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MSocial: Practical Integration of Social Learning Analytics Into Moodle

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ABSTRACT In the last years, educational community is asking for a change by introducing social tools in formal learning contexts. Besides, although meaningful research on the effects of social learning can be found in the literature, all authors agree that further research is needed. Social Network Analysis (SNA) has been proven to be a useful tool for both researchers and teachers. However, both standard SNA tools and the most popular social network sites are external to the Learning Management Systems (LMS) anda, therefore, they are hard to integrate by teachers into their educational designs. This study shows MSocial, a novel tool integrated into the Moodle LMS, that allows students interact in their social networks without losing their presence in the LMS. MSocial monitors student activity in social networks (both inside and outside of Moodle), calculates SNA metrics and shows the results promptly in the Moodle course site. Therefore, teachers can easily understand, visualize, and analyze the social participation and interaction of students and incorporate these results to improve the learning process.

INDEX TERMS Electronic learning, learning management systems, social network services.

I. INTRODUCTION

Online social learning is an emergent phenomenon that has been facilitated by the breaking of the barriers between formal and non-formal learning [1]. In fact, many authors recommend using social media for education purpose [2].

Social networks sites (SNS), such as Facebook, Twitter, Instagram and Pinterest, are becoming increasingly important in everyday life of students. These social media applications have a user-friendly interface and are very convenient when using mobile devices, especially for the youngest generations [3]. Introducing the use of these SNS in education could improve students' motivation, engagement, preparation and performance [4]. Vate-U-Lan [3] shows that social networks can be an effective communication and discussion channel for learning and that have a psychologically positive impact in secondary and higher education. Facebook and Twitter are the most popular social networks for educational purposes, although Facebook prevails while Twitter is the winner in mobile contexts [5]–[7]. Facebook allows create interactive forums and facilitates teamwork, while Twitter encourages students to participate and facilitates communication and exchange between teachers and students [8]. Moreover, some authors advocate for considering other more visual social media, such as Instagram and Pinterest, that could be surpassing the former for young students [9]–[11].

Compared to classical SNS, some authors define Educational SNS (ESNS) as social networking sites that are built to promote collaboration among learners [5]. These sites, unlike official course sites, allow students to have a higher level of interaction and a less formal way of communicating, which can motivate students to contribute and to share knowledge and information. Al-Dhanhani *et al.* [5] suggest incorporating reward mechanisms such as the use of gaming features (like awarding achievement titles and scores) that can increase or decrease depending on user activity. These incentives do not exist in classic SNS used for educational purposes, but they do in Learning Management Systems (LMS). Moreover, some studies show that, although students like using Facebook as a LMS, many of them find as many advantages as disadvantages when comparing with a traditional LMS, like Moodle [12]. Facebook is clearly preferred by students for instant communications with their instructors and for engagement in discussions, but not for sharing materials and submitting assignments.

It is well known that all LMS include tools like chats and discussion forums, which can be viewed as social networks since users connect with other users and/or with

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user-generated content [4]. However, although LMS, such as Moodle, have mobile-friendly, responsive web interfaces and even native application for phones, students prefer to use social network applications (such as Facebook and Twitter) in smartphones for learning purposes [13]. Students tend to use laptops or computers for accessing LMS, but smartphones for accessing social learning tools. Therefore, social network applications expand the value of LMS and could play a key role when incorporating them in traditional classroom as well as in blended learning contexts [13]. Moreover, this is especially important in contexts where LMS fail, such as developing countries [14].

On the other hand, the use of classical SNS external to LMS allows teachers to design social learning activities in which external experts and professionals can participate and generate content and opinion, getting a much richer educational setting [11].

Combining classical social networks with online learning systems is a relatively new approach, but the first results of this combination are quite encouraging [7]. As we will discuss below, one of the academic benefits of social learning is that learning results are improved as well as that teachers can assess students having into account their interactions [15]. However, it is difficult for teachers to integrate social networks into learning activities in a convenient way [7]. The more teachers introduce active practices, the more overloaded they are. The problem is that social networks are not designed for learning purposes and are difficult to quantify. Teachers need to invest a great deal of personal effort to analyze all the social activity generated by the students. Therefore, the development of tools to automatically monitor the student social activity would be very valuable and would promote the adoption of SNS in learning process [16].

By the other hand, Social Network Analysis (SNA) is a field of knowledge with a high potential for these issues. SNA-based indicators provide information of interest to teachers and allow them to monitor the evolution of participation and collaboration of students [17].

Many learning platforms can monitor students' behavior and interactions, predict their achievements and recommend them interventions to promote learning [15]. However, most of the empirical studies analyze interactions that take place only within the LMS, in message boards or discussion forums, while these are not the most common means of social interactions, as we have previously discussed.

Hernández-García *et al.* [18] analyze the relation between social network parameters and classroom and students' performance in a MOOC context. But they only use LMS message boards. Adraoui *et al.* [19] use social learning analytics to describe the learners' interaction in Moodle discussion forums, but they use external analysis tools and only Moodle forum interactions are analyzed for social learning. The use of a social analysis tool integrated into Moodle would be very important for acting in real-time, for example, on at-risk students. Muñoz *et al.* [20] go one step beyond and create a plugin for Moodle that analyses student participation in discussion forums and identifies the major players within the student network, but they do not consider external social networks.

According to [7], most researchers agree that online social networks contribute positively to students' preparation, engagement, motivation, cooperation and communication, but they find many difficulties in proving the possible improvement in academic performance with empirical data. Moreover, many authors report conflicting or contradictory findings [6], [18], [21], [22]. What is clear is that the debate exists, and further research is necessary.

Research of [7] seems to confirm that the use of social networks could be connected with successful academic outcomes. Huang *et al.* [15] find that students perform better, especially on complex group tasks. Moreover, Lambic [23] also confirms a positive correlation between the frequency of use of Facebook for educational purposes and student academic performance. Weidlich and Bastiaens [24] enrich the existing learning environment with social network features and compare it with a non-enhanced Moodle. They find that students perceived the enhanced environment to be more sociable. Regarding if social aspects impact the effectiveness of online learning, they state that this relationship has not been consistently empirically supported.

On the other hand, Huang [22] finds a small negative correlation between SNS use and student academic achievement, giving objections to positive effects. Joksimović *et al.* [25] do not consider either that social indicators are important for predicting course grades when there is a close interaction between discussion forum participants. Moreover, Wakefield and Frawley [26] conclude that SNS use would put poor performing students at risk. Especially, they find that lower achieving students who spend more time on Facebook (for learning or for non-learning purposes) are likely to perform worse in subjects with lower learning difficulty. It is important to point out that their study is based only on surveys but not on actual use statistics, which would help to a deeper discussion. In any case, there are several factors that could influence the divergent results found in the literature, such as different subjects, student cohorts, background and academic discipline [22], [27]. For example, Kim *et al.* [28] compare results between a whole-class discussion and a team-based discussion and they obtain different results. Moreover, most studies applying SNA to education focus mainly on small groups in collaborative context [18], [29] because it is easier to account and analyze the results.

Student interest and, therefore, engagement could also vary according to the context. Alario-Hoyos *et al.* [30] find that forum was the social tool preferred to contribute to the MOOC, but they recognize that MOOC student profile could be different from blended learning. In fact, some researchers state that students of on-line asynchronous courses have a lower sense of community than those enrolled in blended courses [28]. The work of [31] is performed in a blended learning environment, where only discussion forums are used as social tools. They find that social metrics are useful for predicting performance in blended learning environments, in contrast to prior studies with MOOCs. They indicate differences in the students' relative participation rate in both learning contexts.

Finally, we can find in the literature differences related to the SNA metrics as well. The most frequently used metrics are in-degree, out-degree, betweenness and closeness centralities. Each centrality measures a distinct idea of the vertex/user local/global importance in the network; betweenness indicates an idea of control (the most important vertices are the ones across many paths), closeness captures the idea of independency (the most important vertices are the ones closer to all others and the most independent) while degree quantifies the visibility (the most important vertices are the ones most noticeable and/or directly involved in the substructures of the network) [32]. Researches agree that, in general, a combination of multiple SNA metrics is more suitable than a single one to study student participation and performance [33], [34]. However, new controversy is found about their usefulness in predicting student performance. Saqr and Alamro [16] find that out-degree centrality is positively correlated with academic performance. They apply SNA to investigate how interactions in discussion forums affect academic performance. The same procedure applies to [35]. They also find that out-degree centrality has the highest correlation with academic performance. Kim *et al.* [28] compare results between a whole-class discussion and a team-based discussion format. They find that out-degree centrality is important (related to performance) only in the whole-class discussion format, in which students do not belong to a team. However, in-degree centrality, which represents the student's prominence within the network, does not necessary imply knowledge construction and the consequent student productivity [28]. However, Gitinabard *et al.* [31] find betweenness centrality to be more relevant than degree centralities. Saqr *et al.* [36] focus on the importance of the temporal component. In their study, out-degree centrality is an early indicator of good performance, but in-degree centrality is more significant as the course advances. Therefore, it is important to have a tool that allows easily to register the SNA metrics at different instants of the course, and not only when the activity has finished.

In summary, there are contradictory results about the effect of Social Networks Sites on learning, so many researchers suggest that it is necessary further research [6], [21] and tools that allow to register and analyze student social activity and integrate it into the LMS.

In this complex research context, the novelty of this work is the proposal of a SNA tool integrated into Moodle that registers and analyses not only Moodle social activity (in forums, for example) but also student activity in the most popular social networks (such as Facebook, Twitter...). This tool facilitates the continuous monitoring of student social activity (both inside and outside of Moodle) and allows teachers to have into account social participation and interaction in the learning and assessment process. The new software application, that we have called MSocial, includes both a board with SNA metrics and a data visualization tool integrated into the Moodle course site about the activity and interaction of students in social networks. In the next section, we will explain the novelties or contributions to the state of the art. Then we will describe MSocial. Finally, we will discuss a case of study in order to illustrate its potentiality and utility and we will expose the conclusions of this work.

II. RELATED WORK

Most of research about LMS and social activity only considers interactions in LMS discussion forums [18]–[20], [34], [35], [37], [38]. There have been some efforts to integrate social networks like Facebook and Twitter into Moodle [8], [39]–[41]. However, not one of them incorporates the possibility of SNA.

In fact, SNA tools external to LMS are the most used for studying LMS use and social activity relationship. Very few attempts of SNA tools integrated into LMS can be found in the literature. As explained before, Muñoz *et al.* [20] have created a plugin for Moodle but it analyses only student participation in Moodle discussion forums. Sun [42] has a similar plugin for Moodle, but it is still in an early stage.

On the other hand, the Blackboard e-learning platform includes social media modules, which allow access the posts in the social site, but they do not integrate the SNA and neither do they have visualization tools.

The problem with standard SNA software packages is that they are oriented to experienced users and require format-adaptation of data. For example, Reffay and Martínez-Monés [17] have developed SAMSA, which integrates different data sources (not only discussion forums, since it takes data from any log file that complies with a standardized common format), but it is oriented to CSCL researchers not for teachers to analyze and visualize the participation and interaction and intervene in real-time.

Moreover, data visualization is fundamental for social learning analytics and decision making [18]. We can find external potent SNA tools like Gephy [35] and other visualization tools integrated into Moodle but only working with Moodle forums, as for example, Forum Graph [43]. Saqr *et al.* [37] use Graphes (a web service) to extract interaction data from Moodle forums and generate SNA visualizations; then they process data and use Gephi for the final visualization and quantitative SNA analysis. They show that SNA monitoring enables them to apply a relevant data-driven intervention and then, to enhance medical students' interactions in a collaborative environment. However, on-time intervention would be facilitated with an integrated tool.

In summary, as Filvà *et al.* [44] reported in 2014, the lack of SNA tools integrated into LMS is still a problem today that MSocial could solve. MSocial allows easy and simple integration of the analysis and visualization of student activity in social networks (both inside and outside of Moodle) into the Moodle course site and into the overall learning and assessment process.

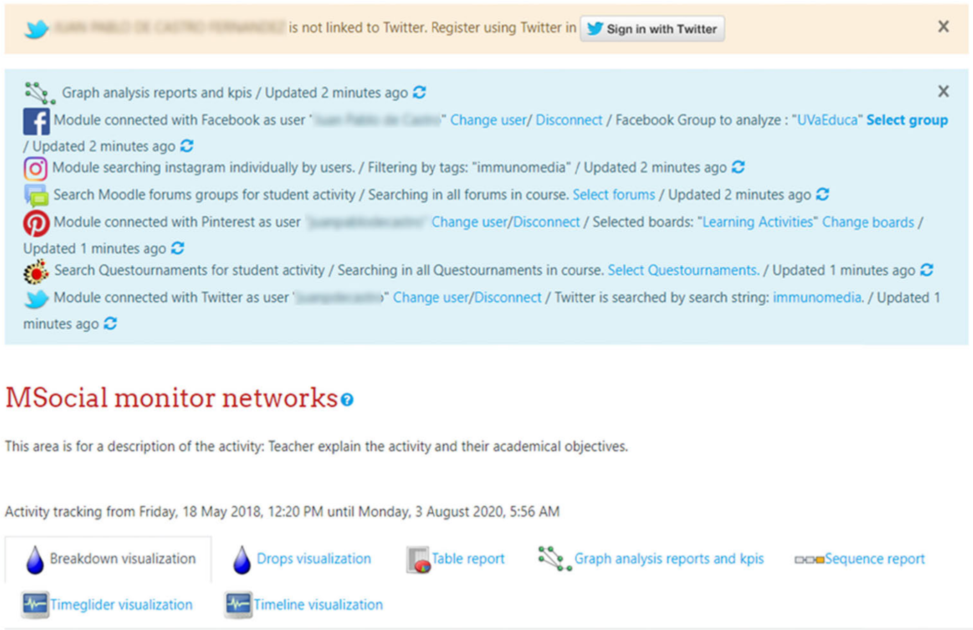

FIGURE 1. Main page of the MSocial activity.

III. THE SYSTEM: MSOCIAL

MSocial focuses on the need of integrating into LMS the learning activities orchestrated around the most popular social networks besides the other internal communication activities. Students can interact in their social networks without losing their presence in the LMS, since MSocial monitors the activity of students and shows the results promptly in the Moodle course site. Besides, teachers can assess quantitatively the students' social activity and compose a new grade item for the gradebook of Moodle as an additional element of evaluation.

As we needed data about student participation and social interactions, we decided to implement a SNA tool integrated into Moodle. We should collect data from social network sites and applications (both internal and external to Moodle), calculate SNA metrics or KPIs (Key Performance Indicators) and provide some sociograms for network visualization. The final objective was to develop a support tool that incorporates these KPIs to predict learning outcomes at an early stage that could conduct on-time warnings and recommendations to students and teachers.

This tool will quantify social participation and interactions in different SNS (Facebook, Twitter, Instagram, and Pinterest), as well as in the social activities of Moodle (such as Forums and Questournaments). Then, it will prevent teachers from having to manually review interactions. They could design learning activities for these SNS according to the capabilities provided by each one:

- Facebook: the Facebook groups are good tools for discussion and collaborative learning. It is possible to create a closed-type group, where all the students attending the course can join and whose content only can be viewed by its members.
- Twitter: it is the most "immediate" social network. Students can be asked to tweet some relevant concepts or some summaries, for example, marked by a teacher-defined set of hashtags.
- Instagram: teachers can ask students for publishing images or videos by using some hashtags predefined by teachers.
- Pinterest: it is also focused on images and videos and it is suitable for collaborative tasks, in which students have to collaborate in curating collections of graphical resources (called boards) predefined by teachers.

A. USER INTERFACE

MSocial has an interface where all social activity is displayed (see Fig. 1) and several operations can be done:

- Registration of students and teachers: All participants must identify themselves in each external social network to correlate the SNS activity with Moodle users.
- Revision of the configuration and state of all social network activity search operations. In this section, students can see what criteria teachers have established to identify the social network activity.
- Description of the activity: Teachers explain the activity and its academical objectives.
- Visualizations of the collected data. Teachers and students can select different filtering criteria and a set of visual analyses of the captured social activity.

All the student activity is got together in a table and different graphs, which are used to generate multiple aggregations and visualizations. Some of them are basic statistics (for each social network and for all together), while other are SNA centralities. For example, we can obtain number of posts, number of replies, number of reactions, highest number of

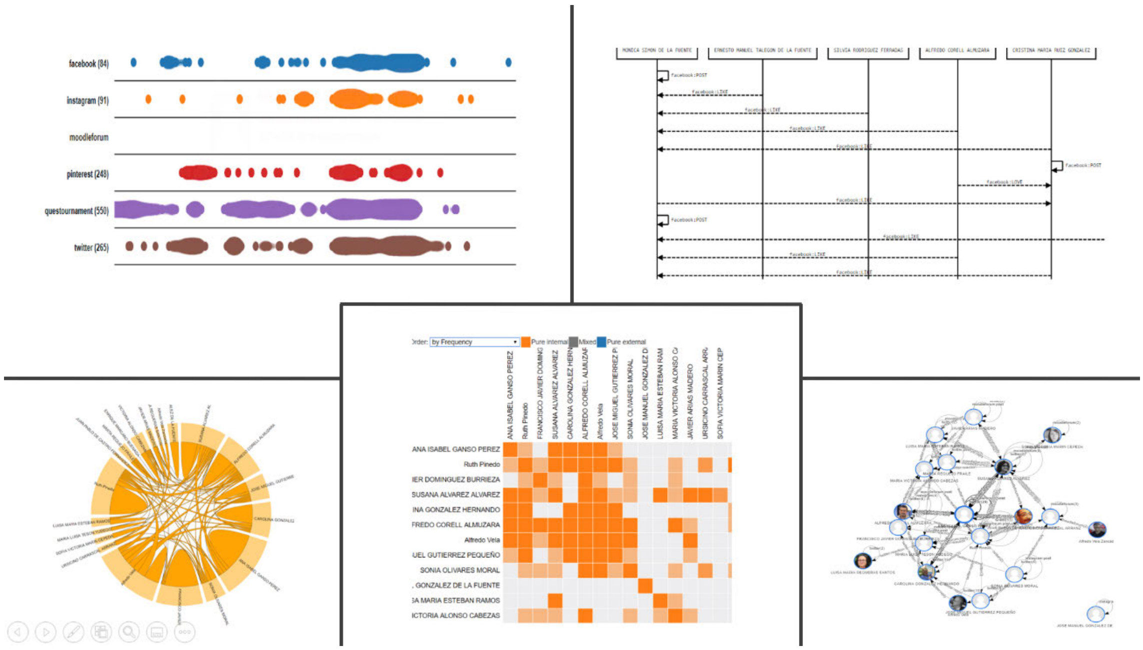

FIGURE 2. **Visualizations available in MSocial.**

posts, highest number of replies, highest number of reactions, closeness centrality, in-degree centrality, out-degree centrality, betweenness centrality and the highest numbers of each centrality measure. In total, there are more than 30 key indicators that can be transformed in a Moodle grade and that could be the base for applying Machine Learning and Data Mining techniques.

We have chosen the closeness, in-degree, out-degree and betweenness centralities [45], since they are the most extended approaches to estimate the social contribution of students and their position inside the network, as we have seen in the introduction section.

MSocial has been implemented as a module that can be integrated into the e-learning platform Moodle. It can be added as a Moodle activity by teachers, who will have to choose which social networks they want to analyze. They could also decide which information will be shown to students. MSocial is a modular system that includes plugins to collect data from four external SNS (Facebook, Twitter, Instagram and Pinterest). It analyses those SNS data as well as data from Moodle discussion forums and a gamification tool called Questournament [46], [47]. MSocial provides different key indicators and data visualization graphs (see Fig. 2). These visualizations can help teachers to design the best strategic collaborations and to establish effective work groups.

In SNA, it is necessary to define which interactions are relevant (discussions, reactions, etc.). Social activity in MSocial comes from different sources in which interactions are not the same and are named differently. In order to perform the combined analysis, we have defined a unified model that is based on the generic concept of interaction. An interaction is an event detected in a social network that is relevant to model the relationships. III-B shows the different interactions defined in the MSocial model and how they are generated out of student activity in the different SNS.

Being each interaction an edge in the graph, the nodes are the social network users. Since not all users will be students or teachers, we should distinguish between known users (users enrolled in the LMS) and unknown users (other users of the social networks). MSocial includes a filtering section in which one can select which interactions will be shown: for example, it is possible to show or to hide interactions from unknown users, to filter by social network and to select which type of interactions of III-B will be shown.

MSocial works mainly in background without the intervention of teachers nor students, by recollecting the users' interactions in the social networks and making calculations.

The interactive interface permits data examination and visualization by means of a set of tools: KPI Table, Drops, Sequence diagram, Timeglider, Timeline, Interactions matrix, Chord graph, Graphviz and Graphvis, as it is shown in Fig. 2. The data visualization provides clarity, saving time, less confusion and an aesthetic appeal that is very interesting for teachers [48].

Finally, the table of KPIs includes all the calculated indicators, which can be used directly for freely calculating the social activity grading. MSocial provides teachers an excel-like formula calculator to introduce a mathematical formula for calculating the grade from the available KPIs. Therefore, teachers can choose the aspects to be evaluated,

TABLE 1. MSocial interactions model and the corresponding features collected from the different SNS.

MSocial	Social Networks					
	Facebook	Twitter	Pinterest	Instagram	Forum	Questournament
POST	Post	Tweet	Pin	Post	Discussion	Challenge
REPLY	Comment	Retweet	Comment	Comment	Post	Answer
MENTION	-	Mention	-	Mention	.	.
REACTION	Like/Love/Angry/Sad/Laugh	Like/Fav	Pinned	Like	.	.

in a flexible and effective way. Students will be able to see their social activity grade in their gradebook.

B. ARCHITECTURE

MSocial has been designed in a modular way with the aim of being able to evolve and to be adapted to many scenarios. It supports the installation and enablement/disablement of plugins of two types (see Fig. 3): visualization/analytics (View) and interaction harvesters (Connector). All plugins use a common data model and common internal APIs so that the consumed and produced information is standardized and shareable.

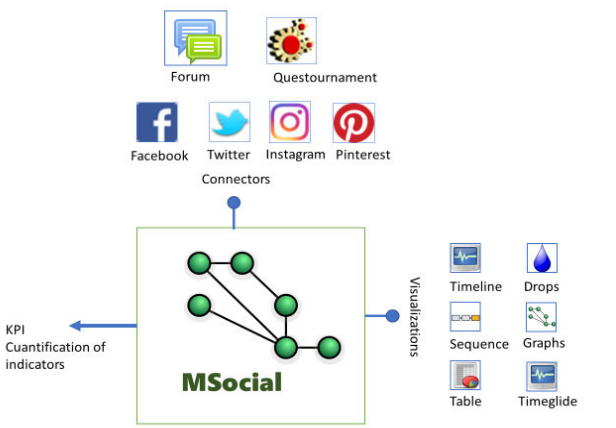

FIGURE 3. Plug-ins for social tools and visualization graphs implemented in MSocial.

View plugins are responsible for generating user interfaces with a visualization about interactions data and, optionally, KPIs derived from the information provided by other plugins. Once installed, the user interface includes proper tabs on the main page of the activity to select the graph to visualize (see Fig. 1).

Connector plugins use the SNS APIs and map the raw information onto the abstract data model used by MSocial. In the meantime, they also calculate specific KPIs out of their own data.

Each plugin declares a set of KPIs, becomes responsible of them and provides the code to populate and calculate their values. When installing or upgrading a plugin, the data model is automatically adapted to the installed KPIs to manage the data generated for each user. Every plugin is designed to be executed periodically by the system scheduler to do maintenance or data gathering tasks (see Fig. 4).

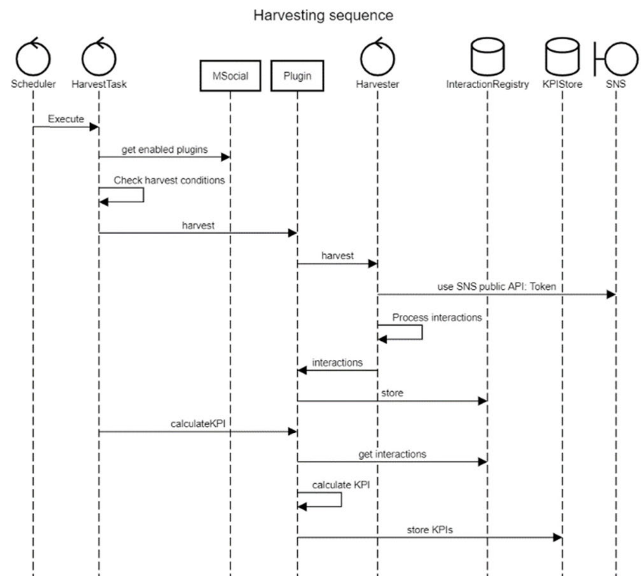

FIGURE 4. Harvesting process sequence diagram.

In order to interact with MSocial, all the plugins use a common data model and a set of internal APIs using the following main abstractions:

- Social Interaction: It represents a quantification of an event between users encoded according to Table 1. It contains references to the author, recipient, timestamp, source (SNS), type of interaction, relation with other interactions, etc. Each activity has a repository of interactions that represents the overall state of the social network created by the students.
- Social User: It stores the mapping between an LMS user and his/her alias in the SNS.
- KPI: Each user has the same number of values calculated by the plugins out of the registered interactions. Some plugins calculate only their own KPIs (for example, Twitter, forum) and other can use the interactions from all the sources (for example, Graph Analysis).

Internal sources (forums, Questournaments, etc.) are harvested by direct access to the LMS database, whereas external sources are scanned using the public APIs of the SNS providers. Each plugin must adapt the available information to the common data model as each API has different functionalities and terms of use. In order to connect to the SNS, the owner of the LMS should sign usage contracts with the SNS and obtain the permissions and cryptographic keys to use OAuth protocol [49] to authenticate the SNS users and ask them for access to their data.

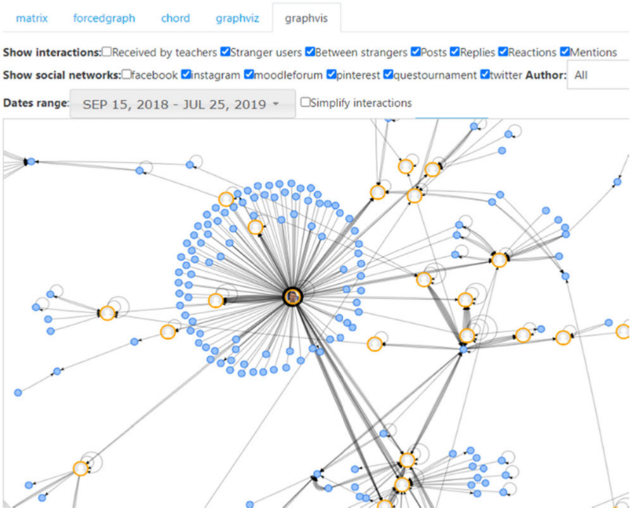

FIGURE 5. Graph visualizations of social activity.

Each "View" plugin additionally implements the code for rendering visualizations about the interaction or KPIs. Details are implemented using some JavaScript libraries such as D3JS, Graphviz, dataTables, Simile Timeline, etc.

IV. EMPIRICAL CASE STUDY

We have validated MSocial in a real blended learning context: Human Immunology course. This one is a compulsory subject in the second year of the Degree in Medicine given at the Medical School of the University of Valladolid (Spain).

In this course, face-to-face classrooms are combined with online learning taught through Moodle, which is the LMS used in the Virtual Campus of the University of Valladolid (UVa), and the use of social networks. Specifically, the teacher has incorporated in the learning process the following social networks:

- Instagram: Students should use the hashtags "#immunomedia" or "#inmunomedia" in their publications to be registered by MSocial.
- Pinterest: The teacher defined some thematic boards about Immunology, Immunotherapy, Gene-therapy for Immunodeficiencies…
- Twitter: Students should use the hashtags #inmunomedia or #immunomedia and #uva in their posts to identify the activity of the course.

The teacher has decided not to incorporate the Moodle forums, because he checked previously that students hardly use them and prefer to use social networks, where they feel more comfortable.

We have used MSocial to collect interactions data throughout the course, integrate them into Moodle and obtain SNA and visualization graphs. Then, once defined the student social activities, the teacher can see in real-time the evolution of student interactions and participation. These visualizations allow the teacher to analyze both the participation and activity of students along the course and their connectivity (Fig. 5), being able to interactively see the most connected users and the relationships between them.

Moreover, the teacher can also see a summary table with all the activity generated by students and their KPIs (number of interactions and value of different centralities), as it is show in Fig. 6.

FIGURE 6. KPI table for social activity.

Finally, it is interesting to indicate that 108 out of the 193 students enrolled in the course have used the tool, which shows a very high degree of interest to use the social networks in the formal learning process. Table 2 summarizes the social activity generated by the students and the total including the reactions of unknown users. We can see how most students have used Twitter as social network for learning purposes.

TABLE 2. Number of registered interactions for each social network.

Social Network	Students' Interactions		Total Interactions (Students&Others)
	Number	Mean (N Students)	
Instagram	336	9.88 (n=34)	502
Pinterest	248	15.50 (n=16)	322
Twitter	949	13.56 (n=70)	1067

V. ANALYSIS AND RESULTS

We have used the collected data to check if social activity indicators are correlated with academic performance. We have used the closeness, in-degree, out-degree and betweenness centralities as well as students' final grades. We have obtained the results shown in Figure 7, Figure 8 and

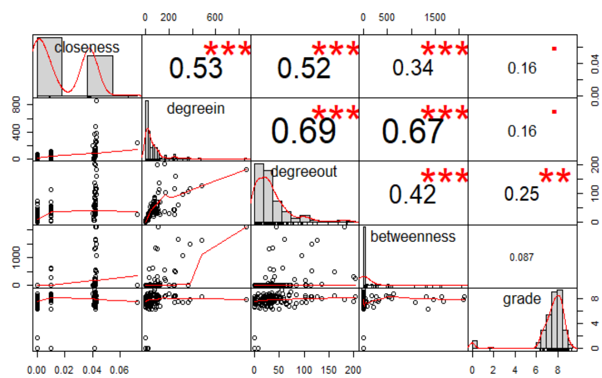

FIGURE 7. Centralities-Grades correlation.

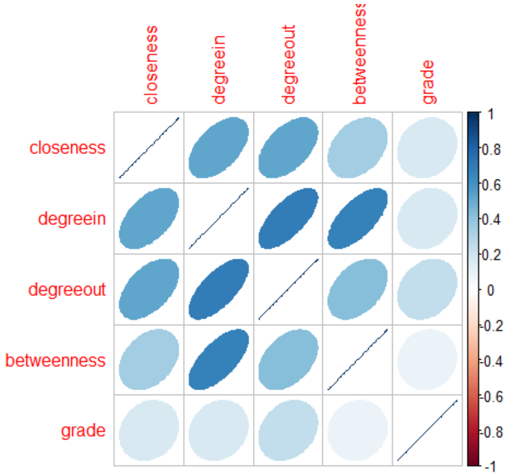

FIGURE 8. Centralities-Grades correlation.

TABLE 3. Pearson's Correlation: Centralities-Grades.

CENTRALITY	GRADE	
	Correlation	P value
Closeness	0.162	0.061
In-degree centrality	0.163	0.059
Out-degree centrality	0.248	0.003**
Betweenness	0.087	0.319

** Results are significantly at p < 0.01

Table 3. We observe that different centralities are correlated among them, but we cannot find a strong correlation with students' grades, except for the out-degree centrality ($R = 0.25$, $p < 0.01$).

We have used the regression analysis to see better the relationship between these two variables (final grade and out-degree centrality). Figure 9 shows that the greater the out-degree the greater the grade. Moreover, the relationship between the two variables is statistically significant. ($p < 0.01$).

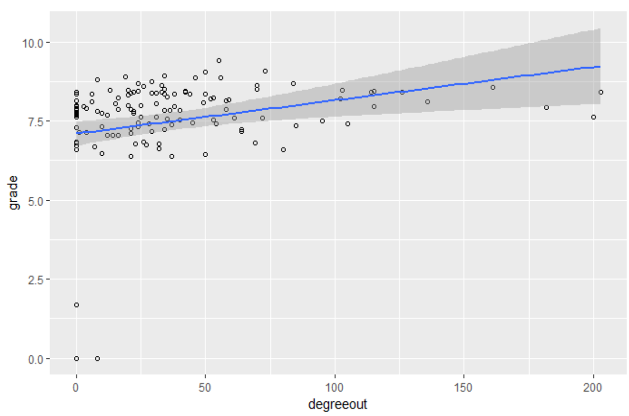

FIGURE 9. Regression analysis for out-degree centrality and grade.

Finally, we have analyzed the satisfaction and usability of the system: a survey based on the CSUQ (Computer System Usability Questionnaire) has been used as standardized measurement.

CSUQ consists of 19 items (OVERALL scale) that can be divided into three factors or subscales: SYSUSE (System Usefulness) for items 1 to 8, INFOQUAL (Information QUALITY) for items 9 to 15 and INTERQUAL (Interface Quality) for items 16 to 18. Each of the items is scored through a seven-point scale, which ranges from 7 (''Strongly Disagree'') to 1 (''Strongly Agree''), and a ''Not Applicable'' (N/A) point outside the scale.

For the analysis, 9 teachers -who have already used MSocial in their courses- have answered the questionnaire. Table 4 shows the average score obtained for each item. From these values, average scores for the SYSUSE, INFOQUAL and INTERQUAL have been calculated too. The SYSUSE factor has a mean score of 1.97, INFOQUAL factor of 2.71 and INTERQUAL factor of 1.94. Moreover, the mean score of overall items (OVERALL factor) is 2.17.

TABLE 4. Average Score obtained in items of CSUQ (1 - Strongly Agree and 7 - Strongly Disagree).

ITEM	AVERAGE SCORE
1.Overall, I am satisfied with how easy it is to use MSocial	1.78
2.It was simple to use MSocial	2.00
3.I can effectively complete my work using MSocial	1.89
4.I am able to complete my work quickly using MSocial	1.89
5.I am able to efficiently complete my work using MSocial	2.11
6.I feel comfortable using MSocial	1.89
7.It was easy to learn to use MSocial	2.22
8. I believe I became productive quickly using this system	1.89
9. MSocial gives error messages that clearly tell me how to fix problems	3.17
10. Whenever I make a mistake using MSocial, I recover easily and quickly	2.50
11. The information (such as online help, on-screen messages, and other documentation) provided with MSocial is clear	2.75
12. It is easy to find the information I needed	2.33
13. The information provided for MSocial is easy to understand	2.78
14. The information is effective in helping me complete the tasks and scenarios	2.11
15. The organization of information on MSocial screens is clear	2.11
16.The interface of MSocial is pleasant	2.11
17.I like using the interface of MSocial	1.89
18 MSocial has all the functions and capabilities I expect it to have	2.11
19.Overall, I am satisfied with MSocial	1.67

These results show a strong satisfaction of teachers with the usability of MSocial. Teachers are satisfied with MSocial and think that this system makes their work easier and enables them to incorporate social media activity into their learning environment.

VI. DISCUSSION AND CONCLUSION

The teachers that have used MSocial are very satisfied with the tool as well as with the motivational effects over their students. They have found with MSocial a useful tool for integrating classical SNS into their educational activities in a constructive and practical way. They can now incorporate the student social activity in the assessment process, what previously was seen as a big difficulty [7]. In addition, the different possibilities of visualization given by the system allow teachers to easily understand and explore the social participation and activity of students as soon as the interactions have place.

Teachers and students agree that privacy is an important concern when dealing with content created outside the LMS. Social Networks are usually used for personal communication by the students, who are reluctant to use their social accounts for interacting with teachers and classmates; this usually is dealt by creating separate accounts for educational activities. Another common concern is about the access to private content not related to the educational activities. The system by default discards the content that does not match the filtering criteria defined by the teacher.

We have proven that the MSocial system can be effectively used in a real learning environment by teachers, who could intervene with different purposes. For example, Kim *et al.* [28] suggest that there should be interventions to encourage students to reply to other's contributions in order to construct knowledge. MSocial is a valuable tool to obtain indicators such as out-degree centrality throughout the course and to be able to intervene on time. It would be possible to establish a minimum number of reply interactions or a threshold for the out-degree centrality value for a student to pass the activity. The objective could be to give incentives to motivate and reinforce the feeling of belonging and the recognition in the community, as suggested by [5].

We have found that out-degree centrality could be correlated with academic performance, which is coherent with findings of [16], [28], [35]. As out-degree centrality captures the participation of a student in the community by means of the content creation and interactions with other's content, higher out-degree may be associated to students who are more active in publishing and curating the content of the social network. Hence, these users process more information (their own and others') and potentially could benefit from the activity more than others. However, the final correlation results are very preliminary, since there are many variables that involve in the blended learning process. Further experiments should be carefully designed by social and educational researchers.

Besides, as we discussed above, a big controversy is found about predicting performance. Many authors are calling for further research in applying SNA not only for predicting performance but for identifying dependencies with the educational context [27], [36]. Also learning styles could be related to roles or positions that students occupy in social learning networks [50]. What all researchers agree is that further research is necessary [6], [21]. In this complex research context, MSocial allows the continuous monitoring of student social activity both internal and external to the LMS, facilitating future educational and social experiments. It will not be necessary to restrict the SNA to discussion forums, as it occurs in most studies found in the literature [35]–[38]. Saqr *et al.* [36] focus on the importance of the temporal component, being necessary to calculate SNA metrics during all the course and not only at the end. Some researchers point out the importance of regularity in discussion participation and communication for predicting student performance [51] as well as for an effective teamwork [52]. To know the temporal distribution of participation is important for intervention in learning by online discussions [53]. Moreover, recent research remarks the importance of temporal perspective for identifying social behaviors and understanding the relationship between social networks and academic performance [21], [50]. MSocial has been designed having into account this temporal component.

By the other hand, MSocial provides a wide group of KPIs that, together with the LMS logs, give a lot of possibilities for researchers to design predictive systems that assist teacher and students. For example, although many authors of SNA and education literature are interested in active (written) interactions [29], other authors state that passive interactions (monitoring and tracking) play an important role in effective teamwork, since they are related to improve coordination [52]. MSocial could be useful also for deepener studies. For example, Dou and Zwolak [33] find that students with a greater out-degree centrality are more likely to experience decrease in anxiety. This is important since authors say that the way social interactions affect learning experiences can vary significantly between individuals. Besides, they discover that repeated interactions with the same students do not contribute to decrease their anxiety. Student interactions could be observed with some of the visualization possibilities of MSocial.

MSocial can be also very useful if you want to use the calculated SNA metrics and visualizations to form effective groups in Moodle for collaborative tasks. Chen and Kou [54] use a genetic algorithm-based group formation scheme that takes into account SNA metrics (to consider learning roles and interactions among peers). They find that the resulting formation of groups is superior to the random grouping in learning performance and superior to the random and self-selection grouping schemes in interaction. Moreover, it would be very immediate to provide a new characteristic to MSocial for students to visualize some structural features of their groups in collaborative work, providing structural awareness and then promoting collaborative interactions [55].

Besides, according to Hernández-García *et.al*. [18], who suggest that the isolated use of SNA parameters could not be sufficient to predict accurately academic performance, further research could take advantage of MSocial. By including the SNA indicators or KPIs together with LMS logs as input variables, it would be possible to define predictive models and implement intelligent tutoring systems to assist students and teachers.

Finally, MSocial is a useful tool for learning communities research, while facilitating the understanding of social presence, which is a difficult but essential task in creating efficient communities of inquiry [56]. Moreover, MSocial could become into an important support software for empirical experiments about social learning frameworks such as learner-generated contexts [57] and pedagogy 2.0 [58], which addresses student participation in networked communities of learning.

To conclude, our team is committed to improve MSocial following those guidelines, but the maintenance of such a complex system has very specific challenges. The main difficulty comes from the integration with external APIs from the different SNS. Each API provides a very different level of detail of information. However, the major problem is that SNS APIs continuously evolve and their capabilities and terms of service change following the changing commercial interests of the service providers. By example, the reaction to Cambridge Analytica data scandal [59] changed radically the access conditions and terms of service of the APIS of Facebook and Instagram. The result was that these APIs ceased providing most of the information that could identify the users, even with their explicit permission to share that information. This greatly cut the ability of MSocial to create graphs with Facebook and Instagram interactions. It still can calculate statistics and some basic centralities for those SNS but not true interactions between students. Moreover, Instagram restricted their public APIs focusing only to business users for marketing objectives. Therefore, privacy policies, legal limitations, commercial strategies will be the most limiting aspects of the integration of these media into effective teaching. However, the highly modular design of MSocial makes possible to easily integrate any other social communication system and exploit this new and rich source of information and visualization.

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