborative ML.

(v) Result analysis

The last stage involves documentation and visualization of the data analyzed. The extracted patterns of information are synthesized with the data selection objectives, in order to achieve the intended results. In the context of this research, the summarization of research done on collaborative ML are compared and analyzed to further find the similar patterns, issues and proliferate potential studies in near future.

DATA COLLECTION

- *Databases search*

The data pool comprised 10 high-ranking journals on education technology based on ISI Web of Knowledge, conducted via manual electronic search. The ranking system is used to select the database for the review to enhance the credibility of the state-of-art researches. The journals chosen were Computer and Education, Journal of Computer Assisted Learning, International Journal of Computer-Supported Collaborative Learning, British Journal of Educational Technology, Interactive Learning Environments, Educational Technology and Society and Educational Technology Research and Development.

- *Search terms*

Keyword mining was the technique chosen in the scope of database search. (Ngai, Xiu and Chau, 2009) opined that extracting or detecting hidden patterns or information from large databases via keyword mining helps to narrow down the gist of the research focus. The search terms that was used in the first stage was “mobile learning” to gauge possible trends, outcomes and current empirical researches conducted pertaining to ML. The search was within the scope of five years span (2010-2014) in order to seek the state-of-art researches. The term “mobile learning” was used in order to determine the scope and trends of ML. After reviewing the output based from keyword mining, the search is comprehensively extended to the abstracts of the reviewed empirical research. From the output of the search, the search term is further refined to “Collaborative ML” where abstract mining is done. This refers to analyzing the abstracts of the papers that match the search parameter. From the abstracts, refined search within Collaborative ML is deduced and comparatively analyzed.

- *Selection of papers for inclusion in the review*

A number of further criteria were specified to select appropriate studies for inclusion in the review. From the 10 ISI top journals in Education Technology, the meta-analysis must comply with 4 inclusion criteria as listed below:

(a) Include empirical evidence relating to collaborative ML
(b) Dated from January 2010 to March 2014
(c) Include an abstract
(d) Set within the parameter of educational institutions

Using these four conditions, 799 papers met the inclusion criteria and were identified as relevant to the current review. Table 1 displays the data coding of the data pool on journals of Education Technology with tabulated analysis of papers reviewed. They were analyzed for relevance to the four criteria identified prior to the analysis. In order to analyze the ten top IS journals on education technology, each database is labeled accordingly from D1 to D10. The labeling is according to the ranking of the journals based on certified IF rankings. This is to expedite the analysis procedure via Mauban’s Knowledge Database Analysis (2010).

Table 2. Total number of papers identified from each database and number shortlisted as relevant

ID	DATABASE	NO. OF PAPER IDENTIFIED IN SEARCH	NO. OF PAPER MEETING THE INCLUSION AREA
D1	Computer & Education	348	158
D2	The Internet and Higher Education	295	181
D3	International Journal of Computer-Supported Collaborative Learning	78	45
D4	Journal of Computer Assisted Learning	40	1
D5	Australasian Journal of Educational Technology	49	29
D6	British Journal of Educational Technology	9	3
D7	Interactive Learning Environments	34	26
D8	Educational Technology and Society	68	37
D9	Educational Technology Research and Development	18	16
D10	Learning, Media and Technology	17	6
Total		**911**	**799**

Table 3. Keyword frequency on ML from the databases (2010-2014)

KEYWORDS	FREQUENCY USED IN ARTICLES	FREQUENCY USED IN NO. OF TOP 10 IS JOURNALS
Collaborative Learning	75	10
Assessment	57	8
Management	56	8
Personalized learning	45	7
Inquiry learning	41	7
Gaming	31	6
Ubiquitous Learning	16	6
Augmentation	5	6

After analyzing the research patterns, collaborative ML ranked as the most coveted topic for all the databases chosen for the review. Collaborative ML was featured in all the 10 IF journals and focused in empirical studies for 75 times compared to other seven keywords. Further data mining is conducted on Collaborative ML in order to identify the areas that are focused in prior empirical researches, using Mauban's classification method via abstract mining. In this context, each abstract of the paper that was discussing Collaborative ML is examined to further identify the areas discussion and designation. Figure 1 below describes the summary of areas in Collaborative ML via this technique.

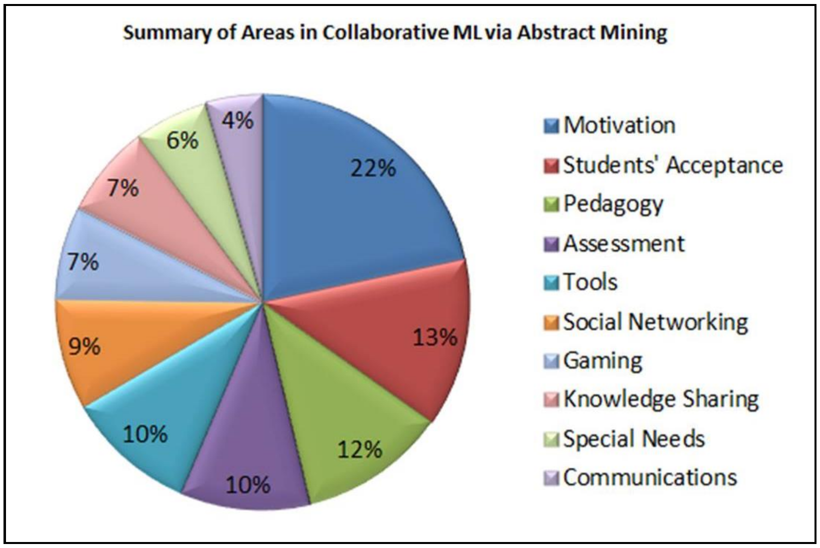

Fig.1 Summary of Areas in Collaborative ML via Abstract Mining (2010-2014)

DISCUSSION OF AREAS IN COLLABORATIVE MOBILE LEARNING SLR (2010-2014)

In order to identify the trends of Collaborative ML, hierarchical taxonomy was conducted via abstract mining from 799 papers that were considered relevant and matched the inclusion criteria of SLR conducted in this research. From 799 papers, abstract mining output revealed that Collaborative ML is the most coveted topic in the database specified which is followed by Assessment, Management, Personalized Learning, Inquiry Learning, Gaming, Ubiquitous Learning as well as Augmentation. In order to have an in-depth meta-analysis of the empirical researches conducted, abstracts of the 75 data pool on Collaborative ML was cross-analyzed, compared and discussed to ascertain the patterns, trends and findings on the areas. As shown in Figure 2, via abstract mining, 75 papers identified 10 main areas that were discussed pertaining to Collaborative ML which are:

i. Motivation
ii. Students' Acceptance
iii. Pedagogy
iv. Assessment
v. Tools
vi. Social Networking
vii. Gaming
viii. Knowledge Sharing
ix. Special Needs
x. Communications

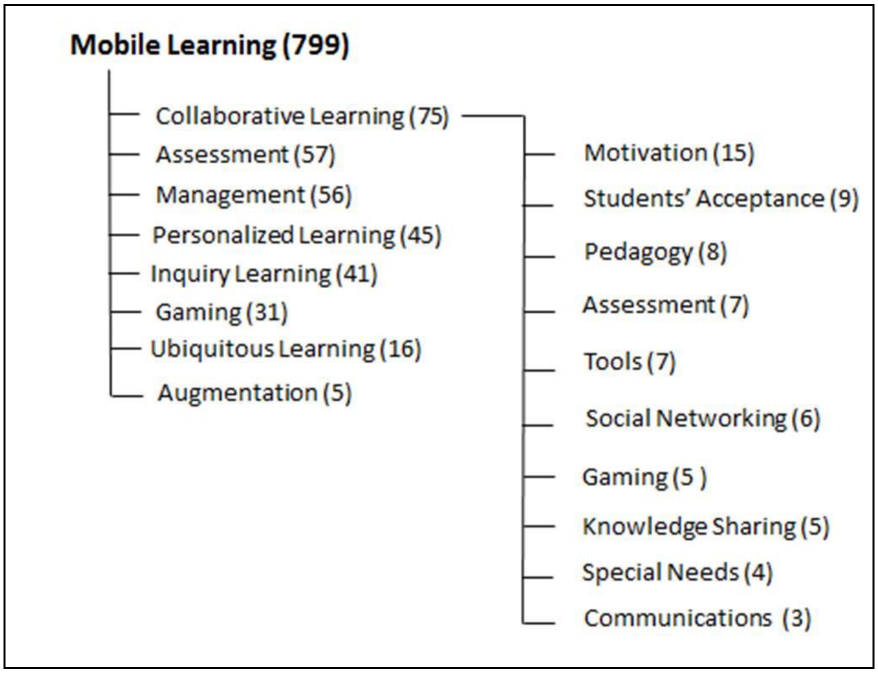

Fig.2 Hierarchical taxonomy on SLR conducted on ML & Collaborative ML via abstract mining

- **Motivation**

Via abstract mining, motivation in Collaborative ML is the top area discussed by researchers in the entire database analyzed. Majority of the papers discussed on intrinsic and extrinsic motivation where the motivation and engagement in learning may derive from the students themselves or influenced by myriad factors such as teachers, peers, learning ethos, tools and non-physical elements such as word engagement (Wong et. al, 2010), body language (Yan and Sie, 2010) and interactive communication between humans or non-human contacts. In this context, mobile devices are utilized to eliminate learning inhibition, verbal incompetency as well as improve psycho-metric efficiency. According to Tsai (2010), students perform better when teacher intervene during the Collaborative ML by providing verbal engagement or learning support. This is supported by a study conducted by Blasco-Arcas et. al (2013) which investigate how interactivity impacts learning engagement during Collaborative ML. Via verbal and non-verbal communication, motivation and learning engagement are fortified through exploration of learning spaces within collaborative learning groups and mobile peer learning. Apart from scores and achievement assessed via ML, motivation can be influenced via verbal and non-verbal communication shared by peers and facilitators during collaborative session.

- **Students' Acceptance**

Students' acceptance is the second most coveted area in researches on Collaborative ML in the database analyzed. From the papers, all of the researchers aimed to identify the factors that influence students' acceptance of Collaborative ML and they are then narrowed down by the use of various methods, techniques and mobile tools that expedite mobile learning in secondary and higher education. Cheung and Vogel (2013) discovered that the ability to share information during Collaborative ML have higher influence in students' acceptance towards mobile learning and collaborating with their peers. Cheng (2014) used gaming as a platform to identify students' acceptance in Collaborative ML and discovered that the level of acceptance varies on students' learning performance but generally, the ease of use and user-friendliness of the learning tools (games) can highly influence the students' attitudes and openness in embracing Collaborative ML. Apart from that, Liaw, Hatala and Huang (2010) discovered in their studies that there are many ways that Collaborative ML can immensely improve students' acceptance towards the teaching and learning process. Through their studies, they discovered that by implementing Collaborative ML, it helps "enhance learners' satisfaction, encourage learners' autonomy, empowering system functions, and enriching interaction".

- **Pedagogy**

In the context of pedagogy, this area studies methods and ways of teaching by implementing Collaborative ML. Martin and Ertzberger (2013) conducted an experimental study on "Here and Now" ML where it studied how ML is used to affect students' learning performance and attitude. The outcome of the research indicated that students preferred authentic learning environment via appropriate ML techniques and methods. Apart from that, some of the techniques used are Jigsaw and Fishbowl Collaborative Learning techniques (Andreas et. al, 2010) can supplement and/or augment face to face interactions, improving upon previous approaches in distance collaboration and communication. Meanwhile, Wang (2010) studies how online shared workspaces can support collaborative ML. It is discovered that it can act as a catalyst to share learning materials, brainstorm and discuss as well as coordinate their learning collaboration.

- **Assessment**

Based on meta-analysis conducted, majority of the papers that focused on assessment in Collaborative ML identify assessment as one of the key focuses in planning an effective ML. Assessment for Collaborative ML can be categorized into formative and summative format and be embedded extrinsically or intrinsically in ML. Hwang and Chang (2011) proposed a formative assessment-based approach for improving the learning achievements of students. From their research, the end result concluded that formative assessment in Collaborative ML helps to promote students' interest and learning performance. From a small to large scale assessment method, Looi et. al. (2014) had designed a mobile learning curricular for Singaporean secondary education which can assess students' performance in ML. From the action research done, it is discovered that by embedding Collaborative ML, students perform better as they set the learning pace rather than conformed to the generalized pace set by the teacher or facilitator. Nonetheless, Hwang et. al. (2011) discovered that there is a need to customize assessment based on several factors such as students' learning pace, socio-cultural suitability, infrastructure, readiness and tools.

- **Collaborative ML Tools**

Based from the data pool via abstract mining, the mobile tools and devices that were studied comprise smartphones, tablets, Ipod and other handheld devices. Viberg and Grönlund (2013) studied how these mobile devices escalate learners' motivation and gratified positive attitudes towards Collaborative ML. Mobile tools and devices were discovered to enhance digital fluency (Wang, Wiesemes and Gibbons, 2012), learning inquisition (Ahmed and Parson, 2013) and social knowledge construction (Lan et. al, 2012). The tools act as platform for students to collaborate with their peers and the devices may be used as primary or secondary learning aid during the teaching and learning process.

Apart from that, using ML tools for collaborative learning positively engaged the learners (Al-Fahad, 2009) as well as scaffold the learning process that may not be effectual using conventional methods of the past (Jones, Scanlon and Clough, 2013).

- **Social Networking**

Social networking is identified as the most popular platform for Collaborative ML (Lan et. al, 2012). Social networking provides online asynchronous discussion via mobile devices that has high popularity rate and likeability among students. Brito (2012) conducted focus-group research that analyzed patterns, factors and drawbacks of Collaborative ML conducted via social networking and discovered that students exhibits both “metacognitive knowledge and personal epistemological observations” due to their familiarity and constant engagement with ML devices. As a result, these enhances learning motivation as well as give learners myriad options on methods of interaction, personalized learning as well as neutralized the perception that social networking benefits would tower solely towards non-academic purposes. A research conducted by Cheon et. al. (2012) studied how ML readiness is gauged by Social Networking platforms and findings showed that learners have higher acceptance and level of readiness in conducting collaborative learning via online asynchronous discussion even with minimal facilitation and limited technical support.

- **Gaming**

Gaming is one of the main areas discussed in Collaborative ML where its usage, limitations and potentials in optimizing learning competence were identified as vital aspects in motivating the use of ML amongst students. Majority of the games reviewed from the data pool are utilizing Second Life as the platform for data collection and analysis. Cheng (2014) uses Second Life as a catalyst to conduct case study on identifying students’ acceptance in Collaborative ML where the virtual gaming platform to engage asynchronous discussion, collaborative learning, problem solving, risk management as well as enhance metacognitive skills. The study showed that gaming enhances cognitive skills as well as contribute positive learning attributes towards Collaborative ML. Apart from that, other façade of gaming is studied where pedagogical aspects of gaming were analyzed to examine the transferability of the Jigsaw and Fishbowl collaborative learning techniques to the Second Life platform (Andreas, Tsiatsos, Terzidou and Pomportsis, 2010). Meanwhile, gaming element is also implemented to scaffold vocabulary learning (Sandberg, Maris and Hoogendoorn, 2014) where learners were able to enhance their vocabulary competence via gaming as well as outperform other learners who were using conventional methods such as dictionary and lexical references. Gaming is widely used to enhance interactivity (Belotti, Berta, Gloria and Ozolina (2011) as well as improve learners’ engagement and motivation. (Liu and Chu, 2010).

- **Knowledge Sharing**

Based from abstract mining conducted, knowledge sharing is considered as bridging the learning gap by collaborating with peers and facilitator via mobile devices and collaborative methods. Sue et. al. (2010) studied the use of knowledge sharing in Collaborative ML. The outcome of their research concluded that knowledge sharing enhancement during collaborative activities via mobile devices increase learning achievement, shared gratification as well as increase motivation to conduct verbal and non-verbal interaction with their peers. Ryu and Parson (2012) uses knowledge sharing as a mechanism to gauge the benefits in Collaborative ML where it is found to incite risk taking as well as expedite higher motivation in collaborating with their peers. Sung, Hwang and Chiu (2012) deduced knowledge sharing to provide intrinsic engagement to explore new disciplines and learning areas that might not be expedited promptly via conventional learning methods.

- **Special Needs**

There is also a growing interest towards utilizing Collaborative ML for special needs. Fernández-López et. al. (2013) opined that students with special needs require learning alternative to cope with physical shortcomings that might be offered via ML. Collaborative ML offers a platform to enhance behavioural support, cognitive flexibility as well as metacognitive scaffolding that conforms to the personalized learning environment and ethos. Looi et. al (2010) discussed on how Collaborative ML can leverage sustainable learning readiness for students with Special Needs as mobile devices are equipped with augmented reality enhancement, larger and more vivid visualization optimization as well as adjustable audio capacity.

- **Communication**

Pertaining to Communication, it is categorized into verbal and non-verbal communications that are synthesized using asynchronous discussion platforms as well as synchronous platform. Chiu & Hsiao (2010) studied the communication differences during Collaborative ML for primary school students and the outcome of the research revealed that it generated active learning and active communication as there is abundant discussion, particularly for continuing task, managing procedure and coordinating efforts.
The communication level were categorized based from four qualities; passive or reticent, frequently off-task, actively participating, and knowledge emphasizing. The research is parallel to the case study conducted by Sung, Hwang, Liu and Chu (2014) where it improves self-efficacy as well as enhances self-esteem and collaboration engagement for future learning activities and assessment.

LIMITATIONS

The current review has a number of limitations. As with all reviews it was limited by the search terms used, the journals included and the time period of papers published. However the papers discussed in this literature review provide a snapshot of empirical research on outcomes and impacts of Collaborative ML and the parameters that surround the research areas. Apart from that, the review is conducted from the Educational Technological perspective. Future review could be conducted from the Information Systems paradigm. Besides that, the review excluded speculative and theoretical papers because it is vital to identify the outcomes and issues of Collaborative ML that could be analyzed and rectified in future studies. While many aspects of Collaborative ML are relevant to improving learning quality, the rest eight areas identified from the 799 papers on ML are equally important to be studied and analyzed.

CONTRIBUTION

As a contribution, this research offers educators and researchers an updated SLR on the current state-of-the-art researches on ML, specifically Collaborative ML. It would assist researchers to identify the issues, patterns of research areas as well as gauge the solution to engage refined methods, system or framework in eliminating any defect, problem or shortcoming in implementing ML for teaching and learning in the classrooms. Apart from that, SLR provides extensive overview on past empirical researches from the top ten IF Journals that provide a high quality input on future studies on Collaborative ML.

FUTURE RESEARCH

According to the SLR conducted, game-based mobile learning, Augmented Reality with virtual information and Virtual world will be the areas to focus for future research. We will see more shareable Mobile learning objects/activities/ resources. Researchers are working on how we could make use of users/learners own devices as well.BYOD (Bring your own device) concept will gain popularity.

CONCLUSION

The Systematic Literature Review conducted enables researchers and educators to identify latest trends. In conclusion, mobile learning is immanent in the dynamics of education and will revolutionize the pace and impact the learning boundaries. In order to identify the trends and better prepare for the needs and roles of ML for future education, it is imminent that SLR is conducted that review the latest focus on mobile learning. Based on the SLR conducted, Collaborative ml is the top trend pertaining to ML and further analysis and discussion on the literature are conducted. For future work, the authors hope to conduct feasibility analysis on Collaborative ML and gauge its impact on teaching and learning process to bridge learning gap.

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KEYWORDS

Collaborative: To work with another person or a group in accomplishing a task.

Mobile Learning: Learning across multiple contexts, through social and content interactions, using personal electronic devices.

Systematic Literature Review: A research question that tries to identify, appraise, select and synthesize all high quality research evidence relevant to a particular topic.

AUGMENTED REALITY: Augmented reality (AR) is a live direct or indirect view of a physical, real-world environment whose elements are augmented (or supplemented) by computer-generated sensory input such as sound, video, graphics or GPSdata.

GAMIFICATION: It is the use of game thinking and game mechanics in non-game contexts to engage users in solving problems and increase users' self contributions.

WEARABLE COMPUTING :Wearable computers, also known as body-borne computers or wearables are miniature electronic devices that are worn by the bearer under, with or on top of clothing.