Learner Models for MOOC in a Lifelong Learning Context: A Systematic Literature Review

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Abstract. While setting up a Massive Open Online Course for Lifelong Learners, the choice of the most adequate Learner Model for this most current context is paramount: not all Learner Models are created equal, despite their overall added value to facilitate the learner's follow-up, course content personalization and trainers/teachers' practices in various Learning Environments. This systematic review of literature defines, compares, and highlights eight features of interest of Learner Models for Massive Open Online Courses from a Lifelong Learning perspective. It discerns 17 of the most-current, existing Learner Models out of 442 search results. It concludes on the four most adequate, and current Learner Models in this context. In addition, we study how they handle the learning experience personalization. This work is primarily dedicated to MOOC designers/providers, pedagogical engineers and researchers who meet difficulties to model and evaluate MOOC's learners using Learning Analytics.

Keywords: Learning Analytics, knowledge representation, Technology Enhanced Learning, Lifelong Learning, Learner Model, Learning Environment, literature review, MOOC.

1 Introduction

In the last decade, the world has seen a mass proliferation of Massive Online Open Courses (MOOC). Moreover, during the worldwide pandemic of COVID-19 (December 2019 – July 2020 and ongoing), educational institutions experienced a quick adoption rate to their increased MOOC platform attendance. The importance of MOOCs and online Learning Environments' (LE) was recognized as an indispensable tool to bring the classroom to the learners [1]–[6], despite the many difficulties encountered in the way. Nevertheless, MOOC world success goes back to their original concept: offering free and open access courses for a massive number of learners from anywhere all over the world [7]. Despite this global reach, their immense popularity and their -very often- low-to-none costs, MOOC learners feature very low completion rates, with most research metrics agreeing on an overall median of about 6.5% MOOC completion rate [8], [9]. Even when looking at fee & certification-based MOOCs, completion rates top around 60%, a tenfold difference propelled under a different motivation. Research shows that engagement, intention and motivation [10]–[12] are among the top factors to affect performance in MOOCs. Research [13] suggests this is a complex, multi-factor phenomenon, i.e. MOOC participants have reasons to enroll other than course completion. Reasons can be as different as auditing knowledge on the material, and/or the difficulty level, dabbling topic courses or even course-shopping. The obvious heterogenous nature of global MOOC learners, along with their heterogenous needs, is a major factor to ponder when analyzing this worrying phenomenon [14].

Studies suggest that a possible approach to increase MOOC completion rates, and hence improving academic success, relies on personalizing content and learning paths for MOOC learners [15]. To achieve this, [16], [17] highlight the added value of Learner Models (LM) and their importance to facilitate learner's follow-up, course content personalization, and trainers/teachers practices in various LE, with the support of Learning Analytics (LA). At the same time, [18] considers that learner's personalization is one of the essential concepts in Lifelong Learning (LLL), and Life-wide Learning contexts.

Learner Modelling is an abundantly researched subject: at the time of writing of this paper, Google Scholar returns about 2 million results on the simple query [learner model]; about one million results on [lifelong learning] and about a fifth of that on [mooc]. This study aims to bring a more discerning perspective to MOOC designers /providers, pedagogical engineers and researchers having difficulties to evaluate LM for MOOC, with LA in mind. More specifically, this paper aims to define, differentiate, and highlight LM's features, as well as their relevance to MOOC's learners' personalization in an LLL context. For this, we review the most recent works in the fields of "LM for MOOC in an LLL context": papers written in the last five years proposing or extending an architecture, concept, design or implementation of LM for a MOOC environment, while taking into account the LLL learner's situational context. We discern and define relevant features from LMs for MOOC while highlighting their LLL comprehension. We finally compare the resulting LMs and propose a set of most adequate LM for MOOC in an LLL context, while distinguishing their personalization claims.

We differentiate our work from that of [16], [19]–[23] in that 1) we cover only the most recent (five years) proposals, extensions and implementations of LM for MOOC; 2) we discern and compare LM features that may play an important role in LLL in MOOCs, and finally 3) we distinguish the object of personalization of the LM and its complexity.

The remainder of this article is structured as follows. Section 2 of this paper oversees the theoretical works behind this paper, namely the role of LMs and their importance in MOOCs, highlighting the importance of the LLL dimension as the surrounding context and the considerations taken when comparing LMs. 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: the LM and its role in personalization, the importance of the Lifelong dimension on MOOCs, and finally the considerations to observe when reviewing and comparing LMs.

2.1 Learner Models and personalization

We begin by describing what LM are, how they constitute, and for what purpose; we then proceed to detail their various classifications, relevant to our research.

LMs represent the system's beliefs about the learners' specific characteristics, relevant to the educational practice [24]. LM aim to encode learners in an individual fashion, using a well-defined set of dimensions [25], such as cognitive states, behaviors, learning and/or personal preferences and others. Learner Modelling is a complex task relying mainly on three main fields: educational science, psychology and information sciences [20]. According to [26], it implies 1) the identification and selection of learners' features that are relevant to their learning, and 2) the acknowledgement of the psychological states present during the learning process, with the ultimate goal of choosing the most adapted technologies, each and every one of them modelling the previously identified features as best possible.

LM are usually enriched by data collecting (and updating) techniques and mechanisms [27], which [28] observe as an on-going, continuous process.

Modelling the learner aims allowing adaptation and personalization of environments and learning activities [15], [29] while considering the unique and heterogenous needs of learners. Studies have long shown linking evidence between having a LM and making a system more effective in helping student learn: the LM allows the Learning Environment to adapt to the learners' differences [16], [17].

Among all the characteristics that LM encode, *knowledge representation* is one of the most important and then, one of the most recurrent. Depending on which family of techniques is used to represent knowledge, an LM can be classified into a stereotype model, an overlay model, a differential model, a perturbation model, or a plain model. Each of these classifications comes with its own set of techniques to represent learners [27], [30], [31]. For instance, depending on each technique, the knowledge representation of the learner (learner's knowledge) can take either the form of an instantiation of the model, a differential from a known, predetermined representation, a set of relationships, or a subset of the knowledge representation of the topic (a.k.a. domain's knowledge). As we can see, the LM choice conveys the choice of the techniques and mechanisms used to represent the learner whilst it is very depending on the context of its ulterior usage [20].

Open Learner Models (OLM) 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 [19], [32]. This contrasts to the view of a Closed Model, in which the student has no direct view of the Model's contents [33]. OLM can be classified into three categories [34], according to the Model's edition and communication modes. They can be inspectable; simply not allowing editing of any kind, leaving solely its updating mechanisms to interactions with the system, negotiable; if the OLM will ask for factual evidence from the learner to admit any given modification, and verify its accuracy, or editable; where the OLM will not require proof but instead will allow direct data edition, under a set of permissions and access controls to prevent data corruption. [33] brings up to the table that *transparency* is a desirable trait for OLM to feature. By revealing the internal works of a hosting system -meaning the LE and hosting platforms themselves- it helps to “engender trust, permit error detection and foster learning” about how the system as a whole works.

Many research studies [19], [35] show the importance of Models that are *independent* of any system by being able to accept data from a multitude and variety of sources (online, offline, digital, analog, data formats, data structures, etc.). 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”. Nevertheless, this *independency* should not lead to isolation. The LM should communicate with the hosting system, and an independent LM must support specific technical connectors (API) to different CMS or LMS platforms, or other data sources.

The *independence* of a LM is paramount, as a way for the learner to take possession and control of its own data. As we have seen, 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 to keep it up to date through evidence.

Personalization allows adapting the learning process (whether it is content, courses, and pedagogical style) to the learner’s needs [36]. That is why we consider that personalization is a “learning tailored to the specific requirements and preferences of the individual” [37], [38]. As such, this notion also englobes terms such as personalized learning [38], adaptive learning [39], or adaptivity [40]. In this direction, [36] recently identified five key characteristics of personalization in MOOC, according to the subject of personalization; personalized learning path; for adjustment of the course content according student’s competences, skills, and goals, personalized navigation; accounting for direction of the student to the appropriate learning material using navigation cues, recommendation system; which is the recommendation of learning objects or courses, personalized assessment; comprised as the adjustment of the knowledge validation materials to the needs of a student, and finally personalized feedback; which accounts for personalized communication as a part of MOOC pedagogy learning method, such as forum discussion or individual communication with mentor. Note that for clarity reasons, we will refer to letters R to V to represent the previously mentioned features, respectively.

Furthermore, according to its complexity parameter, personalization is divided into five groups [41]–[43], with ever increasing levels of complexity (1-5): name based personalization, self-described personalization, segmented personalization, cognitive personalization and whole-person personalization.

We aim for an LM to provide the most complex form of personalization (5. Whole-person personalization) as the other forms of personalization may not offer the necessary finesse to adapt to heterogenous groups, and/or may represent more of a hindrance to the learner rather than a 'preference' [20].

Lastly, we acknowledge the difference between LP and LM in that the former can be either considered an instantiation of the latter, in a given and specific moment of time, through the use of educational data [44], or, put in another way, it can simply static uninterpreted information about the learner [28]. For example, a LP 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 [19].

In this subsection we discussed the notion of LM and some of its characteristics. In the following section we treat the importance of the role of LM in MOOC.

2.2 Role 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 [45]. As a quantitative and clear example of the dynamic nature of MOOC and of their learners, yearly reports (2015-2019) from Class Central [46], [47] reports a steady increase in people signing up for courses just like in the number of courses being opened worldwide. That is, from over 500 universities, 4200 courses and 35 million students in 2015, numbers have climbed in 2019 to over 900 universities, 13500 courses and 110 million students. Yet, these numbers exclude China, the second largest and the fastest economy in the world[1] [48], whose metrics are "difficult to validate", according to Shah. Furthermore, in 2019, MOOCs have come a long way to include not only micro-credentials but also MOOC-based degrees. This clearly shows a diversification in their offer and an adaptation to their massive public learning needs. As we have seen in the previous section, LMs allow for individualization [30], personalization [49]–[52] and recommendation [53], [54], which improve learning metrics by providing learners with an individual, tailored learning experience suited to their own uniqueness [55]. LMs in MOOC bridge the gap between heterogenous learners' needs and training by allowing the personalization of the learning activities [15].

These staggering 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 plays undoubtedly a substantial role, allowing the MOOC anywhere and anytime the tailoring of content and activities that the learners need.

After discussing the importance of the role of LMs in MOOC, we introduce in the next subsection the importance of the context surrounding the study.

[1] People's Republic of China has experienced economic growth rates averaging 6% over the last 30 years. When comparing based on purchasing power parity (PPP), China is the largest world economy.

2.3 Importance of Lifelong Learning in MOOC

For more than four decades [56] consider that the term LLL holds the idea that learning should occur through a person's lifetime, involving formal and informal domains [57]. This distinction is further advanced in a two-dimensional holistic view of education: LLL; recognizing that individuals learn throughout a lifetime, and life-wide learning; recognizing the formal, non-formal and informal settings [58]–[60]. The European Lifelong Learning Initiative (ELLI) coined 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" [58], [61]. Moreover, the ELLI emphasized at the dawn of the century that "lifelong learning is no longer just one aspect of education and training; it must become the guiding principle for provision and participation across the full continuum of learning contexts".

When envisioning a LM for MOOC, [50] 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 appeal to its multi-sourced and availability capabilities for it to be a useful lifelong LM. This notion is later shared by [29] who sees a Lifelong Learner Model (LLM) as a "store" where the learner can archive all learning activities throughout her / his life [20].

Thus, we see that lifelong learner modelling [29], as a 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", is not devoid of difficulties of implementation: [20], [29] 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 [29], [62]–[64] have been undertaken to address some of these challenges and difficulties, with varied results in their own domains.

Despite the LLL notion passing through a few changes over the years, especially with the upcoming of MOOCs [15], we retain that access to, and effective use of relevant information and continuously learning in MOOCs is essential for Lifelong learners.

2.4 Considerations when contrasting Learner Models

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 considerations to keep in mind when reviewing LM.

Knowledge representation. We have seen how in an LLL context learning evolves in a time continuum, implying the need for the LM to also evolve continuously. The LM is to assure and to reflect this evolution by establishing the mechanisms to accept, hold and analyze the data in a precise and known way. We are not to forget that, in one hand, data can exist in a multitude of formats and origin from a multitude of sources. The LM must be capable of accepting, understanding, and holding this variety of data. 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 oversees the handling of learner's data. This means that the LM's designer's choices of the data a given LM can accept (represent and process) will reverberate how personalization is pursued and achieved.

Data Interoperability. This dimension is twofold: how the LM aims to communicate with its technical environment, and how the LM aims to share data with its final users. An isolated, data locking LM cannot assure the portability needed by a heterogeneous learner public, with unique learning needs, in a multitude of heterogeneous environments, during different moments of a learner's lifetime. Such learner target public requires an independent, customizable, and unlocked LM, with cemented communication flexibility. Thus, data interoperability and modelling dynamism play a crucial role in allowing for the LM to transcend its LE and to be adopted as a long-term, dynamic portfolio of knowledge, competences, skills, preferences, credentials, certifications or badges, among many others, as demanded by the LLL context. Within this LLL context, it is preferable that the LM allows its inspecting and visualization. In this way, the learner is actively made aware of the contents of his / her model, eventually permitting its editing or negotiation through institutional policies, or other similar instruments. Making the learner aware of his/her learning activities through a continuously updated LM may contribute to foster trust, engagement, and learning.

Sparse Data handling. During the first stage of the learner modelling process (or 'initialization' process), when the model gathers initial data related to the learner's characteristics, the LM may encounter what is known as a 'cold start' problem. This exceptional situation may lead to an improper LM instantiation. Likewise, a similar situation -known as the 'data sparsity' problem- may also arise this time during the updating phase, preventing the proper update and maintaining of the LM, or worst, leading to serious data corruption and/or to a system halt. Being able to handle these exceptional situations is a strongly desired trait in an LM, not only from a technical point of view but also from an LLL perspective. During a lifetime, the variety of knowledge representations the LM is to handle may not always be in a complete for. It is up to the LM to cope with these two problems to its best, never to the detriment of the learner and regardless of the data source incompleteness.

Learning experience personalization. As personalization covers more and more ground, its diversification may be perceived as enriched. However, a minimum set of core Personalization features are to be supported by the LM, with others topping up for added value. We know that MOOC learners want to acquire knowledge according to their competences and goals; this being the highest priority criteria, and we posit that the MOOC learner cannot be left under the impression of being isolated in the learning process (learning is a social experience). We intend to see reflected these two positions in an adequate LM for MOOC in LLL.

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

3 Literature Review methodology

This review of literature follows the methodology described by [65] in order to reflect the specific problems of software engineering research. We shortly summarized it and identified as follows: [A] identifying the need for a literature review, [B] specifying the research questions, [C] development of the review protocol (including identification of research databases), [D] selection of quality studies (including screening the papers), [E] data extraction and monitoring and, [F] interpreting the results.

3.1 Need for a literature review [A]

The goal of this review of literature is to analyze the most recent works in the field of "LM for MOOCs in an LLL context" and how they achieve personalization. This is in general terms, how a given LM coupled with(in) a MOOC can support LLL and what mechanisms are used to adapt to the lifelong learners' needs. More specifically, first, we aim to differentiate and highlight LMs' features and their relevance to a MOOC usage in an LLL experience. Second, we intend to discern and highlight the mechanisms the LM employs to personalize the learning experience to the learner.

We base this study in the recent research of [23], where the issue of existing LM for MOOC in this context is addressed. We review and compare the mechanisms used to achieve personalization by the selected LM in each study.

In the following subsections we detail additional planning information required for the development of the literature review protocol [65], such as the rationale of the review, the selection criteria, the procedures, and data extraction strategies.

3.2 Research questions [B]

This research work aims to answer the following research questions (RQ):

- RQ1: What LM features are most relevant for a MOOC in an LLL context?
- RQ2: What are the most suitable LM for MOOC in an LLL context?
- RQ3: What personalization acts upon an LM for MOOC in LLL, and what mechanisms are mobilized to achieve it?

3.3 Review protocol [C]

Selection criteria. 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.
As inclusion criterion:

- Works that present a LM in the context of a MOOC, or that present a new LM and compare it to an existing LM.

As exclusion criteria:

- Works not written in English, under embargo, not published, or under work.
- Works that do not treat LMs directly, but only peripherally, i.e. LMs 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, i.e. the LM proposal.
- Works published on journals take precedence over those on conferences.

Our search terms were `"learner model"` and `"mooc"`. These search terms concede for plural, gerund, and agent-noun results, such as “learners”, “modelling”, “modeling” or “models”. 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 reviewed LM and this is why it does not figure in the search terms. This same logic applies for the personalization mechanisms.

Research databases identification. We chose to perform this research within the last five year’s timeframe (2015-2020) at the beginning of January 2020 in the following Web of Science and Scopus scientific databases. In addition, we used Google Scholar to access results from Taylor & Francis Online, Science Direct, Sage Publications, Springer and IEEE Explore.

External tools selection. We chose and used the search software tool ‘Publish or Perish’ [2]. This choice presents the following advantages:

1. It allows us to search into these databases at once (except for Web of Science and Scopus, which is why we accessed them separately)
2. It facilitates the identification of highly sought, quality research, through filtering, aggregation, filtering repeated publications, extracting articles’ metadata, and calculating various research indexes [3], commonly known to the scientific community.

[2] https://harzing.com
[3] i.e. Hirsch’s h-index, Egghe’s g-index, and Zhang’s e-index.

For a more streamlined paper selection process, we designed and developed an external tool (publication under way) that, coupled with the previously mentioned 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. 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 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.

3.4 Selection of quality studies [D]

The paper selection process [23] happened as follows:

First, we used a CSV (Comma-Separated Values) 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, through the institutional university access.

Second, we automatically extracted relevant metadata related to the previous results (abstracts and keywords) from the corresponding articles’ Web Pages or PDF (Portable Document Format) files. This process aims to present this metadata in a bias-free context by purposefully omitting the article title and authors in the data presentation.

Third, we read all the abstracts and roughly categorized papers into a first dismissing process. This is detailed in the next subsection “Paper screening process”.

Fourth, we then read the full text of the Passing papers. This is explained in subsection “Detailing the selection process”.

Paper screening process. We read 422 automatically extracted abstracts (419 + 17 + 6) and filter-categorized them. In this first dismissing process, we dismissed publications whose abstract was out of the scope of this paper while registering the main subject [4] of the 364 dismissed paper. As previously 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. When in doubt, and only after careful and multiple abstract readings, we recurred to the ‘keywords’ and the ‘title’ fields, in that pondering order. Such dismissed papers fell into one of the following main categories:

1. ‘Another kind of Model’: Among the 32 results, this category describes mostly pedagogical models (7 papers) but also teaching practices and methods, relationship models, system models, etc.

[4] e.g. “ethical concerns of AI in education”, “panorama on open source LMS” or “evolution of higher education”

2. ‘Profile’: 18 publications explicitly treated LP instead of LM, often under a completely different concept [5].
3. ‘Not on topic’ results contain the search terms in the text, title, or bibliography but in a disconnected manner [6]. Most dismissed papers fell into this category.
4. ‘Citation’ results were usually removed automatically by the ‘Publish or Perish’ tool but not always. These are articles citing studies that treated the searched Topic without treating it themselves.

We also dismissed articles (minor categories):

- Whose main content was ‘Not in English’, even if the abstract was.
- ‘Duplicates’ or ‘Previous Work’ (from the same author, c.f. the following:).
- ‘Most Recent Work on Topic’ publications from the same year from the same author were detected and we kept only the most recent item.

Please note that many articles fell into more than one category, e.g. a Doctoral dissertation proposing an improvement of a LM where only the abstract is in English; a thrice repeated article not in English plus its one citation in English; or a proposal of a ‘Learner Profile’ for personalization. Also notice that during the Selection process, the full-text reading of the seemingly promising articles (based on abstract reading only) led to many more dismissals, i.e. we could not know that the text of a given article was in Korean by reading a promising English abstract until we downloaded and opened the corresponding file in the next phase of the process. This means that while we present these processes as separate, they were performed often hand in hand.

While in this subsection we have detailed the dismissing process and its categories, in the next one we go into depth in the selection process.

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), i.e. 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 LM.

We begin by mentioning that out of the 419 results from Google Scholar, 342 publications were rapidly 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 from Google Scholar requiring a more in-depth review. During this initial search phase, the other two search engines (Scopus and Web of Science) provided relatively few results compared to Google Scholar. Surprisingly, it turned out that all their results, except for one, were already within the Google Scholar results. That is, for:

- Scopus: out of 17 results, 12 had already been found in the Google Scholar results and another eight (4 out of 17 + 4 out of 12) had already been classified as ‘Out-of-scope’. This led to the one (1) result from this search database not found in the

[5] e.g. “discovering learner’s profiles in web browsing”

[6] e.g. “Solar Models in a Geography Class: a Learner’s first experience with MOOCs”

Google Scholar results and not dismissed (c.f. Subsection "Paper screening process").
- Web of Science: all the six results were 'Passing' but repeated[7] within the Google Scholar results.

For this second dismissing stage, we proceeded to fully read the 'Passing' papers. We accessed and read the full text of the remaining '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.

From this initial 78 papers (77 from Google Scholar + 1 from Scopus + 0 from Web of Science) only 17 became 'Proposals' (16 from Google Scholar, 1 from Scopus, 0 from 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. The duplication of (dismissed) results among the three search engines greatly contributed to the final tally of results.

For the sake of exhaustivity and according to our exclusion criteria, we registered not only the topic the authors claimed to treat in the abstract but also the reason any result was removed. The possible values of this second dismissing process are 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, from the previous categories.
- 'Peripheral' – The field "Learner Modelling for MOOC" do not constitute the core of the publication. This includes 'LP' and 'Analysis on a LM'.
- '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. As a side note, we were able to pinpoint (and dismiss) a total of 19 publications that either used LM when referring to LP, either used the terms 'Learner Model' and 'Learner Profile'

[7] As the largest block of results was constituted from Google Scholar's results, we considered logical to tackle it first. When we passed to the other two search databases and some of their results were found within the first, largest block already analyzed, we simply considered them as "Repeated" and only counted as part of the Google Scholar results, even if they were not repeated on their own search database.

interchangeably, or effectively only used the term 'Learner Profile'. A summary of the selection process is illustrated in the PRISMA Chart [66] in Figure 1.

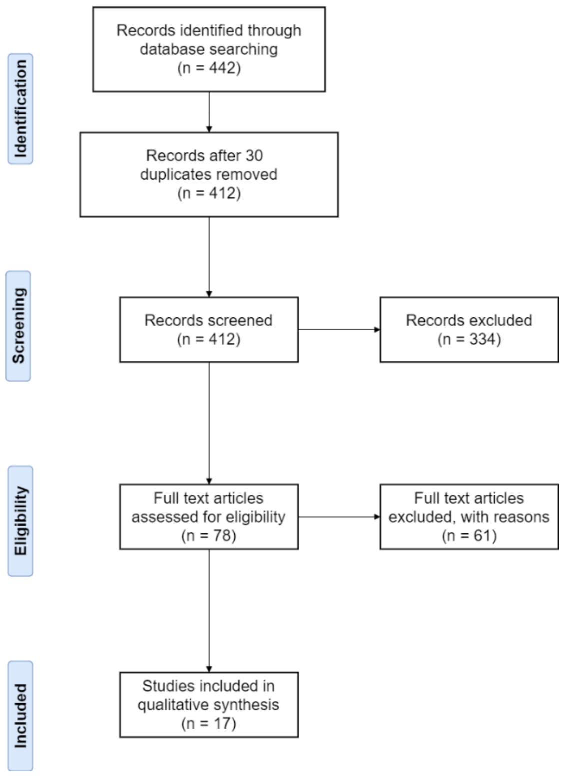

Fig. 1. PRISMA Chart of the publication screening process.

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

3.5 Learner Models comparison [E]

In this section we address which considered features contribute in the compositing of meaningful dimensions that allow comparison between LM. We address why and how these new dimensions assist when comparing LM.

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[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).

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 points mentioned in Section 2.4, i.e. their openness or interoperability with other platforms, etc. We consider the mechanisms, if any, explicitly mentioned by the authors to indicate these or any of the other features.

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 eight features into four dimensions, namely Interoperability (I), sparse Data handling (D), Knowledge representation (K) and LLL (LLL). We also review what the LM aims to personalize and what mechanisms are put in motion to achieve it. We represent it in a fifth dimension Personalization object (O).

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.

Very closely related to the Knowledge representation, we deepen into the Personalization of the LM through the Personalization object (O) dimension. This dimension categorizes what the LM aims to personalize and how it achieves it.

Finally, the LLL dimension illustrates how well the LM is prepared to cope with the exigences an LLL context demands.

All these dimensions are important components of a LM in an 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 the number of dimensions proposed by the authors as they depend greatly on the purpose of each of their infrastructure. Factoring this in would render a 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 [X]. However, evidence of regard to any of our considered dimensions but without an explicit description of the mechanisms to achieve it were marked with a Question mark symbol [?].

The interoperability (I) dimension. It was granted a Tick if a platform connector was specified, and presented a Question mark [?] if only an implementing platform

[9] If any paper did not explicitly have 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.

had been mentioned, hinting the reader to a successful implementation in a LE. In terms of operability, a working connector [✓] allows for portability of the LM, important characteristic in LLL. This way, the confirmation of an existing implementation of the proposed LM assures that some form of communication exists with a given host system. This cannot be said when the portability [?] has not been described.

The sparse data handling (D) dimension. It 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 an LLL context: a serious problem arises if a model does not implement solutions to assure a proper instantiation or updates with missing data. Whilst we do not expect any of the proposed LM to fully solve any of these issues, acknowledging them is to be in the path to avoid disastrous situations.

The knowledge representation (K) dimension. It was granted [✓] if both features (knowledge representation and recommender's method) were elaborated beyond a mere mention, we used [?] if at least the knowledge representation was explained and a Cross [X] in all the other cases. As we have mentioned, 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. It is composed of our *openness*, *dynamism* and *LLL* features. Proposing an OLM (presented with [?]) is a desired but insufficient condition for LLL. However, explicitly describing a mechanism to assure the *openness* of the Model grants it a Tick [✓]. If an OLM is proposed and a consideration of *dynamism* is found, a [✓] is also granted. The *dynamism* feature on its own is insufficient to grant a [?] or a [✓] and is presented with an [X].

The personalization object (O) dimension. Personalization metrics [36], [41]–[43] were used to describe the object of personalization and the degree of complexity of each object of personalization. Letters R, S, T, U, & V identify the object of personalization: personalized learning path, personalized navigation, recommendation system, personalized assessment, and finally personalized feedback.

Numbers from 1 to 5 correspond to the complexity scale employed for each personalization object, with 1 being the less complex rating and 5 the most complex rating (Section 2.1 Learner Models and personalization):

1. Name based personalization: System addresses user by his/her name when user logs into system by username and password.
2. Self-described personalization: System takes user's preferences, attributes, and past experiences by tools like questionnaires, pre-tests, and registration forms.
3. Segmented personalization: Learners are grouped by common attributes (class, department, degree etc.) and demographic information. In this method, teaching is applied to whole group.
4. Cognitive personalization: In this method, content and teaching is delivered according to cognitive process, strategy, skill, and preferences of learners. System will adapt content by user's working memory capacity, user's preference of text or image-based representation etc.

5. Whole-person personalization: This method is a combination of cognitive based personalization and psychological resources that affect learning and performance. In this method, the system inferences over user model in learning process and constantly updates user model. So, user can be represented in all aspects.

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

A summary of the dimensioning of the publications (shown by author name alphabetical order) is presented in Table 1. For clarity reasons R represents 'personalized learning path', S represents 'personalized navigation', T represents 'recommendation system', U represents 'personalized assessment', and finally V represents 'personalized feedback'. Each of these personalization objects is followed by a complexity scale level qualifying it: from level 1 (less complex personalization) to level 5 (whole-person personalization).

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.

Table 1. LMs found, with Interoperability (I), sparse data handling (D), Knowledge representation (K), LLL, and personalization Object (O) dimension analysis. Finalist LM are highlighted in gray.

LM name	Reference	I	D	K	LLL	O
TrueLearn	Bulathwela *et al.*, 2019 [67]	?	?	✓	✓	T4
SBGF	Calle-Archila *et al.*, 2017 [68]	✓	?	x	x	U5 V5
MOOClm	Cook *et al.*, 2015 [69]	✓	x	x	✓	T4
STyLE-OLM	Dimitrova *et al.*, 2015 [70]	✓	?	✓	✓	U4
None-MOOCTAB	El Mawas *et al.*, 2019 [71]	✓	?	✓	✓	R4 S4 U4
None-Tunis	Harrathi *et al.*, 2017 [72]	x	x	✓	x	T4
None-China	He *et al.*, 2017 [73]	?	?	x	x	T2
EDUC8	Iatrellis *et al.*, 2019 [74]	?	?	✓	x	R5 V5
DiaCog	Karahoca *et al.*, 2018 [75]	x	x	✓	x	U5
None-China	Li *et al.*, 2016 [76]	x	x	x	x	T4 V3
None-ODALA	Lynda *et al.*, 2019 [77]	✓	?	✓	✓	U5
None-Tunis-France	Maalej *et al.*, 2016 [78]	?	x	✓	x	R3 U4
GAF	Maravanyika *et al.*, 2017 [79]	x	?	x	x	R5 T5 U5
AUM (AeLF User Model)	Qazdar *et al.*, 2015 [80]	✓	?	✓	✓	R4
MLaaS	Sun *et al.*, 2015 [81]	x	x	x	x	T5
Logic-Muse	Tato *et al.*, 2017 [82]	?	?	✓	✓	U4 V4
None-Adaptive Hypermedia	Tmimi *et al.*, 2017 [83]	x	x	x	x	U5

3.6 Interpretation & Discussion [F]

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. We complement these four dimensions with a fifth -Personalization object- detailing the LM object of personalization and how complex are the mechanisms to achieve this. A summary of this work is presented in Table 1 in the previous section.

Furthermore, our proposed dimensioning, based on key features 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, able to communicate with other systems while retaining its independence, with a comprehensive theoretical background in knowledge representation and/or suggesting engine, likely able to handle the problems of missing or incomplete learner data, and with a clear view on what and how personalization is achieved.

Out of an initial pool of 442 results, our review of literature led us to analyze 17 LM proposals. In a first moment, seven of these 17 papers [67], [69]–[71], [77], [80], [82] fulfill 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 [70], [71], [77], [80] 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 and in Table 1): 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. Moreover, the personalization object dimension in all 17 papers, answers RQ3. We strongly believe that this LM result set is of uppermost interest to actors other than our target public.

Discussion. When we look at the techniques implemented by the authors to represent Knowledge, we notice that rules (or another similar hard-encoded method) is the preferred approach for the recommender system (and for knowledge representation, for that matter). Out of the 17 publications, eight papers [68], [69], [72], [74]–[77], [80] base their LM proposal on rules.

Bayesian strategies are a second popular choice. Four papers [67], [71], [79], [82] rely heavily on some form of Bayesian techniques to represent knowledge and to suggest or update the LM, usually coupled to other probabilistic models.

Ontologies follow up closely, with three articles [72], [74], [77] employing them, and a couple of them formalizing their use of the Web Ontology Language (OWL).

Conceptual Graphs [70], Machine Learning [54], Pearson correlations [73] and k-means clustering methods [76] 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, the use of standards by the reviewed LM is limited. Most of the LMs 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 [72], [77] allowed LMs designers to benefit from the OWL ease of communication. Furthermore, two papers [77], [80] proposed the use of the xAPI (Experience API, application programming interface) 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 [69], [71] 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 seem to 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.

According to [36], an 'average level of personalization' implies support personalization on learning path and personalized feedback (personalization object dimension), while an 'advanced personalization' should add support for one more personalization feature. According to our results, only one LM proposal [74] fulfilled this requirement, although it did not present enough evidence to be among the four finalists of the subject of this study. We also noticed that Personalized assessment is the most (9 papers) present form of personalization among the evaluated LM, followed by Recommender Systems (6 papers) and Personalized Learning Paths (5 papers). This made sense in that these proposals focus on initial, gradual evaluations to populate the LM to then recommend learning objects or courses or adapt their learning paths. However, this trend is inconvenient to qualify for an 'average level of personalization', given the ponderation granted to features 'personalized learning path' and 'personalized feedback' (R & V). Furthermore, while none of the LM presented a low level of personalization complexity (level 1), many could not go beyond level 4 ('cognitive personalization') while targeting more complex personalization. A general trend was that each of the proposed LM seemed to aim for a very specific type of personalization, scoring high (levels 4 & 5) in complexity in only one or two features. Special mention go to [71], [79], whose LM proposals comprised the most features with high complexity levels (R4 S4 U4 & R5 T5 U5, respectively).

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 [80] 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 [67], [69]–[71], [80], Negotiable and fully Open are the preferred choices over Visualization 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).

4 Conclusion and Perspectives

This review of literature addresses the question of LM for MOOC in an LLL context, namely the most relevant features in a LM for a MOOC in an LLL context, and how the LM claims to achieve personalization. This study aims to differentiate and highlight LM's features and their relevance to a MOOC usage in an LLL experience. We review the most up-to-date LM for MOOC proposals that can handle the exigences of an LLL context. It covers the research works published in the last five years (2015-2020) that explicitly mentioned a LM proposal in their abstract core.

Thus, we identified and reviewed 442 publications issued from academic databases search results. We selected 17 papers for their relevant features to be highlighted and compared. We recognized eight features to be key points to consider when choosing an LM for a MOOC in an LLL context, which we aggregated into four gauging dimensions, namely Interoperability (I), sparse Data handling (D), Knowledge representation (K) and (LLL). Finally, we integrated a fifth descriptive dimension we named Personalization object (P). This dimension details on what the reviewed LM claims to personalize as well as the complexity of the mechanisms of such personalization, noted in an increasingly complex scale.

Four LM finalists, (highlighted rows in the Appendix and in Table 1) [70], [71], [77], [80] fulfilled most 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 either a composite LM (comprising characteristics of our four finalists) or, select and extend one of our four finalists. Then, couple it with a performing and adapted machine-learning LM updating algorithm. For this, a literature review to discern and discriminate currently used machine-learning algorithms for LMs for MOOCs in a LLL context is in order.

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Appendix

The summary table of LM for MOOC that support LLL can be found at:
https://nextcloud.univ-lille.fr/index.php/s/Gse9Aj4SY4xErT8

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