Personalisation of MOOCs
The State of the Art

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Abstract: Researchers in the field of educational technology are paying huge attention to the widespread adoption of Massive Open Online Courses (MOOCs) in the study of learning online. MOOCs are discussed in many angles including pedagogy, learning sustainability, and business model. However, there are very few discussions around MOOCs personalisation. In this paper, it is aimed to examine and analyse the literature on personalisation of MOOCs to identify the needs, the current states and efforts to personalise learning in MOOCs. The findings denote that the pedagogical design of MOOCs is currently insufficient due to massive and geographically dispersed learners with diverse educational backgrounds, learning requirements and motivations. Many believe that personalisation could address this lacking in MOOCs. Among the most popular services being proposed or implemented in the literature are personalised learning path, personalised assessment and feedback, personalised forum thread and recommendation service for related learning materials or learning tasks.

1 INTRODUCTION

Massive Open Online Courses (MOOCs) is an emerging area in technology-enhanced learning (Jona and Naidu, 2014). Even the first MOOCs course, Connectivism and Connective Knowledge 08 (CCK08), has attracted thousands of learners. It should be noted here, this online course was not announced as a “massive open online course”, the term “massive open online course” was first introduced in 2008 by Dave Cormier to describe George Siemens and Stephen Downes’ CCK08 online course (McAuley et al., 2010). The first MOOCs course was based on connectivism theory that addresses issues about connecting people and resources to construct knowledge. It emphasises the importance of providing social platforms to learners to support their interactions with the course content, rather than just transmitting knowledge to them (Siemens, 2005). This kind of MOOCs is later known as cMOOCs.

In 2011, Sebastian Thrun designed a MOOCs course on Artificial Intelligence at Stanford University. Pedagogically, this MOOCs course was different from the first MOOCs. It is more teacher-centric in which learning goals and learning plans were predefined for potential learners. This kind of MOOCs is named as xMOOCs, and it is based on the behaviourist learning theory (Daniel, 2012).

Even though MOOCs is relatively a new trend in technology-enhanced learning, concerns on teaching and learning with MOOCs are still the same with those on online education (Hollands and Tirthali, 2014; Shaw, 2012), for instance, how can MOOCs be pedagogically efficient to address different needs of its learners? Research attempts to address this issue are discussed further in Section 3. One proposed study is to provide MOOCs personalisation through educational data mining in order to improve learning experience in MOOCs. In this paper, the state of the art of personalisation in MOOCs based on a study on the related literatures is presented. The methodology is presented in Section 2. Analysis and findings are reported in Section 3 in order to identify the aspects of MOOCs’s personalisation that are commonly addressed by researchers and those that are still not sufficiently look into. The existing personalisation approaches and report of the critical reviews on them are further investigated in the sub sections of Section 3. Based on the findings, suggestions on ways to improve the delivery of personalised learning in MOOCs are provided in Section 4. Section 5 concludes the study and presents suggestions for future work.

2 METHODOLOGY

In order to review the literature, similar methodology used by Liyanagunawardena et al. (2013) and Yousef et al. (2014)'s researches is applied. The articles between 2011 and 2014 (by November, 30) are searched by the keywords "MOOCs personalisation" and "adaptive MOOCs" on several academic databases, Google Scholar, The British Journal of Educational Technology, American Journal of Distance Education, Journal of Online Learning and Technology, ISI Web of Knowledge and IEEEXplore. The reason of choosing this particular time period is that 2011 is the year in which both xMOOCs and cMOOCs have been discussed (Daniel, 2012) and MOOCs has become rapidly and widely used in online learning as reported in (Liyanagunawardena et al., 2013). Not only peer-reviewed articles were analysed in this paper, but also the grey literature, for example institutional reports were also searched and analysed.

Table 1: The result of the search by the keyword "MOOCs personalisation".

Year	Search result	Relevant
Google Scholar		
2011	17	0
2012	29	1
2013	313	11
2014	427	14
The British Journal of Educational Technology		
2011	0	0
2012	0	0
2013	0	0
2014	1	0
American Journal of Distance Education		
2011	0	0
2012	0	0
2013	0	0
2014	4	0
Journal of Online Learning and Teaching		
2011	0	0
2012	0	0
2013	0	0
2014	0	0
ISI Web of Knowledge		
2011	0	0
2012	0	0
2013	4	1*
2014	0	0
IEEEXplorer		
2011	0	0
2012	0	0
2013	0	0
2014	0	0

Table 1 and 2 illustrate the number of papers that have been retrieved, along with the number of relevant papers to the personalisation of MOOCs over the years based on the searched keywords "MOOCs personalisation" and "adaptive MOOCs", respectively. While the year 2012 is called and referred many times as "the year of the MOOC", personalisation of MOOCs has been on the rise since 2013 (The New York Times, November 2, 2012: http://www.nytimes.com/2012/11/04/education/edlife/massive-open-online-courses-are-multiplying-at-a-rapid-pace.html?pagewanted=all&_r=0).

Table 2: The result of the search by the keyword "adaptive MOOCs".

Year	Search result	Relevant
Google Scholar		
2011	19	0
2012	72	1*
2013	422	18***
2014	623	17***
The British Journal of Educational Technology		
2011	0	0
2012	0	0
2013	3	0
2014	1	0
American Journal of Distance Education		
2011	0	0
2012	0	0
2013	0	0
2014	2	0
Journal of Online Learning and Teaching		
2011	0	0
2012	0	0
2013	0	0
2014	0	0
ISI Web of Knowledge		
2011	0	0
2012	0	0
2013	3	1*
2014	4	0
IEEEXplorer		
2011	0	0
2012	0	0
2013	1	1*
2014	5	3**

* 1 same result with the other search.
** 2 results of them are the same with the other search.
*** 8 results of them are the same with the other search.

Figure 1 clearly illustrates that the amount of attention for personalised learning in MOOCs is drastically increased in the last two years.

Even though, the number of search results is over 600 papers (see Table 2), relevant papers are only a few among them (40 papers in total). Papers on studies regarding adaptive online education systems, and other issues related to MOOCs are also retrieved along with papers on mass personalisation in MOOCs with these keywords. However, the relevant papers only indicate studies that are based on mass personalisation.

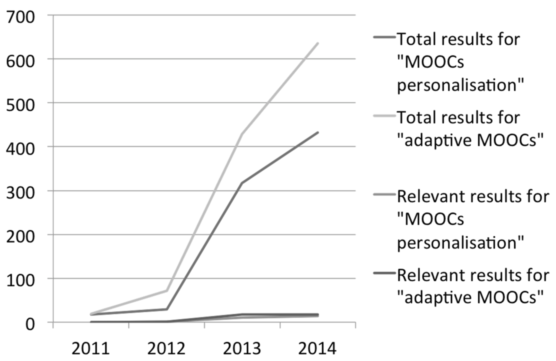

Figure 1: The total number of papers and relevant papers by the searches for the keywords "MOOCs personalisation" and "adaptive MOOCs".

This study only considers the relevant papers for analysis. The analysis is organised according to the purposes and scoped of the studies, and the personalisation or adaptation techniques used.

3 DATA ANALYSIS

Once the redundant papers are eliminated from the collection of relevant papers, it is observed that some papers rhetorically indicate needs for personalisation in MOOCs while some others attempt to develop personalisation services in MOOCs. Therefore, the relevant papers are clustered into three categories in this study:

1. NEEDS: Represents the '*Need for personalisation in MOOCs*'. This category of research papers indicates the need or opportunity for MOOCs personalisation. They mainly report findings that lead to the need for personalised learning in MOOCs. However, the papers in this category do not propose any project, framework or system for designing or implementing personalisation in MOOCs.
2. PROPOSALS: Represents the '*Plan to implement personalisation in MOOCs'*. This category of research papers expresses ideas and proposals for personalisation projects in MOOCs. However, the plans for the intended personalisation systems have not yet been implemented.
3. IMPLEMENTATIONS: Represents the attempts for '*Personalisation Service in MOOCs*'. This category of papers expresses partly or fully implemented and experimented proposals for personalisation in MOOCs. However, majority of researches in this category are in progression state with no definitive outcome yet.

Figure 2 illustrates the number of papers in each category over the years. The figure denotes that only one paper emphasises the need for personalisation in MOOCs in 2012 while 2013 is the year with the highest number of papers (13) calling for personalisation. In 2013, there are 5 descriptive papers on proposals for personalisation in MOOCs but only 3 papers proposed partly or fully personalised MOOCs functions in MOOCs learning environment. Generally, the number of papers in categories of Proposals and Implementations increases in 2014 after the call for adaptive MOOCs in the previous year. The results show that there is a rapid growing of interest towards personalised and adaptive learning in MOOCs. Additionally, it is predicted that there will be more implemented and fully experimented studies in the coming years.

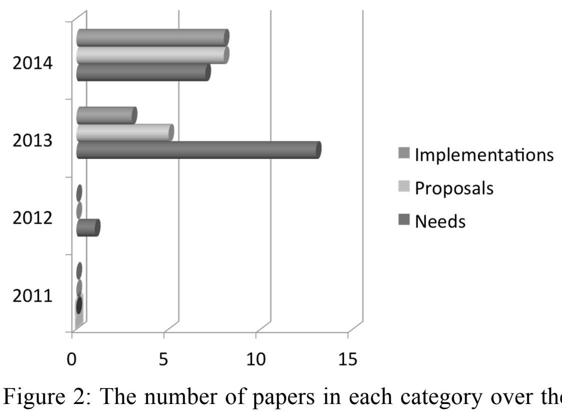

Figure 2: The number of papers in each category over the years.

3.1 Needs

Fasimpaur (2013), Freeman and Hancock (2013), Godwin-Jones (2014), and Harman and Koohang (2013) indicate that a huge amount of human data can be collected through MOOCs. The availability of the big data in MOOCs, and tools to perform learning analytics would make it possible for a personalised system to predict learners' learning behaviours and preferences in order to deliver personalised learning and assistance to MOOCs learners. Shaw also (2012) points out that this pool of human data could be used to create a human model in intelligent tutoring system (ITS) for MOOCs. Similarly, Yates (2013) and Knox (2014) highlight that data mining and data analytics for prediction could make MOOCs adaptive. Slightly on a different note, Kay et al. (2013) predict that educational data mining and learning analytics should be applied for MOOCs's social network analysis to enable personalised learning in MOOCs. Kalz (2014) further supports the argument by highlighting that these techniques could make MOOCs a more suitable technology to support lifelong learners.

The importance of offering personalised learning in MOOCs is further expressed by the following researchers. For instance, Amo (2013) believes that MOOCs should offer student-centred learning for effective and quality education in order to meet each individual learner's learning expectations in MOOCs. However, she emphasises that current pedagogy and design of MOOCs is not enough to improve students' outcomes. As there are many exciting and available pedagogies in technology enhanced learning such as peer assistance and assessments, social networking, and gamification, the author suggests for the incorporation of these pedagogies into MOOCs. This can be accomplished through the use of learning analytics and continuous monitoring of students' interactions so that automated assessment with instant feedback can be personalised to every student to improve quality learning in MOOCs.

McLoughlin (2013) and Knox et al. (2014) also address the current inefficiency of learners' feedbacks in MOOCs. They point out that MOOCs environment is convenient for offering personalised contents and feedbacks to learners based on their learning goals. This is because MOOCs provides learning flexibility and sense of independence between learners and teachers which are important when implementing personalisation in technology-enhanced learning.

Additionally, Kalz and Specht (2013) point out that the current MOOCs design does not consider the diversity of its learners. The authors suggest that building sub groups that share similar attitudes and interests could be a solution. The authors further indicate that the heterogeneity problem in MOOCs community is akin to the problem of learning network. The authors describe learning network as a connection of humans, actors, agents, institutions and learning resources organised for a learning program/course. To deal with diversity in learning networks, several services for learner support in learning networks should be utilised, such as placement support service (navigation support), a recommender service, and knowledge matchmaking service. By using these intelligent personalisation techniques, different needs and interests among diverse learners community in MOOCs can be addressed. To further support the importance of addressing diversity among learners, Cavanaugh (2013) whose work focuses on MOOCs assessments for credits for the post secondary education, states that personalised learning pathways for learners could help them build their capabilities to obtain credits.

Kizilcec et al. (2013) are concerned with low completion rate in MOOCs. Therefore, they have conducted a study to examine patterns of learners' engagement and disengagement with the MOOCs course, and consecutively they have suggested for MOOCs to offer adaptive content or assistance to learners according to their needs. Their suggestion is further supported by Martin et al. (2013) who believe that learning in MOOCs can be encouraged by providing predefined personal path and super badges that indicate the competence level of each individual learner.

On the other hand, Aoki (2013) and Stine (2013) focus on business model for MOOCs. While Stine (2013) indicates mass personalisation can have a positive business impact to MOOCs, Aoki (2013) points out that MOOCs is representing a new business model. Aoki (2013) states that content providers for lectures, assessments/accreditation and tutorial supports will eventually be separately established and organised. The author presumes that the learners' data will be shared among separate organisations to enable personalisation in MOOCs.

Despite the apparent needs for personalised learning in MOOCs, Kay et al. (2013) point out that the existing MOOCs courses are not even half way through in implementing personalisation. Nevertheless, without personalisation, learners may reduce their participations and eventually drop out from a MOOCs's course, which is one of the biggest concerns of MOOCs (Stevanović, 2014). Noteworthy that even though, there is nonexistence of personalisation practice on the existing MOOCs platforms, Hollands and Tirthali (2014) point out that MOOCs still present the term POOC "Personalised Open Online Course" into their full report. It is also stated that the success of MOOCs will depend on how much the learning process is personalised.

3.2 Proposals

The literature that is considered under this category mainly involves project launches which are funded for the aim of personalising online education for masses, projects' proposals for implementing personalisation in the existing non-personalised MOOCs, and conceptual research frameworks.

Most of the research works are driven by concerns over the inefficiency of MOOCs design, delivery, and assessments. For instance, Daradoumis et al. (2013) and Bassi et al. (2014) voice their concerns in several different research papers. According to the authors, as most of MOOCs courses are not learner-centric, and they provide same content for all learners, the effectiveness of the tutoring is generally poor, feedbacks are insufficient and peer-based evaluation is usually unprofessional. To address these deficiencies, the authors propose an agent-based framework for MOOCs. Agents collect data and analyse them according to several perspectives including educational goal, pedagogical preferences, time management and so forth. The analysed data is used by other agents for content customisation, tutoring feedback, system-learner alert as well as assessing and monitoring learners' learning progress in MOOCs. The authors indicate that intelligent agents could also be used for reducing fraud and cheating during online tests.

Broun et al. (2014b) propose a personalisation component which will be integrated to the existing EMMA platform. EMMA platform is a MOOC platform delivering courses in different languages from different European Universities; therefore, learners may be overwhelmed with huge number of courses and language choices. Through this personalisation component, EMMA aims to provide personalised feedback and individualised learning paths to support learners to achieve their learning goals.

De Maio et al. (2014) believe that learners' engagement with the video lecture materials in MOOCs as passive. To improve learners' engagement with MOOCs, the authors propose a methodology to support learners to navigate the fragments of one or more videos lectures so that learners could connect their goals and prior knowledge with the key concept of the lectures. The authors use taxonomy building for constructing a knowledge model for the concepts of lectures. The main idea is to enable inter-linking between different MOOCs courses and navigate learners to related ones. However, this part of the research has not been conducted.

Similarly, Wilkowski et al. (2014) have conducted an analysis on learners' goals and their achievements on the tested skills and activities by executing "Mapping with Google" course in MOOCs. Each learner was asked to complete a questionnaire about their learning goals to join the course and their previous experiences with the Google map. The authors then compared learners' learning goals with their behaviours in the course (i.e. watched videos, completed activities), and found out that their behaviours were very much determined by their goal. Therefore, the authors conclude that the course delivery could be personalised based on learners' goals. Their proposed system could be adapted to learner's requirements in two ways. First is to ask for learners' goals prior to delivering personalised learning pathway to each of them. Secondly, to have learners select the course elements such as some video lectures and assessments from a list for a customised course.

Fasihuddin et al. (2014) propose an approach for personalised learning experience in MOOCs based on learners' learning styles. The authors define the kind of material that should be included in the lecture for a particular learning style. For example, while visual learning objects should be accessible for visual learners, such need is not a necessity for verbal learners. However, this is an ongoing research and a prototype is still not yet completed.

Elkherj and Freund (2014) have developed an adaptive hint system for the undergraduate online course "Introduction to probability and Statistics" on the Webwork, which is a platform for managing homework assignments in mathematics. This course was attended by 176 students and hints were written by the tutor each time learners made a mistake or failed a test. The authors express that the need for manual labour for analysing learners' failure and writing helpful hints makes the system inconvenient for MOOCs. Therefore, they propose some possible approaches that could address this problem. The first is for students to hints to their peers. Secondly, create hint libraries. Finally, use machine-learning techniques to map students' mistakes with hints and consecutively send the most relevant hint to them.

Brouns et al. (2014a) propose ECO sMOOC for the EU-funded project called Elearning, Communication and Open-data: Massive Mobile, Ubiquitous and Open Learning (ECO). sMOOC refers to being a social-based MOOCs which is accessible from different types of social media and mobile devices. Learning is executed devices through content contextualisation based on learners' interactions and participations in the course using mobile and gamification approaches. The ECO sMOOC environment is described as learner-centric approach, which is adaptable to learners' intention. However, the project is in the very early stage, and any real experience with it has not yet available.

Bain et al. (2013) propose AMOOC (Accessible Open Online Course) movement to make MOOC courses more accessible for learners with disabilities. The paper focuses on delivering course content in appropriate forms for disable learners. They also mention that the system will be conducted using Adaptive Mobile Online Learning (AMOL) for adapting coursework to each learner's learning style.

Collet (2013) proposes POEM (Personalised Open Education for the Masses) platform project for designing personalised learning management system (LMS) for massive learning. The author believes that personalisation of massive education is only possible with intelligent ICT (Information and Computing Technology) platforms. In POEM, visual and dynamic Knowledge Maps of domains for each course are constructed to provide different possible learning paths to learners. POEM will also provide inter-tutorship and automatic assessments. Apart from that, the system will ask learners to post new questions or new contents to the platform.

Bansal (2013) and Birari (2014) have utilised the concept of ITS for personalising learning experiences with MOOCs from different perspectives. Bansal (2013) focuses on providing recommendations for learners to do additional learning activities to improve their lack of knowledge on a particular topic. In order to model learners' knowledge, the author uses the fuzzy cognitive map. On the other hand, Birari (2014) models learners' cognitive state by Bayesian network so that adaptive testing and adaptive guidance can be delivered to learners.

Slightly on a different note, Blanco et al. (2013) has identified three weaknesses in MOOCs: high dropout rate, lack of cooperative activities among learners, and poor continuity of learning communities when a MOOCs course ends. According to the authors' definition, learning community includes activities, resources, and similar groups. To improve learning experiences in MOOCs, the authors have outlined the components of learning community that should be personalised based on learners' learning goals, previous knowledge, etc. These personalisation inputs are captured and diagnosed through initial assessments.

Similarly, Zhuhadar and Butterfield (2014) point out that providing a singular curriculum to a diverse MOOCs community has caused low completion rates in MOOCs. To address this problem, the authors propose Personalised Open Collaborative Courses (POCCs) which tracks learners' attitude during the course and delivers the personalised content based on learners' activities and their prior-knowledge. In order to achieve this goal, the authors examine sub communities in MOOCs to design a personalised social recommender system.

3.3 Implementations

Research works reported in this category provide a more concrete evidence of approaches towards implementing personalisation in MOOCs, such as early stage experimental results, a system framework or results of system performance tests. This category considers either partly or fully implemented personalised systems that may have performed some kind of testing on either system performance or student performance. Noteworthy that majority of the systems have not yet completed their final evaluations, and the projects are still ongoing.

An algorithm of an adaptive study planner for MOOCs learners, targeted to novice learners in MOOCs is presented by Alario-Hoyos et al. (2014) and Gutiérrez-Rojas et al. (2014a). The adaptive planner creates a personalised study schedule for each learner based on their priority of the course, available time slot and the course requirements. However, this system has not yet been evaluated.

Burgos and Corbí (2014) present a rule-based technology-enhanced learning recommendation model in order to improve users' performance in MOOCs and other Open Educational Resources (OERs). The model tracks learners' performances and their interactions with the lectures. It consecutively map the related data according to the tutor's rules for recommendation such as minimum number of required activity in a lecture and minimum score on a given test. Based on the results of rules mapping, a recommendation is made. If a learner satisfies the tutor's rule to be successful, then the learner gets positive comment such as "Well done!" and gets recommendation for the subsequent tasks. Otherwise, the system gives alert feedback to the learner to request support from the online tutor and peers, and locks any further activities.

Ketamo (2014) utilises ITS technologies for providing recommendations to support learners' cognitive progress and motivation in MOOCs. The content that will be provided to learners is defined as semantic network. This approach requires a learner to complete and succeed relevant test on a learning concept prior to recommending the next related learning concepts. According to the preliminary evaluation results, learners' performances were improved when using the recommendation service. However, a considerable portion of learners was still not motivated to learn, and eventually dropped the course.

Shatnawi et al. (2014a, 2014b) propose system architecture for providing personalised feedback to learners in MOOCs by using text-mining technique. Since the course creators are not able to provide timely feedback due to massive number of learners, the authors propose a method for providing automatic content related feedback by using domain ontology, machine learning, and natural language processing. When a learner writes a post, the system will determine its type, whether it is a question, a comment, or a feedback, and organised it into a suitable domain under the related topic in a repository. If a learner posts a question, the system will automatically search the repository and returns semantically relevant information or personalised feedback to the learner.

Sonwalker (2013) proposes an adaptive MOOC that offers adapted learning contents based on learning styles with the concern of pedagogical effectiveness of MOOCs. The author proposes the learning cube that illustrates organisation of learning objects developed in text, graphics, audio, video, animations, and simulations according to different learning styles. In this study, learners' learning style is diagnosed via a diagnostic test as suggested by Blanco et al. (2013). The performance test result is promising.

Yang et al. (2014) propose a personalised support on MOOCs discussion forums for helping learners to reach the topics in which they are interested. The authors use both collaborative and content filtering techniques to capture the most relevant forum threads. Their system performance test results show that the system performance of the proposed personalisation model is satisfactory, however, learners' satisfaction test has not yet examined.

Some researchers modify existing personalised technology-enhanced learning systems for MOOCs courses. For example Miranda et al. (2013)'s work aims to provide a pedagogy-based guide for items assessment based on the ontological relations between learning subjects in the lectures which are defined by the course creator. According to a learner's assessment's score, a personalised learning pathway is constructed for the learner. Similarly, Henning et al. (2014) also adapt an existing technology-enhanced learning system into MOOCs. The system supports learners through personalised navigation based on their learning performances and the association between learning subjects.

4 DISCUSSION

Result from the analysis of the needs related literature shows that the pedagogical design of MOOCs is insufficient, therefore, educational data mining should be applied to provide personalised services such as personalised learning pathways, personalised assessments, adaptive feedbacks, and recommender services. To address the needs for personalisation in MOOCs, researches in category Proposals and category Implementations have proposed several outlines, frameworks, and projects' proposals, as well as prototypes for implementing personalisation and adaptation in MOOCs.

For instance, Kalz and Specht (2013) and Kizilcec et al. (2013) from category Needs suggest to cluster MOOCs's learners for personalisation. The suggestion was implemented by Blanco et al. (2013), Fasihuddin (2014) and Sonwalker (2014) in which they applied a diagnostic test at the beginning of the course to understand which group (i.e. learning style) a learner belongs to. However, this method is based on learners' participations in the diagnostic test, and majority of learners are not interested in doing tests. Realising this problem, Zhuhadar and Butterfield (2014) have suggested using some social networking analysis (SNA) techniques to diagnose learners and automatically cluster them according to the most suited sub community in MOOCs based on their activities. Even though this method does not need learner's self-statement, a learner is required to participate in the course's lectures and activities until the system can gather sufficient information about the learner in order to determine a suitable cluster for the learner.

Another example is by the work of Shaw (2012) who believes that the application of ITS technique can actualise mass personalisation in MOOCs. The belief was translated by Bansal (2013), Bariri (2014) and Ketamo (2014) who implemented ITS techniques in MOOCs for personalising contents, learning pathways, and providing recommendations.

Note that even though Yang et al. (2014) and Brouns et al. (2014a) did consider the social feature of MOOCs, for example they personalise online forum threads to learners based on their forum activities and peers connections, they did not build a personalised learning network in MOOCs or social network analysis for improving learning networks as suggested by Kalz and Specht (2013) and Kay et al. (2013). Therefore, continuity problem of learning communities identified by Blanco et al. (2013) remains unsolved.

5 CONCLUSION AND FUTURE WORKS

In conclusion, this literature survey has demonstrated that there is a growing trend of researchers embarking in the possibility of implementing personalisation and adaptation in MOOCs in order to improve users' engagements, hence reduce MOOCs' drop-out rate problem. The trend is mainly motivated by the fact that MOOCs's learning has the potential to spark demands for personalised learning due to its massive and geographically dispersed learners with diverse background. In addition to that, MOOCs environment does provide the basic requirements for personalised learning such as the availability of huge learners' data, flexible learning, and learner-teacher independence. Our categorisation of the literature identified three distinct types of papers. 1) These concerned with the need or motivation for personalisation in MOOCs. 2) Outlines of plans or proposals for implementing personalisation in MOOCS. 3) Accounts and evaluations of the implementation of personalisation services in MOOC. We found that data mining techniques are often used to exploit huge learners' data in MOOCs, and majority of the studies are concerned on the pedagogical design issues. Therefore, many researchers have proposed solutions based on personalisation and adaptation techniques such as personalised learning pathways and personalised feedback. However, there is not yet any tangible research that focuses on building personalised learning networks even though the need has been identified by Kalz and Specht (2013), Kay et al. (2013) and Blanco et al. (2013). It is expected that this issue will gain more attention in the nearest future.

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