# Systematic Literature Review: Colaborative Engagement on MOOCs[☆]

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**Abstract**

*Context:* Afford satisfactory enough education to everybody who are willing has been one of the biggest challenges in the modern world. Mass education, mainly associated to connectionist tools, has been seen as a feasible solution.

*Objective:* This study assess the impact and aggregate those most relevant frameworks and tools proposed to improve engagement in connectionist learning.

*Method:* We use a systematic literature review spread in two steps. First we proceeded a snowballing search from those most import researchers down. Second we did a simple research base in five data-sets.

*Results:* Based on the lack of collaborative structured support tools, we propose a new tool gathering some skills of all ones. This has the mission of provoke the student that seeking for knowledge.

*Conclusion:* Maybe the e-learning demands different goals and skills, and this never shall replace or equate regular education, but we could improve the student experience in order to facility those goals.

*Keywords:* MOOC, forum engagement, Connectionist learning, education, mass education, leaning support tools

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[☆]Additional information about researched references and data are available on `https://data.mendeley.com/data-sets/7t7dz233k2/1`Mendeley repository.

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## 1. Introduction

*Massive Open Online Course (MOOC).* Mass education would be a promising academic inclusion tool in order to afford "education satisfactory enough" for who could not attain that otherwise. However, achieve mass education using strategies at scale which does not jeopardize quality is one of the key issues target.

*Connectionist learning.* Faced with this problem, the connectionist paradigm, which learning takes place horizontally (students to students), seems like a feasible solution. Based on this principle, connectionist tools like forums and blogs are state of practice alternatives [1] which may help to improve that "satisfactory enough".

*Problem.* Specifically regarding the use of discussion forums, the challenge is motivating students' active (writing) and passive (read) participation, which has had below-expected engagement rates (mainly about active participation) [2].

The purpose of this study is to gather and assess tools and frameworks with the potential to improve community engagement in MOOCs. To achieve that was performed a systematic literature review divided in two steps: main research and validation, as described in Section 2.

## 2. Method

Below we describe those two steps of our method.

### *2.1. Research question*

The research question reflects the main research goal.

*RQ:.* How, in some way at scale, to motivate students to use connectionist learning tools (forums) in mass education (MOOC)?

#### *2.1.1. Sub-questions*

About the connectionist learning tools, the main question deals with engagement. It might be vague to answer why do not the students use forums as much as we hope, so we divided the research question in two more specific ones below.

RQ1: Could a discussion forum with some different and new structure be more effective?

RQ2: Which tools or devices could we implement into or out of forums in order to optimize staff time?

As you may see below, inside these questions you can see three semantic elements as described in Table 2.1.1.

| | Population | Intervention | Outcome |
|---|---|---|---|
| RQ | Students enrolled in MOOCs | Educational forums as connectionist learning tool | Engagement and effectiveness concerning connectionist learning from educational forums |
| RQ1 | Teachers or students enrolled in MOOCs | Changing the forum community settings | Improve student engagement and effectiveness in MOOCs |
| RQ2 | Staff and students enrolled in MOOCs | Features or tools to improve scale at forum support | Improve scale in educational forum support |

Table 1: Four main elements of each research question

### *2.2. Search process*

The search process follows two distinct strategies and, if correctly executed, must validate each other.

#### *2.2.1. Validation*

Here I use the h-index and Google Scholar[1] to compose a list of the researchers responsible for the most representative advances.

[1] https://scholar.google.com.br/

*Google Scholar.* It is a web search engine dedicated to finding academic papers. In addition to be able to search for papers by date, year of publication, number of citations and relevance, the user can also access a network of ranked researcher profiles based on the h-index and total citations, directed to their publications.

*h-index.* It describes an academic performance metric that correlates the total number of researcher publications to the number of research citations [3].

This process will start from a keyword-set obtained from terms present in the research questions, synonyms and linguistic derivations (plurals, conjugations, etc.). At the end of this process, the final keyword-set are as follows:

| | terms | synonyms | | | |
|---|---|---|---|---|---|
| + | mooc | massive learning | | | |
| + | forum engagement | educational community engagement | forum commitment | educational community commitment | |
| + | forum participation | forum communication | forum motivation | forum hand | educational community motivation |
| + | educational forum | educational community | | | |
| + | connectionist learning | horizontal learning<br>horizontal knowledge | peer learning | distributed learning | |
| + | learning support tool | | | | |
| + | forum posts | | | | |
| - | predict<br>predictive<br>predicting<br>prediction | | | | |
| + | intelligent tutoring system | | | | |

Table 2: First keyword-set to perform the search

This first process of validation seems like a Snowballing[2] research down through researchers found in Google Scholar. After we have identified incrementally the main set of researchers and sources through the system of Google Scholar researcher profiles, the keyword set grew up along with that as described above.

Knowing the key researchers and their five most representative publications, we manually assemble the set of main publication sources (conferences and journals) adhering to the research question. Therefrom we manually select the references which does not match the exclusion criteria listed in Table 4. This will enlarge my keywords-set and my reference base to be analyzed.

### *2.2.2. Search*

The second search strategy is based on the final keywords-set extracted from the first one. Starting from this set, automatic and filtered searches will be performed based on those terms. These searches must be applied to the automatic research engines in Table 2.2.2. In this table you can see the associate experts to their respective engines suggested.

| Research Engine | Experts who indicated |
|---|---|
| Science Direct[3] | Phd. Francisco Villar Brasileiro |
| ACM D. L.[4] | Phd. José Anto Beltrão Moura |
| IEEE Xplorer[5] | |
| Scopus[6] | Phd. Adriano Santos |

Table 3: Research engines and their perspectives expert indicators

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We parted the term "Intelligent Tutoring Systems" in a different string because we perceived that as a quite recurrent tool in this field. The final strings applied to those research engines are

[2]Snowballing search consists of finding relevant articles through regular scholar search and going down by the their relevant references
[3]https://www.sciencedirect.com/
[4]https://dl.acm.org/
[5]http://ieeexplore.ieee.org/
[6]https://www.scopus.com/

these below[7]:

- About general tools:

  *("mooc" OR "massive learning") AND (("forum engagement" OR ("forum" AND "engagement") OR ("educational" AND "engagement" AND "community") OR "forum commitment" OR ("forum" AND "commitment") OR "educational community commitment") OR ("forum participation" OR ("forum" AND "motivation") OR "forum hand" OR "educational community motivation") OR ("educational community" OR "educational forum") OR ("connectivist learning" OR "horizontal learning" OR "horizontal knowledge" OR "peer learning" OR "distributed learning" OR "cmooc")) AND "tool" AND NOT ("prediction" OR "predictive" OR "predict" OR "predicts" OR "predicting");*

- About "Intelligent Tutoring Systems:

  *("mooc" OR "massive learning") AND "forum" AND "intelligent tutoring system" AND NOT ("prediction" OR "predictive" OR "predict" OR "predicts" OR "predicting").*

### *2.3. Article selection process*

To make the selection we have two sets of articles, each one coming from one of the two search strategies. However, if the process was successful, At the end of exclusion and inclusion, validation group should be contained in search group.

Every analyzed paper had to be approved in the rejection criteria. After that, we have a group of promising papers which were submitted to acceptance criteria in order to evaluate relevance, method and results. Notably rejection criteria was performed using diagonal reading and acceptance criteria needed a deeper reading. The Table 4 presents all rejection and acceptance criteria.

Table 4: Table of selection criteria. Acceptance criteria have the icon ☑ and rejection do ☒

| | Criteria | type | Phase[9] | Score | Threshold |
|---|---|---|---|---|---|
| C1 | Adherence with research questions | exclusion | one | 1. Full adherent, 0.5 adherent with one questions and 0. not adherent | 0. ☒ |

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[7] The real search strings here: Mendeley repository `https://data.mendeley.com/data-sets/7t7dz233k2/1`

[9] One of those two research phases.

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| | | | | | |
|---|---|---|---|---|---|
| C2 | Dealing with connectionist learning. Preferably educational forums | inclusion | one | 1. connectionist learning and educational forums, 0.5 just connectionist learning and 0. neither | 0.5 ☑ |
| C3 | Objective to improve students' engagement with these tools (forums) | inclusion | one | 1. improve, 0.5 just measure and 0. neither | 0.5 ☑ |
| C4 | Subject to peer-review | exclusion | one | 1. yes and 0. no | 0. ☒ |
| C5 | Non-English language publication | exclusion | one | 1. yes and 0. no | 0. ☒ |
| C6 | Fragility in validation | exclusion | two | Based on Mary Shaw [4] criteria: Analysis scores 1., Experiment scores 0.8, Example scores 0.6, Evaluation scores 0.4, Persuasion scores 0.2 and Blatant assertion scores 0. | 0.4 ☒ |
| C7 | Research results | exclusion | two | Based on Mary Shaw [4] criteria: "Procedure or technique" scores 1., "Qualitative or descriptive model" scores 0.85, "Empirical model" scores 0.7, "Analytic model" scores 0.55, "Notation or tool" scores 0.4, "Specific solution" scores 0.25, "Answer or judgment" scores 0.1 and Report scores 0. | 0.25 ☒ |



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| | | | | | |
|---|---|---|---|---|---|
| C8 | Shows some connectionist tool or feature | exclusion | one | Yes or No being 0. or 1. | 0. ⊠ |
| C9 | Whether the study focuses exactly on MOOC students or whether that focuses in other population, but it is easily extended to MOOC students | exclusion | one | 1., 0.5 or 0. (the article is not adherent to population target) | 0. ⊠ |

*2.4. Quality analysis*

For the purpose of a paper be well scored in the quality criteria, it must match some characteristics. This requisite is needed in order to extract properly the useful data and to rank the studies to infer the final results. Most of quality aspects refers to elements from the research question like type of intervention, population and outcomes, in addiction to publication quality, date and citations are also observed. See below all the quality criteria and a brief description:

Q1: Type of intervention: Describes what demands from students in the solution proposed. A tool that does not demand any new skill or procedure from students, scores 1.0. If the intervention demands some skills or procedures from students, but the focus is completely transparent to them, scores 0.5. A framework consisting mostly of new skills and procedures, without any tool transparent, scores 0.0;

Q2: Outcomes: This criterion deals with threats to validity and any unexpected outcomes, beneficial or not, like performance increase or decrease, competition rate variation, etc. For such criterion, the article shall be assessed case by case, scoring from 0.0 to 1.0. For each article 0.5 points shall be exclusive to threats to validity (0. if these are not present in the article);

Q3: Publication quality: For this purpose we shall use h5-index ranking from Google Scholar for reputation of sources. The best scored source in the selected papers shall score 1.0, the others shall score proportionally low in sequence;

Q4: Date and citations: Publication date and citations shall be assessed trading off against each other. As much citations such paper has gotten, its outdated publication will be tolerated. The score start at 1.0 for 2018, and go down linearly to 0.0 for 2008. Each two hundreds citations in Google Scholar outweighs one year.

## 3. Results

This section summarizes the results from our review.

### *3.1. Search results*

As we describe in the Section 2 “Method”, our review was performed in two steps, Validation and Search. In the end of Validation process we found two relevant articles that match to our criteria [5, 6].

The second and most important phase was the search itself. Thereby we perform two searches in each one of all four scholar engines, as described in Subsection 2.2.2. Those two references selected in Validation phase were found here too [5, 6], validating our method. Table 3.1 describes the results from every scholar search engine.

After to perform the very first reading, we could notice that the number of articles presenting new tools with some feature directly associated to students is very low. So this criterion was the guilty for the most of excluded articles.

We decide to order the accepted articles and choose just the first 6, summarizing the results.

| | | *General String* | | | *ITS String* | | |
|---|---|---|---|---|---|---|---|
| Dataset | Date of search | Returned articles | Accepted articles | Included articles | Returned articles | Accepted articles | Accepted articles |
| ScienceDirect | 09-22-2018 | 407 | 14 | 1 | 40 | 1 | 1 |
| ACM | 09-22-2018 | 144 | 4 | 0 | 9 | 1 | 1 |
| IEEE Xplorer | 09-22-2018 | 33 | 1 | 1 | 0 | 0 | 0 |
| Google Scholar | 09-22-2018 | 1820 | 68 | 1 | 186 | 3 | 2 |
| Total | | 2404 | 87 | 3 | 235 | 5 | 4 |

Table 5: Data-sets and their outputs in number of articles and articles accepted

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| References | title | Authors | Method | Conclusions | Year | Source | Quality score | General score | Mary Shaw score |
|---|---|---|---|---|---|---|---|---|---|
| [7] | A visual recommender tool in a collaborative learning experiment | Antonio R. Anaya, Manuel Luque and Manuel Peinado | This work was demonstrated by example | That demonstration showed that the tool is easy to use and could improve the collaboration | 2016 | Expert Systems with Applications | 4.3 | 11.3 | 1. |
| [8] | A Framework for Topic Generation and Labeling from MOOC Discussions | Thushari Atapattu and Katrina Falkner | Its method consisted in an analysis of correlation between the thread classification and thread generation of its tool, and the classification performed by humans | The analysis found significant correlation between that two classifications, but some sources of threads used by its generator could influence the users | 2016 | ACM Conference on Learning @ Scale | 3.47 | 11.65 | 1.55 |
| [9] | Exploring the Effect of Confusion in Discussion Forums of Massive Open Online Courses | Diyi Yang, Miaomiao Wen, Iris Howley, Robert Kraut and Carolyn Rose | Here was used a survival analysis which consists of a set of methods for analyzing data where the outcome variable is the time until the occurrence of an event of interest. In this case the events are confusion measures | They concluded that confusion is related to dropout rates and the strength of this relation | 2015 | ACM Conference on Learning @ Scale | 3.37 | 10.92 | 1.55 |
| [6] | Mining for gold: Identifying content-related MOOC discussion threads across domains through linguistic modeling | Alyssa Friend Wise, Yi Cui, Wan Qi Jin and Jovita Vytasek | The method was based on the validation of a linguistic model which identifies discussions related to course content | The model was able to classify the relevance of discussion with good confidence | 2017 | Internet and Higher Education | 3.99 | 10,39 | 1. |
| [10] | Supporting effective collaboration: Using a rearview mirror to look forwarde | Margaret M. McManus and Robert M. Aiken | Two experiments was conducted with undergraduate students enrolled in a statistical programming course | The results of the experiments indicated that the students were satisfied with the system and most thought that it was useful for working collaboratively | 2015 | International Artificial Intelligence in Education | 2.86 | 9.36 | 1. |
| [5] | From insights to interventions: Informed design of discussion affordances for natural collaborative exchange | Sreecharan Sankaranarayanan, Gaurav Singh Tomar, Miaomiao Wen, Akash Bharadwaj and Carolyn Penstein Rosé | Two experiments was performed based in four steps | Results show that teams exposed to community deliberation prior to group work demonstrated better team performance and that teams assigned based on observed transactive communication during deliberation demonstrated better team performance | 2016 | AAAI SPRING SYMPOSIA | 2.88 | 10.33 | 1.45 |

Table 6: Details of articles.

### 3.2. Quality evaluation

As described above, some used criteria have not the role to accept or reject the article, but only classify their contribution. Some features like date of publication and citations are good but not are our target. In other hand some quality criteria were classified as acceptance criteria, like validation and results, because we need some minimum score.

### 3.3. Quality points

The Table 3.1 describes the results about quality, acceptance and rejection. As we could notice, quality criteria take lower grades compared to others. Much of this result are because a lot of acceptance and rejection criteria are binary and every selected article must scores one.

Looking at the Mary Shaw [4] criteria (C6 and C7) we can notice that validation and results are low graded in this article in despite of publication sources have been well scored. It could happen because articles that describes tools often pay less attention to those.

| | *references to papers* | | | | | |
|---|---|---|---|---|---|---|
| | [7] | [8] | [9] | [6] | [10] | [5] |
| QC1 | 1. | 1. | 1. | 1. | 1. | 0.5 |
| QC2 | 0.5 | 0.4 | 0.4 | 0.6 | 0.4 | 0.4 |
| QC3 | 1. | 0.27 | 0.27 | 0.49 | 0.26 | 0.18 |
| QC4 | 0.8 | 0.8 | 0.7 | 0.9 | 0.7 | 0.8 |
| C1 | 1. | 1. | 1. | 0.5 | 0.5 | 1. |
| C2 | 1. | 1. | 1. | 1. | 1. | 1. |
| C3 | 1. | 1. | 1. | 0.9 | 1. | 1. |
| C4 | 1. | 1. | 1. | 1. | 1. | 1. |
| C5 | 1. | 1. | 1. | 1. | 1. | 1. |
| C6 | 0.6 | 1. | 1. | 0.6 | 0.6 | 0.6 |
| C7 | 0.4 | 0.55 | 0.55 | 0.4 | 0.4 | 0.85 |
| C8 | 1. | 1. | 1. | 1. | 1. | 1. |
| C9 | 1. | 1. | 1. | 1. | 0.5 | 1. |
| Total | 11.3 | 11.65 | 10.92 | 10.39 | 9.36 | 10.33 |

Table 7: Articles and their grades.

## 4. Discussion

In this section we discuss about what ways the researchers are tanking to develop tools and new features to improve collaborative learning.

### *4.1. Distribution of publications*

From the result of this review we can see that the most studies in this field are about analysis of student behaviour during discussions [6, 10, 9]. In contrast, those tools that aims to expose some result to student appreciation, represents only a half of results [7, 5, 8]. Other points is that Machine Learning ML is the main trend and none of the first six was released this year.

### 4.2. What research topics are being addressed?

The main topic addressed is Intelligent Tutoring Systems (ITS) [7, 5, 10, 8]. Recommending Systems [7], User Profiling [9] and Educational Design [6] are present too.

Anaya et al. [7] presented a visual recommender tool that describes to student her own collaborative interaction affording a self reflection.

Atapattu and Falker [8] showed us an ITS able to generate and label discussions in collaborative forums. Other ITS are presented by Sankaranarayanan et al. [5], and McManus and Aiken [10]. That first presented a collaborative strategy based in team formation. The second described an Intelligent Collaborative Learning System (ICLS) which foments collaborative skills.

Yang et al. [9] describes a student profiling model based on confusion behaviour during the use of collaborative environment. At the end, Wise et al. [6] showed us a mining tool useful for directs the course staff about the most important discussion threads to answer.

### 4.3. Validation Strategies

Experiments was the main validation way took [5, 10, 8]. Analysis [9], examples [7] and mathematical model validation [6] were used too. Some times, even when the authors are experienced and the source are well known, the validation method could be poor.

## 5. Threats to validity

Here we point out every identified limitation or threat to validity.

### 5.1. Construct Threats

When we stat the research quest about collaborative learning we hold that the solution for student lack of engagement comes from it, which may no be the right way. However, taking into account that we are working for massive learning, collaborative support seems to be at least a very feasible way for affording human interaction.

### 5.2. Internal Threats

Even using automatic search tools, much of our enforces are manual and it implies a natural error. In order to minimize this we have a validation phase which gives us more confidence in the results.

### 5.3. External Threats

Automatic search engines demand a lot of not very clear processing and it might put some bias into the results. Besides that, a lot of new material might not be mapped by these engines. On other hand, face to that such amount of content developed by science community, it is difficult to figure any alternative.

In those article that we analyze, much because they were working with a massive and very heterogeneous population, sampling the population was a significant trouble. Our criteria C6 and C7, and quality criteria Q3 may minimize that.

## 6. Conclusions

From this review we can conclude that much research just was made about the student behaviour and their goals. The argument of those comes around improvements in course design and likely personalizing.

As pointed by Sankaranarayanan et al. [5], lack of structured support during synchronous collaboration has been demonstrated to produce significantly less learning. On the other hand, it is known that the role of teacher is to provoke learning but not to afford knowledge. We stat as a hypothesis that some structured synchronous collaborative support which provoke learning instead just to solve some doubt or afford knowledge, could set the massive education closer to some class room.

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