A Literature Review on Learner Models for MOOC to Support Lifelong Learning

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Abstract: Nowadays, Learning Analytics is an emerging topic in the Technology Enhanced Learning and the Lifelong Learning fields. Learner Models also have an essential role on the use and exploitation of learner-generated data in a variety of Learning Environments. Many research studies focus on the added value of Learner Models and their importance to facilitate the learner's follow-up, the course content personalization and the trainers/teachers' practices in different Learning Environments. Among these environments, we choose Massive Open Online Courses because they represent a reliable and considerable amount of data generated by Lifelong Learners. In this paper we focus on Learner Modelling in Massive Open Online Courses in an Lifelong Learning context. To our knowledge, currently there is no research work that addresses the literature review of existing Learner Models for Massive Open Online Courses in this context in the last five years. This study will allow us to compare and highlight features in existing Learner Models for a Massive Open Online Course from a Lifelong Learning perspective. This work is dedicated to MOOC designers/providers, pedagogical engineers and researchers who meet difficulties to model and evaluate MOOCs' learners based on Learning Analytics.

1 INTRODUCTION

Massive Online Open Courses (MOOC) have proliferated in the last decade all around the world. Their global reach and popularity steams from their original concept to offer free and open access courses for a massive number of learners from anywhere all over the world (Yousef et al., 2014). However, despite their global reach, popularity and often low-to-none costs, they have very low completion rates (Yuan & Powell, 2013; Jordan, 2014) with research metrics agreeing at median of about 6.5%. As this percentage increases and tops to about 60%, a ten-fold difference, for fee-based certificates, studies of both cases show that engagement, intention and motivation (Jung & Lee, 2018; Wang & Baker, 2018; Watted & Barak, 2018) are among the top factors to affect performance in MOOCs. DeBoer, Ho, Stump, & Breslow (2014) confirm the multifactor complexity of this phenomena by concluding that MOOC participants have reasons to enrol other than course completion [1]. We extend this affirmation by attributing a part of this phenomena to the obvious heterogenous nature of these new global learners and their heterogenous learning needs; a situation also highlighted by M. L. Sein-Echaluce et al. (2016).

Thus, improving academic success in MOOCs by increasing the learning outcome and the average completion rate of learners creates the need to personalize content and learning paths by modelling the learner (El Mawas et al., 2019). Research studies (Bodily et al., 2018; Corbet & Anderson, 1995) focus on the added value of Learner Models (LM) and their importance to facilitate the learner's follow-up, the

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[1] e.g. course-shopping, dabbling topic courses, auditing knowledge on the material and on its difficulty level, etc.

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course content personalization and the trainers / teachers' practices in different Learning Environments (LE) through Learning Analytics (LA). Moreover, it has been considered by Sloep et al. (2011) that learner's personalization is one of the essential concepts in Lifelong Learning (LLL) and Lifewide Learning contexts.

However, in the current context of Big Data, it is very difficult to make a clear view of the research landscape on works on Learner Models for MOOCs in an LLL context. For instance, a simple, unrestricted Google Scholar query on the term "learner model" returns about 2 million results, about 1 million results on "lifelong learning" and about 200 thousands on the term "mooc" at the time of the writing of this paper (early 2020). The goal of this literature review is to analyse the most recent works in the field of "LM for MOOC in an LLL context". This is in general terms, how a given LM coupled with(in) a MOOC can support an LLL. More specifically, we aim to differentiate and highlight LM's features and their relevance to a MOOC usage in an LLL experience. To our knowledge, currently there is no research work that addresses the literature review of existing Learner Models for Massive Open Online Courses in this context.

So, in order to try to bring up a more adequate and accurate panorama on the topic of LM for MOOC in a LLL context to the target public of this paper (MOOC designers/providers, pedagogical engineers and researchers who meet difficulties to evaluate MOOC's learners based on LA) we decided to limit [2] our literature review to the terms "learner model" and "mooc". We performed this research in the Google Scholar, Web of Science and Scopus databases, within the last five years (2015-2020) timeframe. The thought behind these choices is to obtain the most recent and high-quality corpus on the topic.

This work is different from previous literature reviews (Sergis & Sampson, 2019; Bodily et al., 2018; Abyaa et al., 2019; Liang-Zhong et al., 2018; Afini Normadhi et al., 2018) in that, not only it covers the most recent proposals, extensions and implementations of Learner Models (last 5 years) but that it discerns features in Learner Models that may play an important role in the case of Lifelong Learning in MOOC, such as its openness, independence and dynamism. This specific context led us to skip considering general models (such as User Models) as well as more specific models (Student Models, Professional Models or even explicit Lifelong Learner Models).

We also focus on (1) which dimensions are modelled, more precisely the way Knowledge is represented (both Domain and Learner's) and, (2) what strategies the Model implements to ensure its own accuracy, that is, its updating methods and / or techniques. We believe that this approach may help our target public (MOOC designers/providers, pedagogical engineers and researchers who meet difficulties to evaluate MOOC's learners based on LA) to take better informed decisions when choosing a MOOC and its accompanying LM, namely within the scope of LLL.

The remainder of this article is structured as follows. Section 2 of this paper oversees the theoretical works concerning this paper, namely the concept of Learner Models and their importance in MOOCs as well as presenting the Lifelong Learning dimension as the surrounding context. Section 3 details the methodology steps and discusses the results of this review of literature. Finally, Section 4 concludes this paper and presents its perspectives.

2 THEORETICAL BACKGROUND

In this section we present the theoretical background put in motion behind this research, namely the Learner Model and the considered features, its importance on MOOC platforms and the Lifelong dimension as the surrounding context.

2.1 Learner Models

Learner Models represent the system's beliefs about the learner's specific characteristics, relevant to the educational practice (Giannandrea & Sansoni, 2013), they are usually enriched by data collection techniques (Nguyen & Do, 2009) and they aim to encode individual learners using a specific set of dimensions (Nakic, Granic & Glavinic, 2015). These dimensions may or may not include personal preferences, cognitive states, as well as learning and behavioural preferences. Modelling the learner has the ultimate goal of allowing the adaptation and personalization of environments and learning activities (El Mawas *et al.*, 2019; Chatti *et al.*, 2014) while considering the unique and heterogeneous

[2] We note that, adding the LLL ("lifelong learning") term in the search query would have had the undesirable effect of excluding LM which did not explicitly contemplate this context but could still have characteristics that would eventually accommodate it.

needs of learners, which in turn improves learning metrics. Evidence from a number of studies have long linked having a learner model can make a system more effective in helping students learn, by using the model to adapt to learner's differences (Corbett & Anderson, 1995; Bodily *et al.*, 2018). Learner modelling relies on three scientific fields (educational science, psychology and information technology) and it involves (1) the identification and selection of learner's characteristics that influence learning, and (2) take into account the learner's psychological states during the learning process, in order to choose the most adapted technologies to model precisely each characteristic (Abyaa et al., 2019). One of the most important characteristics of LM is Knowledge representation. According to the family of techniques used to represent knowledge, LM can be classified into stereotype models, overlay models, differential models, perturbation models or plan models, each with its own set of techniques to model them (Assami et al., 2018; Herder, 2016; Nguyen & Do, 2009). Moreover, depending on each technique, the knowledge representation of the learner (learner's knowledge) can take the form of an instantiation or a differential or a relationship or a subset of the knowledge representation of the topic (domain's knowledge), while depending heavily for this choice on the context of utilisation (Abyaa et al., 2019).

Many studies (Somyürek, 2009; Vagale & Niedrite, 2012; Abyaa et al., 2019) hold that learner modelling is a process that follows these stages (1) gathering initial data related to the learner's characteristics (or initialization), (2) model construction, and (3) keeping the LM updated by analysing the learner's activities. During the initialization process (1) the LM may encounter what is known as a 'cold start' problem, where insufficient data on the learner is made available to properly instantiate the model. A similar situation ('data sparsity') may also arise during the updating phase (3), preventing the proper update on the LM or worst, leading to data corruption.

We acknowledge the difference between Learner Profile and Learner Model in that the former can be either considered an instantiation of the latter in a given moment of time, using educational data (Martins, Faria, De Carvalho & Carrapatoso, 2008), or, put in another way simply static uninterpreted information about the learner (Vagale & Niedrite, 2012). For example, a Learner Profile can hold data that may include personal details, scores or grades, educational resources usage(s), learning activity records, etc., all of which emerge during the delivery of the learning process (Sergis & Sampson, 2019).

Another additional classification for LM are Open Learner Models (OLM). They are a type of LM where the model is explicitly communicated to the learner (or to any other actors) by allowing visualization and / or editing of the relevant profiles (Bull & Kay, 2010; Sergis & Sampson, 2019). This contrasts to the view of a Closed Model, in which the student has no direct view of the Model's contents (Tanimoto, 2005). OLM can be classified int three categories (Bull & Kay, 2016), based on the model's edition and communication modes: inspectable, negotiable or editable. In one hand, a negotiable OLM will ask and check for factual evidence from the learner to accept any given modification, whereas an editable OLM will not rely on proof, requiring instead a set of permissions and access controls to avoid data corruption. An inspectable OLM, in the other hand, simply does not allow editing of any kind, leaving solely its updating mechanisms to the hosting system. Concerning the hosting system itself, Tanimoto, (2005) brings up the notion that Transparency is a desirable trait for LM to feature because, by revealing the internal works of a system, it helps to "engender trust, permit error detection and foster learning" about how the system works.

Many research studies (Bull, Jackson, & Lancaster, 2010; Sergis & Sampson, 2019) show the importance of Models that are independent of any system [3] by being able to accept multi-sourced data. Hence, we consider a LM as Independent if it is not "[…] part of a specific system and may collect or exploit educational data from diverse sources". Regarding the communication with the hosting system, an independent LM requires specific technical connectors (API) to different CMS or LMS platforms.

We consider paramount the independence of a LM, as a way for the learner to take possession and control of its own data. This cannot be accomplished without a sound support for technical connectors and interoperability. However, even an independent LM makes no difference if the data is locked within: we posit that OLM are a way to empower educators and learners by allowing them to peek inside the LM and keep it up-to-date through evidence.

In this part we discussed the notion of LM and some of its features. In the following section we treat the importance of LM for MOOC.

[3] Note that an LM does not need to be specific to a defined system or platform.

2.2 Importance of Learner Models in MOOC

We highlight the importance of MOOCs as means and tools for people from different countries and backgrounds to interact, collaborate, share and learn without the usual geographical or temporal constraints (Brahimi et al., 2015). As a quantitative and dynamic example, Shah from Class Central (2015; 2016; 2017; 2018; 2019) has been reporting a steady increase in people signing up for courses as well as in the number of courses being opened worldwide. That is, from over 500 Universities, 4200 courses and 35 Million Students in 2015, 2019 has seen over 900 Universities, 13500 courses and 110 Million Students. Yet, these numbers exclude China, whose metrics are “difficult to validate”, according to Shah. Furthermore, in 2019, MOOCs have come a long way to include not only microcredentials but also MOOC-based degrees, showing a diversification in their offer and an adaptation to their massive public learning needs. Thus, LM play also an important role in MOOC, as they allow for individualisation (Assami et al., 2018), personalization (Kay, 2012; 2019; Woolf, 2010) and recommendation (Morales et al., 2009; Sunar et al., 2015), which improve learning metrics by providing learners with an individual, tailored learning experience suited to their own uniqueness (Chatti et al., 2012).

These usage figures are a living testimony that MOOCs are a platform of choice for knowledge-eager lifelong learners worldwide. Such large number of platforms from so many universities convey the challenge of adapting first, the platform itself and second, the course contents to an equally large diversity of learners. A challenge where the LM can play a substantial role, by coupling it to a MOOC, allowing anywhere and anytime a tailoring of content and activities to the learner’s needs.

After discussing the importance of LM for MOOC, we introduce in the next section the context surrounding the mixed notion of LM for MOOC.

2.3 Lifelong Learning in Learner Models

(Knapper & Cropley, 2000) consider that the term Lifelong Learning (LLL) holds the idea that learning should occur through a person’s lifetime and that it involves formal and informal domains (Cropley, 1978). This is also supported by the European Lifelong Learning Initiative, which defines this term as a “continuously supported process which stimulates and empowers individuals to acquire all the knowledge, values, skills and understanding they will require throughout their lifetimes and to apply them with confidence, creativity and enjoyment in all roles, circumstances and environments” (Watson, 2003). In addition, Kay & Kummerfeld (2011) underline not only the need for a lifelong LM as “a store for the collection of learning data about an individual learner” but they also cite its multi-sourced and availability capabilities for it to be a useful lifelong LM. This definition is later reprised by Chatti et al., (2014) who defines Lifelong Learner Model (LLM) as a “store” where the learner can archive all learning activities throughout her / his life (Abyaa et al., 2019).

Thus, lifelong learner modelling (Chatti et al., 2014) is the process of “creating and modifying a model of a learner, who tends to acquire new or modify his existing knowledge skills, or preferences continuously over a longer time span.”. However, this process is not devoid of difficulties of implementation: Abyaa et al. (2019) and Chatti et al. (2014) mention data collection, activity tracking, regular updating, privacy, reusability, forgetting modelling, data interconnection, autonomy and self-directed learning instigation as some of the challenges and difficulties faced by LLM. Nevertheless, some efforts (Chatti et al., 2014; Ishola & McCalla, 2016; Swartout et al., 2016; Thüs et al., 2015) have been undertaken to address some of these challenges and difficulties, with varied results in their own domains.

2.4 Stakes in Learner Model Comparison

As we have exposed in this section, learner modelling for MOOC in a lifelong learning context is a complex task facing many challenges. In this section we outline the stakes to consider when reviewing LM.

First, in an LLL context, learning evolves in a continuum so, the LM must also be evolving continuously. This evolution must be assured and reflected by a close follow-up by the LM itself, which must establish the mechanisms to accept, hold and analyse the data in a precise way. In one hand, we consider that data can be multi-format and multi-sourced and so, the LM must be capable of accepting, understanding and holding an ample variety of it, in time. In the other hand, the mechanisms to process data are closely linked to the way data is represented in the LM, namely the Knowledge representation and the Recommender / Predictive system that is in charge of handling learner’s data.

Second, interoperability and dynamism play a crucial role in allowing for the LM to transcend its hosting platform and be used as a long-term, dynamic portfolio of knowledge, competences, skills, preferences, credentials, certifications or badges, among many others, as demanded by the LLL context. An isolated, locked LM cannot assure the portability needed by a heterogeneous learner public, with unique learning needs, in a multitude of heterogenous environments, in different moments of a lifetime. Such learner public requires then an independent, personalizable and unlocked LM, with cemented communication flexibility.

Third, within this LLL context, it is also desirable that the LM allows its inspecting and visualization so that the learner is actively made aware of his / her model, eventually permitting its editing or negotiation, through institutional policies or other similar instruments. By making the learner aware of its learning activities, that is, of its LM and of its maintaining mechanisms, it would foster trust, engagement and learning.

In the following section we present the methodology followed for the literature review whilst considering the previously presented stakes in LM comparison. It details into the paper selection process and it briefly introduces our developed tool that allows automatic metadata detection and organization from academic sources.

3 REVIEW METHODOLOGY

This review of literature follows the methodology described by Kitchenham & Charters (2007), which enumerates the following steps: [A] Identifying the need for a literature review, [B] Development of the review protocol, [C] Identifying the research questions, [D] Identifying research databases, [E] Launching the research and saving citations, [F] Screening the papers, [G] Summarizing the selected papers and, [H] Interpreting the results.

3.1 Identification of the Need for a Literature Review [A] and Development of the Review Protocol [B]

This work is dedicated to MOOC designers/providers, pedagogical engineers and researchers who meet difficulties to evaluate MOOCs' learners based on Learning Analytics. The goal of this review of literature is to analyse the most recent works in the field of "LM for MOOCs in an LLL context". This is in general terms, how a given LM coupled with(in) a MOOC can support an LLL. More specifically, we aim to differentiate and highlight Learner Models' features and their relevance to a MOOC usage in a Lifelong Learning experience. To our knowledge, currently there is no research work that addresses the literature review of existing Learner Models for Massive Open Online Courses in this context. As a side note, according to Kitchenham et al. (2007), the development of the protocol includes "[…] all of the elements of the review plus some additional planning information […]" that we have detailed in each of the subsequent steps of their methodology, such as the rationale of the review, the selection criteria and the procedures and data extraction strategies.

3.2 Identification of Research Questions [C]

Therefore, this article aims to answer the following research questions (RQ):

- RQ1: What Learner Model features are most relevant for a MOOC in an LLL context?
- RQ2: What are the most suitable LM for MOOC in an LLL context?

3.3 Selection Criteria and Research Databases Identification [D]

In this section we describe the inclusion and exclusion criteria used to constitute the corpus of publications for our analysis. We also detail and justify our choice of the search terms, the identified databases as well as the used software tool.

In one hand, our Inclusion criteria are: Works that present a Learner Model in the context of a MOOC or that present a new Learner Model and compare it to an existing Learner Model. In the other hand, our chosen Exclusion criteria consist of: Works not written in English, under embargo, not published or in the works. Also, works that do not treat Learner Models directly or only peripherally, that is: LM are not the main topic of the publication. Works of the same author for the same year (we keep only the last published contribution on the same subject) and finally, works published on journals take precedence over those on conferences.

Our Search terms were "learner model" and "mooc", which in most of the search engines conveniently translates as a Boolean query of the form { (learner* AND model*) AND (mooc*) }. This translation allows us to include plural, gerund and agent-noun results. It is important to note that the term LLL, while being very important as the context of our research, does not constitute nor an inclusion nor an exclusion criteria but a characteristic of the LM and this is why it does not figure in the search terms.

We chose to perform this research within the last five year's timeframe (2015-2020) at the beginning of January 2020 in the following scientific databases: Web of Science, Scopus and Google Scholar. Please note that within the Google Scholar results we are primarily interested in the results from Taylor & Francis Online, Science Direct, Sage Publications, Springer and IEEE Explore. The thought behind this choice is to have the most current and quality-proven scientific works in the domain. We chose and used the search software tool 'Publish or Perish'[4] not only to search into these databases at once (except Web of Science and Scopus) but also to profit from the software's feature to filter, regroup repeated publications and calculate different indexes, such as Hirsch's h-index, Egghe's g-index and Zhang's e-index, commonly known to the scientific community.

3.4 Launch of the Research [E]

For a more streamlined paper selection process, we designed and developed an external tool (publication under way) that, coupled with the software 'Publish or Perish', recovers and organizes metadata from a list of academic sources and presents it to the reviewer in a bias-free context (Step: Automatic Metadata Collection). This external tool allowed us to refine the results in terms of publication abstracts instead of publication titles only. Also, it prevented us from manually loading, saving and reading all of the articles' abstracts by hand and one by one. Its main advantage resides in facilitating a bias-free dismiss process by presenting only the publication's abstract text.

The paper selection process is pictured in Figure 1 and it happened as follows: First, we used a CSV file as a data concentration hub to hold the search query results issued from:

1. The Google Scholar search engine, using the software Publish or Perish.
2. The Scopus database, using the software Publish or Perish.
3. The Web of Science database.

Second, we automatically extracted relevant metadata related to the previous results (abstracts and keywords) from the corresponding articles' Web Pages or PDF files. This process aims to present this metadata in a bias-free context.

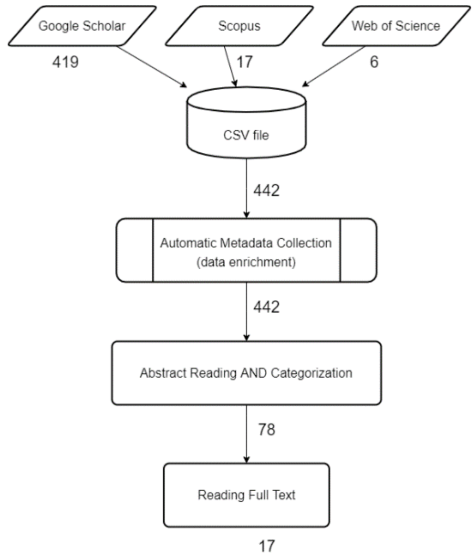

Figure 1: Overview of the publication selection and categorization process. A flowchart[5] is used to represent this process.

3.5 Paper Screening [F]

Then, we read all of the automatically extracted abstracts and filter-categorized them. We dismissed publications whose abstract was out of the scope of this paper while registering the main subject[6] of the dismissed paper. As mentioned, we focused primarily in the abstract to determine the articles' subject or topic. We intentionally avoided relying on the 'keywords', 'authors' or 'title' fields to avoid a possible bias. Although in doubt we recurred to consider the 'keywords' and the 'title' fields, respectively. The Dismissed Papers fell into one of the following categories:

1. 'Another kind of Model': it describes pedagogical models, relationship models, system models, etc.
2. 'Profile': it treats explicitly Learner Profile instead of Learner Model.
3. 'Not on topic' results contain the search terms in the text, title or bibliography but in a disconnected manner[7].
4. 'Citation' results were usually removed automatically by the 'Publish or Perish' tool but not always.

[4] Link: https://harzing.com
[5] https://www.lucidchart.com/pages/flowchart-symbols-meaning-explained

[6] e.g.: "ethical concerns of AI in education", "panorama on open source LMS" or "evolution of higher education".
[7] e.g. "Solar Models in a Geography Class: a Learner's first experience with MOOCs"

We also dismissed articles of which the content was not in English, Duplicates or Previous Work (from the same author). Most Recent Work on Topic publications from the same year from the same author were detected and only the most recent item kept.

Finally, we accessed and read the full text of the Passing papers through our institutional subscription or Open Access for full-text reading. We kept only articles from Book Chapters, Journals and Conference Proceedings and we dismissed Unpublished (or in the works) papers, White Papers, PhDs and Master works.

In the following part we deepen the paper screening phase by detailing the selection process, contrary to the first addressing in this section the dismissing issue.

3.5.1 Detailing the Selection Process

In this section we detail how we pass from a full set of search databases results to our research pool of selected articles. From the entire set of results given by the three search databases (442), that is 419 results from Google Scholar, 17 from Scopus and six from Web of Science, we constituted a final pool of 17 publications mentioning in their abstract their intention to propose a Learner Model. Unwittingly, the other databases did not provide results fitting neither our inclusion criteria, nor our search query.

Out of the 419 results from Google Scholar, 342 publications were quickly dismissed thanks to our developed bias-free method as it made very clear that they did not fit the inclusion criteria. That is, 77 were 'Passing' papers that required a more in-depth review.

During this initial search phase, the other engines (Scopus and Web of Science) provided relatively few results compared to Google. Surprisingly, it turned out that all of their results, except for one, were already within the Google Scholar results. That is, for Web of Science, all of the six results were 'Passing' but repeated, and for Scopus, out of 17 result, 12 were repeated and mixed with eight out-of-scope. This mix left us with only one 'Passing' result from Scopus, none from Web of Science and 77 from Google Scholar, after reading all of the extracted Abstracts.

Then, we proceeded to fully read the 'Passing' papers. From this initial 78 (77 + 1 + 0) papers only 17 became 'Proposals' (16 Google, 1 Scopus, 0 Web of Science). The dismissed papers group in this phase consisted of a mix of PhD and Master publications, one missed Not-in-English publication, a few most recent publications but mostly papers either out-of-scope or not fulfilling the inclusion criteria correctly. As a side note, we were able to pinpoint (and dismiss) 19 publications that either used the terms LM and Learner Profile interchangeably, or omitted LM.

For the sake of exhaustivity and according to our exclusion criteria, we registered not only the topic the described in the abstract but also the reason any result should be removed. The possible values are described in the following list:

- Language – The main text of the publication is not in the English language.
- Unrelated – Neither the title, nor the abstract, nor the keywords treat the terms "Learner Model" and "MOOC" in a connected manner. This includes works in the categories Citation, Another Kind of Model, Learning Modelling.
- Peripheral – The field "Learner Modelling for MOOC" do not constitute the core of the publication. This includes Learner Profile and Analysis on a Learner Model.
- Substitute – Discerning metadata given by the search engine was malformed (e.g. wrong title, wrong source). A correction was done after we could determine its pertinence by a reading review.
- Repeated – It was already within the results, usually from another search engine, but sometimes as a miss from the 'Publish or Perish' tool.
- None – The articles that did not get discarded.

This allows us to justify the classification and its dismissal.

The selection process concluded with 17 LM 'Proposals' which are shown in the Appendix [8] section, along with our considered features, which are in turn addressed in the following section, namely why and how they group into dimensions.

3.6 Summary [G] and Learner Models in LLL Criteria Comparison

A summary of the 17 LM found and its describing features is presented in the Appendix. In this section we address why and how these considered features weight in in the compositing of meaningful dimensions that allow comparison between LM.

As mentioned beforehand, the purpose of this paper is to detail the LM for MOOC features that could play an important role in LLL, while considering the stakes mentioned in section 2.4, e.g.,

[8] To identify an LM, we kept the LM name given by its authors, if any, otherwise we prepositioned 'None' to the country of origin of the publication (which led to a few repeats, unfortunately).

their openness or interoperability with other platforms. We consider the mechanisms, if any, mentioned by the authors to achieve these and the other features.

Thus, we begin by introducing our considered features; (1) the platform connection approach, (2) the cold start handling, (3) the data sparsity handling, (4) the learner knowledge representation, (5) the recommender / predictive method, (6) the openness of the LM, (7) its dynamism and, (8) its LLL consideration. This review of literature led us to consider these features to be key points to consider when choosing an LM for a MOOC in an LLL context.

We synthesized these nine features into four dimensions, namely Interoperability (I), sparse Data handling (D), Knowledge representation (K) and LLL (LLL). The Interoperability (I) dimension illustrates if the LM allows for standard connectors to external hosting systems. The sparse Data dimension (D) reflects if any given approach is considered in the event of missing data. The Knowledge representation dimension (K) pertains to the level of detail considered into the representation of the Learner's and / or Domain's Knowledge as well as the mechanisms used to update the LM or to recommend / personalize content. Knowledge representation is an important feature since it is closely linked to the way the LM keeps its integrity and/or predicts or suggest LM states. Finally, the LLL dimension illustrates how well the LM is prepared to cope with the exigences a LLL context demands.

All of these dimensions are important components of a LM in a LLL and its creation takes into consideration the presence, partial presence or absence of evidence from the corresponding integrating features found in the LM. We chose not to assess nor the number nor the authors' chosen characteristics of their proposed LM as they depend greatly on the purpose of each of their systems. This makes a straight and direct comparison between LM unfeasible and meaningless.

We represent then the authors' explicit consideration and description[9] of the method(s) used to enforce any dimension by a Tick symbol [✓]. The absence of evidence is represented by a Cross symbol [×]. Evidence of regard to any of our considered dimensions without an explicit description of the mechanisms to achieve it were marked with a Question mark symbol [?].

Table 1: LM found, with Interoperability (I), sparse Data handling (D), Knowledge representation (K) and LLL (LLL) dimensions analysis.

LM	Reference	I	D	K	LLL
TrueLearn	Bulathwela *et al.*, 2019	?	?	✓	✓
SBGF	Calle-Archila *et al.*, 2017	✓	?	x	x
MOOClm	Cook *et al.*, 2015	✓	x	x	✓
STyLE-OLM	Dimitrova *et al.*, 2015	✓	?	✓	✓
None-MOOCTAB	El Mawas *et al.*, 2019	✓	?	✓	✓
None-Tunis	Harrathi *et al.*, 2017	x	x	✓	x
None-China	He *et al.*, 2017	?	?	x	x
EDUC8	Iatrellis *et al.*, 2019	?	?	✓	x
DiaCog	Karahoca *et al.*, 2018	x	x	✓	x
None-China	Li *et al.*, 2016	x	x	x	x
None-ODALA	Lynda *et al.*, 2019	✓	?	✓	✓
None-Tunis-France	Maalej *et al.*, 2016	?	x	✓	x
GAF	Maravanyika *et al.*, 2017	x	?	x	x
AUM (AeLF User Model)	Qazdar *et al.*, 2015	✓	?	✓	✓
MLaaS	Sun *et al.*, 2015	x	x	x	x
Logic-Muse	Tato *et al.*, 2017	?	?	✓	✓
None-Adaptive Hypermedia	Tmimi *et al.*, 2017	X	x	x	x

The Interoperability (I) dimension was granted a Tick if a platform connector was specified and considered a Question mark [?] if only an implementing platform had been mentioned, hinting to a successful implementation. In terms of operability, a working connector [✓] allows for portability of the LM, important characteristic in LLL. So, the confirmation of an existing implementation of the proposed LM assures that some form of communication exists with a host system but does not on its portability [?].

[9] If any paper did not explicitly had a quotable line as evidence to justify its inclusion / exclusion in the corresponding feature, we handled it as if they did not consider it at all.

The sparse Data handling (D) dimension was granted [✓] if both of its composing features (cold start and data sparsity problems) were addressed. A Question mark [?] was given if any one of them was explicitly detailed. Data sparsity represents a challenge in LM in a LLL context: a serious problem arises if a model does not implement solutions to assure a proper instantiation or updates with missing data.

The Knowledge representation (K) dimension was granted [✓] if both features (knowledge representation and recommender's method) were elaborated beyond a mere mention, Question-ed [?] if at least the knowledge representation was explained and a Cross [×] in all the other cases. Knowledge representation is one of the most important characteristics of a LM, almost universal in all the LM reviewed. Its representation lies very close to the updating or suggesting mechanism of the LM.

The LLL dimension (LLL) is composed of our Openness, Dynamism and LLL features. Having an OLM (represented with [?]) is a desired but insufficient condition for LLL. However, explicitly describing a mechanism to assure it grants it a Tick [✓]. If the presence of a OLM and a consideration of Dynamism is found, a [✓] is also granted. The Dynamism feature on its own is insufficient [×] to grant a [?] or a [✓].

Thus, the composited dimensions, based on features we consider key points when choosing an LM for MOOC in an LLL context, answer RQ1, namely "What Learner Model features are most relevant for a MOOC in an LLL context?".

A summary of the dimensioning of the publications is presented in Table 1. The LM presented in Table 1 are shown by author alphabetical order. We represent with a Tick [✓] a desirable characteristic for LM in MOOC in LLL context as fulfilled. We used a Question mark [?] to express a characteristic as partially fulfilled or requiring additional steps to be fulfilled. Lastly, a Cross [x] shows that not enough evidence is found in the publication to give any other mark.

In this section we have presented our considered features and explained the dimensioning and the train of thought behind it. The following section presents the interpretation of our work results.

3.7 Interpretation [H]

The selected papers (17 LM 'Proposals') and the considered features are shown in full in the Appendix. The features we considered for our study and detailed in the previous section were (1) the platform connection approach, (2) the cold start handling, (3) the data sparsity handling, (4) the learner knowledge representation, (5) the recommender / predictive method, (6) the openness of the LM, (7) its dynamism and, (8) its LLL consideration. These features translate into four dimensions that we believe to be paramount points to consider when choosing an LM for a MOOC in an LLL context. A summary of this work is presented in Table 1 in the previous section.

Furthermore, our proposed dimensioning, based on features we consider key points for LLL, allows as well to discern the most appropriate LM for MOOC in this context. That is, an LM ready to cope with the exigences of an LLL, capable of communicate with other systems while retaining its independence, with a comprehensive theoretical background in knowledge representation and/or suggesting engine, whilst preferably being able to handle the problems of missing or incomplete learner data.

Out of an initial pool of 442 results, our review of literature led us to analyse 17 LM proposals. In a first moment, seven of these 17 papers (Bulathwela et al., 2019; Cook et al., 2015; Dimitrova et al., 2015; El Mawas et al., 2019; Lynda et al., 2019; Qazdar et al., 2015 ; Tato et al., 2017) fulfil the LLL dimension, comprised of Openness, Dynamism and explicit LLL consideration, features paramount and an explicit requisite for LLL. Five out of these seven publications have considered fully the Interoperability dimension as well. Nevertheless, only four remaining LM proposals (Dimitrova et al., 2015; El Mawas et al., 2019; Lynda et al., 2019; Qazdar et al., 2015) provide the explicit methods for Knowledge representation and LM updating necessary in an LLL context as well. We can affirm that the answer to RQ2 is represented in these remaining four selected LM publications (highlighted rows in the Appendix): they provide sufficient evidence (I, D, K and LLL dimensions) to conclude that their LM proposal are the most suitable candidate when choosing a LM for MOOC in a LLL context. We strongly believe that this LM result set is of uppermost interest to actors other than our target public.

4 DISCUSSION

In this section we will discuss the feature analysis on the 17 LM reviewed publications addressed in the precedent section.

When we look at the techniques implemented by the authors to represent Knowledge, we could not help but to notice that Rules (or another similar hardencoded method) is the preferred approach for the recommender system (and for knowledge representation, for that matter). Out of the 17 publications, eight papers (Calle-Archila *et al.*, 2017; Cook *et al.*, 2015; Harrathi *et al.*, 2017; Karahoca *et al.*, 2018; Li *et al.*, 2016; Iatrellis *et al.*, 2019; Lynda e*t al.*, 2019; Qazdar *et al.*, 2015) based their LM proposal on Rules.

Bayesian strategies are a second popular choice. Four papers (Bulathwela *et al.*, 2019; El Mawas *et al.*, 2019; Maravanyika *et al.*, 2017; Tato *et al.*, 2017) rely heavily on some form of Bayesian technique to represent knowledge and to suggest or update the LM, usually coupled to other probabilistic models.

Ontologies follow up closely, with three articles (Harrathi *et al.*, 2017; Iatrellis *et al.*, 2019; Lynda *et al.*, 2019) employing them and some formalizing their use of the Web Ontology Language (OWL).

Conceptual Graphs (Dimitrova *et al.*, 2015), Machine Learning (Sun *et al.*, 2015), Pearson correlations (He *et al.*, 2017) and k-means clustering methods (Li *et al.*, 2016) are sparsely used, with only one paper featuring each one of these techniques. Please note that some proposals use a combination of these and other *ad-hoc* techniques, detailed in the Appendix. Finally, only one paper was ambiguous enough for us to discern its approach to represent and/or predict Knowledge.

Concerning their Interoperability, use of standards by the reviewed LM is limited. Most of the LM do not mention their communication method or platform connector. This was the case of LM used in an *ad-hoc* learning platform (five cases), where a monolithic design is common. Nonetheless, a few standards were mentioned. For instance, the use of Ontologies for Knowledge representation (Harrathi et al., 2017; Lynda et al., 2019) allowed LM designers to benefit from the OWL ease of communication. Furthermore, two papers (Lynda et al., 2019; Qazdar et al., 2015) proposed the use of the xAPI specification as a communication protocol and one proposal envisaged the use of the LTI standard, a more recent communication method. When the reviewed LM was evaluated in a learning platform (not in an *ad-hoc* solution) edX was used twice (Cook et al., 2015; El Mawas et al., 2019), with Moodle, Coursera and Claroline being mentioned once each. We assume this is due to the most novel design of edX, comprising support for communicating technologies and other standards. In any case, the interoperability dimension constitutes a challenge most LM avoid or contour by implementing their LM in an *ad-hoc* solution.

Besides, the approach to missing data situations (sparse Data handling) considered by our reviewed LM was ill-defined: the cold start problem was scarcely addressed, usually with a starting questionnaire but often with a vague reference to some 'registration' or 'external' data input, whilst none of the papers took into consideration the Data Sparsity problem.

We regretted to acknowledge that our LLL studied context is not yet an explicit consideration by most of LM designers, with a clear minority of five publications addressing the issue at a minimum. However, among these, one paper (Qazdar et al., 2015) detached itself from the rest by providing details on the technical implementation to fulfil this dimension (OpenID). OLM models are yet to be universally recognized as part of an LLL solution and, for the few proposals in our sample who do (Bulathwela et al., 2019; Cook et al., 2015; Dimitrova et al., 2015; El Mawas et al., 2019; Qazdar et al., 2015), Negotiable and fully Open are the preferred choices over Visualisation in OLM. Thus, regrettably, LLL is not a priority for many LM designers, whose proposals highlight mostly the application of a novel technique, (e.g. machine learning) or focus on a specific delivery content (e.g. video for mobile learning).

5 CONCLUSION AND PERSPECTIVES

This review of literature addresses the question of LM for MOOC in a LLL context, namely the most relevant features in a LM for a MOOC in an LLL context. This study aims to differentiate and highlight LM's features and their relevance to a MOOC usage in an LLL experience. To our knowledge, currently there is no research work that addresses the literature review of such topic. This study intents to fill in that gap by reviewing the most recent LM for MOOC proposals that can handle the exigences of an LLL context. Thus, it covers only the works published in the last five years (2015-2020) that explicitly mentioned in their abstract a LM proposal central to their article.

Out of an academic database search result pool of 442 publications, 17 papers were reviewed, their feature highlighted and compared. This study led us to consider the following features to be key points to consider when choosing an LM for a MOOC in an LLL context: (1) the platform connection approach, (2) the cold start handling, (3) the data sparsity handling, (4) the learner knowledge representation, (5) the recommender / predictive method, (6) the openness of the LM, (7) its dynamism and, (8) its LLL consideration. We synthesized these nine features into four dimensions, namely Interoperability (I), sparse Data handling (D), Knowledge representation (K) and LLL (LLL). Four LM finalists, highlighted rows in the Appendix, (Dimitrova et al., 2015; El Mawas et al., 2019; Lynda et al., 2019; Qazdar et al., 2015) fulfilled most though not all, of our comparing criteria. We concluded that their LM proposal were the most suitable candidates for a LM for MOOC in LLL.

Currently, our next research step is to propose a LM that considers the features and dimensions we have reviewed in this study. Given that none of the reviewed LM fulfil completely our presented comparison criteria we envisage to either, propose a composite comprising characteristics of the final four LM or, select and extend one of them. Such an LM would be the object of a first use and evaluation for the MOOC [10] “Gestion de Projet”: the largest French-speaking MOOC, addressed primarily to engineers worldwide, operating continuously since 2013 and counting close to 265,000 students inscribed since its creation, with a total of about 40,000 laureates.

We feel confident that actors other than MOOC and LM designers/providers, pedagogical engineers and researchers can benefit from this study to help them asses features in LM for MOOC in an LLL that are of vital importance.

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APPENDIX

The summary table of LM for MOOC that support LLL can be found at the following address: https://nextcloud.univ-lille.fr/index.php/s/wjsFrYP5P5BFPKo