in memory of Luigi Colazzo

Je-LKS

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The Italian e-Learning Association Journal

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In memory of **Luigi Colazzo**

We dedicate the issue of Je-LKS to the memory of our Director, Prof. Luigi "Gino" Colazzo.

Gino left us suddenly on the afternoon of Friday, the 6th of September. It was a bolt from the blue. The news caught us all by surprise, and filled us with a sense of sadness and solitude.

This is therefore the last issue of the journal signed off by Gino, which I have the honour of closing and passing into the hands of our readers. However, before we turn our attention to all the interesting articles of this month's issue, I would like to say a few words in memory of our Director.

Certainly, others could write, and have written, much better than me of his career, his important role within the University, in particular the University of Trento, and even more so as one of the pioneers of distance learning in Italy.

This is why, in his memory, I would like to say a few words about our shared experience.

I met Gino as a graduate student in 2004; we immediately developed a great mutual understanding that grew over time. After graduating and starting work at the University, Gino chose me as his research collaborator; indeed, one of his great merits was to believe in young people, to the point of remaining in the background to help them grow.

Our professional relationship quickly turned into a deep friendship.

We assembled the management of Je-LKS together in 2010 when Gino became its Director; his objective from the start was to open up the journal to the world even more, transforming it into an independent, scientifically strong publication. He wanted to grow it into a familiar point of reference in the national and international context.

I like to remember his first editorial, when he introduced himself as Director with the following phrase:

> *[…] First of all I would like to be a discreet director. So I will not use the editorials to tell you what I think except in exceptional cases. This because the journal, and in reality also the editorial project is made by the authors. Without good articles one cannot make a good journal and one cannot write good articles if these are not preceded by good research. Therefore everything depends on the quality of the research of the authors. Task of the Scientific board, of the editorial board, of the friends who have accepted to review the papers and of the director is to publish the best of what the authors will want to present us. […]*

He respected this commitment throughout his tenure, linking the journal's quality exclusively to the quality of the published works, without any imposition and based only on their contents.

I also like to recall how he ended his piece:

> *[…] In conclusion I would like to do this job with many friends, with those who are already here and with those who I hope will join in. […]*

I would say that, thanks to his vision and commitment, we have successfully achieved these and other objectives in almost ten years of dedicated work; a quality journal published by a group of good friends.

I will always remember Gino not only for his competence, knowledge and honesty, but above all for his kindness, his irony and his engaging laughter.

I will forever be grateful to Gino for believing in me, for helping me to grow, for the hundreds of hours we spent writing at the PC and for the good times spent talking about politics and history.

Gino is someone who is difficult to forget, who enriched all those who have had the good fortune and the pleasure of meeting him.

Thank you Gino, also from all the editorial staff, for giving us the opportunity to know and appreciate you, and for all the gifts of knowledge and wisdom that you have given us.

Nicola Villa
Managing Editor
Journal of e-Learning and Knowledge Society

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EDITORIAL

by Antonio Marzano and Antonella Poce

Focus on: Learning Analytics: for A Dialogue between Teaching Practices and Educational Research

Learning Analytics is a new field of techniques widely used in a number of communities. Some of them are Statistics, Business Intelligence, Web analytics or Operational research. The use of the Analytics approaches in the context of the learning process is called Learning Analytics (LA). A widely accepted definition of LA, provided at the 2012 International Conference on Learning Analytics and Knowledge, describes the field as "*the measurement, collection, analysis and reporting of data about learners and their contexts, for the purpose of understanding and optimizing learning and the environments in which it occurs*" (Siemens & Baker, 2012). The rise of LA comes from the chance of observing and tracking the learners' activities through log files. Logged data describes who the students are, which activities they carried out and when, and sometimes how and where, they worked. Such intensive data collection produces the so-called Big Data that facilitates the use of data analysis procedures (de-la-Fuente-Valentín *et al.*, 2015).

Non-intrusive measurement and collection is difficult to achieve in the learning context. The most popular method is to capture web interactions in a Learning Management System (LMS), but the captured data may not be fully representative of the student activities and other monitoring methods are required. Methods include social network analysis, collaborative filtering, clustering, neural networks, just to mention some. LA attempts to discover the factors that affect learning in a certain context, so that instructors and learners reflect on these factors and improve their experience.

LA will explore continuous monitoring of learner progresses and traces of skill development of individual learners as well as learning groups, both within and across programs and institutions. It will discuss issues concerning

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continuous evaluation of achievements resulting from institutional educational practices to gauge alignment with strategic plans and alignment of governmental strategies. It will examine assessment frameworks of academic productivity to continuously measure impact of teaching. It will discuss concerns such as quality of instruction, attrition, and measurement of curricular outcomes using big data and associated methods and techniques as the premise.

In this special issue, we have worked to publish research initiatives related to LA and really in line with its principles, its ideas and its goals.

The theme of L.A. is differently dealt, focusing on the use that such data can play to improve learning. Different contributions, in particular, are devoted to identify solutions that support both MOOCs and Open Resources' effectiveness in teaching and learning processes. **Fazlagic and Cecconi** discuss the topic, describing the characteristics of the case of the Eduopen platform from a quali-quantitative point of view. The instance of the Eduopen platform is central also in the paper by **Dipace, Fazlagic and Minerva** to highlight how the process of innovation and redefinition of L.A is carried out in the dashboard of the platform itself. In such a setting, formative assessment to support learners in the completion of online courses is developed from different perspectives: **Marchisio *et al.*** describe how formative assessment can offer a more consistent use of OERs at different levels of teaching and learning; **Cecconi and Fazlagic** focus, then, on the quality and assessment tools used in the MOOCs at Unimore and on data on completion rates; **Fissore *et. al.*** use L.A. to improve formative assessment strategies; **Palmiero and Cecconi** propose then an innovative model for assessment in combining formative and summative data with the information collected through the log files produced by the administration. **Miranda *et al.*** show how data can support both teachers and learners is the theme developed.

In the field of assessment through L.A, the paper by **Re *et al.*** describes a new tool to assess the complex construct of Critical Thinking, attempting also an automatization of the system never experienced before.

From a different angle, **Bellini *et al.*** offer a picture of how protection can be considered as far as data management is concerned. The definition of a new predictive model for completion rate in MOOCs is at the core of **De Santis *et al.***'s contribution, raising the quality dimension, which is relevant also in the review study by **Agrusti *et al.*** where the focus is on how to use data to predict university drop out. Completing Agrusti et *al.*'s study, another review (by **Cadamuro *et al.***), in the present issue, is devoted to deepen the relationship between ICT, metacognitive skills and learning outcomes. In general, the authors conclude that the interaction between ICT and metacognition in producing better learning outcomes appears well established and the results highlight a bi-directional relationship between metacognition and ICT, but also allow to draw attention to gaps requiring further research. The definition of an agnostic monitoring system to use data in a more effective way is developed by **Fallani *et al.*** and how data driven modeling of engagement analytics can be helpful to assess student engagement and promote reflections on the quality of teaching and learning is central in **Yang's et *al.***'s paper.

The paper by **Torsani** can be set too in a view of using information collected online as predictive tools, dealing with user rating as a predictor of linguistic feedback. A critical analysis of the quality of "question and answer" portals is at the core of his contribution.

Content and subject development is developed by the papers on creating videos resources to improve disciplinary skills by **Polo *et al.***, where results of a trial, involving teachers and students from upper secondary in a social network context to inquire the interactive dimension of all the subjects involved, is presented. **Bucciarelli *et al.*** inquire the relation among mathematics, informatics, linguistics in the result of a strongly transdisciplinary domain. The contribution by **Cinganotto and Cuccurullo**, which investigates what impact can a MOOC on language awareness have on teacher's professional development, is set on very close topics.

The papers devoted either to introduce an instance of how to use different solutions and augmented reality, in particular, to improve learning in 3 to 6 year old pupils (**De Angelis *et al.***), or describing the school setting climate are those embracing a learning perspective in the dimension of innovation (**Manna *et al.***).

The contribution by **Sansone and Cesareni** prompts reflection on the possibilities of technological development of L.A. within the learning environment, such as to better support constructivist teaching: L.A. that comes closer to social L.A. techniques provides the teacher with a richer picture of the student's behavior and learning processes.

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DISCIPLINARY AND DIDACTIC PROFILES IN EDUOPEN NETWORK MOOCS

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Keywords: MOOCs, evaluation, assessment, didactic, instructional design

This paper describes the quantitative and qualitative characteristics of the massive open online courses (MOOCs) available in the EduOpen platform. In particular, data (analytics) concerning the variables didactic disciplines and didactic structuring are presented to identify main trend lines and potential critical aspects. Useful elements emerge to enhance our understanding of the main characteristics of the MOOCs offered by the EduOpen network, in particular: a) the quantitative dimensions of MOOC supply and demand, in which a greater flow of enrolment towards courses of a scientific and technological nature is evident; b) the degree of didactic structuring of the courses, where the presence of assessment tools appears to be the element that especially characterises the didactic structure of the EduOpen MOOCs. The conclusions suggest awareness-raising actions to build dashboards that can report to instructors and students in real time the critical and necessary action issues and therefore provide useful guidance both to prevent risky situations and to support teachers in the design and development of new courses.

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1 Introduction

The very name massive open online courses (MOOCs; Conole, 2013) clearly indicates the elements that characterise this type of course: a large number of students, the centrality of the network for educational communication and the openness of access to the educational resources. These characteristics condition the process of designing, developing and delivering the MOOCs. A further element of complexity, from the design point of view, is given by the heterogeneity of the cultural and socio-economic characteristics of the recipients determined by the massive nature of participation.

EduOpen[1] is a project funded by MIUR[2] to create an Italian platform for the delivery of MOOCs and was developed from a standard release of Moodle. A series of factors – including the knowledge and sharing of good practices, the results of research conducted at the international level and the regulatory guidelines provided by the Italian body for the evaluation of academic and research activities (ANVUR) – led the EduOpen network to develop the Guidelines for Educational Design of MOOCs. The Centro Edunova team has also taken over the validation procedures for the MOOCs published on the EduOpen portal, based on checklists and intense interaction with the participants in the courses and with the educational managers of the individual universities participating in the network. This interaction has resulted in ideas, suggestions and proposals that have allowed the identification of some educational and technological principles that have a relevant, and sometimes binding, role in the design and production of MOOCs.

After an introductory reflection on the state of the art and on the main numbers and characteristics of the EduOpen project, this paper describes the analysis conducted on the disciplinary profiles of the educational offer of the universities belonging to the network (i.e. the content and disciplinary areas at the base of the individual MOOCs) and on the demand expressed by the participants through enrolment in individual courses (section 1). Finally, the discussion highlights some of the fundamental elements for the didactic structuring of courses (sections 2, 3 and 4).

2 Academic analytics

Now days society is facing constantly the growing challenge posed by “big data”, ‘datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse’ (Manyika *et al.*, 2011). The educational area sees a widespread introduction of virtual learning environments

[1] https://learn.eduopen.org

[2] Ministero dell’Istruzione dell’Università e della Ricerca

(VLEs) – also known as learning management systems (LMSs[3]) – which place educational institutions as well to deal with increasingly large sets of data. Day by day, these systems collect and store increasing amounts of interaction data, personal data, systems information and academic information (Mazza & Milani, 2004; Romero *et al.*, 2008).

(Campbell *et al.*, 2007) proposed that academic analytics is emerging as a new tool inside the waste field of Learning Analytics that can address what seem like intractable challenges. Campbell and Oblinger (2007) set out a definition of academic analytics. This definition links the technological aspects as, 'Academic analytics marries large datasets with statistical techniques and predictive modelling to improve decision making', with the educational ones as, 'academic analytics has the potential to improve teaching, learning, and student success', in the context of the political, 'by 2020 the overall portion of the U.S. workforce with a college degree will be lower than it was in 2000'.

As suggested by Siemens (2010), as some overlap exists between the learning and academic analytics, it is still possible to distinguish the two fields. While learning analytics are focused on the educational challenge: that is "how can we optimise opportunities for online learning"? The academic analytics are focused on the political/economic challenge: "How can we substantially improve learning opportunities and educational results at national or international levels"? In a nutshell, we might say that academic analytics is not strictly about "learning", but rather about the network within which it takes place, as a macro level of analytics.

3 Research questions and methodology

The research questions underlying this work are:

- What are the constituent (structural) elements of an EduOpen course that most frequently recur in a teacher's choices?
- Which are the most common disciplinary fields in EduOpen's educational offer and to what extent do they cross with the demand expressed by the portal's enrolled students?
- In consideration of the data collected, if there is any, what is the useful or relevant information in a dashboard construction process?

In order to answer the questions listed above, the methodology developed consisted in activating a data collection inherent to the research dimensions.

For the purposes of this work, data was collected through the extraction from the extensive EduOpen dataset. As an LMS, this data relates to the

[3] Such as Blackboard and Moodle

students' interactions with the system, their personal data and a selection of data concerning the educational offer and the course structure. Different levels of data are compared with the intent to cross the "deepest" ones, the data concerning individual interactions and personal data, with the "higher ones", educational offer and political decisions.

4 State of the art/context

The EduOpen network can be briefly described through the following statistics:

17 partner Universities + 2 Associated Members
174 active courses
114 archived courses
20 active pathways
11 archived pathways
6 courseware types
55,286 total users
44,821 active course learners
33,818 certificates issued
(Data updated July 2019)

The majority of time spent by users on the portal is spent inside courses (38,854 h/40,358 h: 96.2%), which is consistent with the ultimate purpose of a MOOC portal (Conole, 2013, p. 6). Only recently, with the transition to version 2.0 of the platform has the renewed dashboard and EduOpen blog[4] increased platform spaces outside the courses, which are used by users and the Edunova team to collect and exchange information.

EduOpen member personal profiles

Regarding user type, it is possible to determine their academic status (students vs. non-students) and distinguish between different access types for registration to the platform: those who have federated[5] access form about a quarter of the total (25.2%), mostly identifiable as students enrolled in one of the partner universities of the network; remainder (74.8%) are registered to the platform with a private account. Although we can say with certainty that a quarter of the subjects registered on the portal are university students, we cannot also say with the same degree of certainty that the remainder (74.8%) are all non-university students. In fact, a university student could still use a personal account to register with EduOpen.

4 https://learn.eduopen.org/blog/

5 IDEM-GARR Federation and GEANT-EDUGAIN Federation

Concerning the geographical origin of the platform users, the data are not available for 11,036 users for a variety of – primarily technical – reasons. Excluding these from the total user count, 95.5% of EduOpen members come from Italy (42.414), followed by Brazil 0.4% (170 users), Spain 0.3% (138 users), Germany 0.25% (127 users) and the United Kingdom 0.25% (127 users). The most common language among members is Italian (87.3%) followed by English (8.8%) and Spanish (1%). The remaining 2.9% use other languages.

Table 1
MOST COMMON COUNTRIES OF ORIGIN OF EDUOPEN MEMBERS (JULY 2019)

Member countries of origin	
Italy	42.414
Brazil	170
Spain	138
Germany	127
United Kingdom	123

EduOpen users are predominantly women (59%) and have an average age of 36.5 years.

Table 2
DISTRIBUTION OF EDUOPEN USERS BY AGE GROUP (JULY 2019)

Age group	%
18-24	21.21
25-34	32.09
35-44	20.87
45-54	15.58
55-65	7.05
> 65	3.19

Among the tools and resources[6] most used by the users in EduOpen, EduPlayer[7] stands out with a 56.6%, followed by Quiz (17.3%) and Forum (11%). These data indicate that most of the courses in the EduOpen catalogue, from the didactic point of view, make use of video lectures, discussion groups and some type of test-based evaluation.

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[6] These data were obtained by analysing the time spent by users (timespent) for each activity/resource listed.

[7] A plugin designed for viewing the EduOpen video lectures developed in collaboration between the Edunova centre and LMS of India

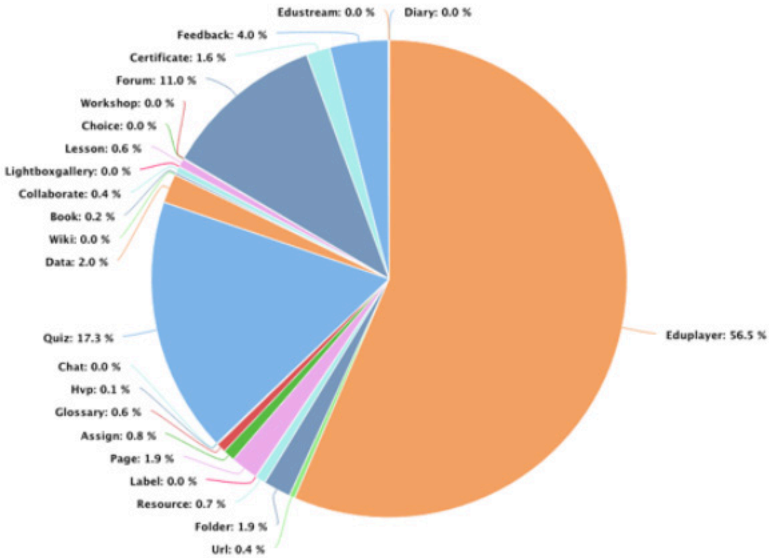

Fig. 1 – Most frequently used activities and resources

EduOpen disciplinary areas

As of July 2019, the EduOpen platform provides 288 courses, 174 of which are active and 114 archived[8]. Some of these courses are also structured into pathways – that is, MOOCs composed of multiple courses centred on a single field of knowledge and linked together to supply more complete and articulated content. EduOpen's educational offer is organised in a catalogue divided into 6 specific categories: Arts and Humanities; Computer and Data Sciences; Health and Pharmacology; Sciences; Social Sciences and Technology, Design and Engineering.

Table 3
COURSES WITH THE HIGHEST NUMBERS OF REGISTERED USERS (JULY 2019)

Course / # Members			
Precorso di Calcolo (Sciences)	5211	Methodologies and practices for Digital Augmented Education (Social Sciences)	1592

[8] A course or a path can be archived for two reasons: the content is no longer current, or a new "tutored" and/or updated edition is planned. It is important to note that the video lessons and activities of the archived training courses remain accessible only to the students enrolled in the archived courses; it is no longer possible for new users to enrol in archived courses and paths or to acquire a participation certificate and the open badge.

Web communication and digital marketing (Social Sciences)	2389	How's my English? (Social Sciences)	1588
Digital natives, a new way of learning (Social Sciences)	2185	Fundamentals of Information Technology (3rd ed.; IT, Data Management and Analysis)	1452
Learning to learn: DSAs in the School of Competence (2nd ed.; Social Sciences)	2061	From data to information (IT, Data Management and Analysis)	1449
Introduction to R (IT, Data Management and Analysis)	1655		

Figure 2 shows the different content categories in which the active and archived EduOpen portal MOOCs have been grouped. The category with the most relevant course offerings is Social Sciences, which alone represents more than half of the total offer (52%), followed by Arts and Humanities (15%), Computer and Data Sciences (12%), Science (11%), Health and Pharmacology (6%) and Technology, Design and Engineering (4%).

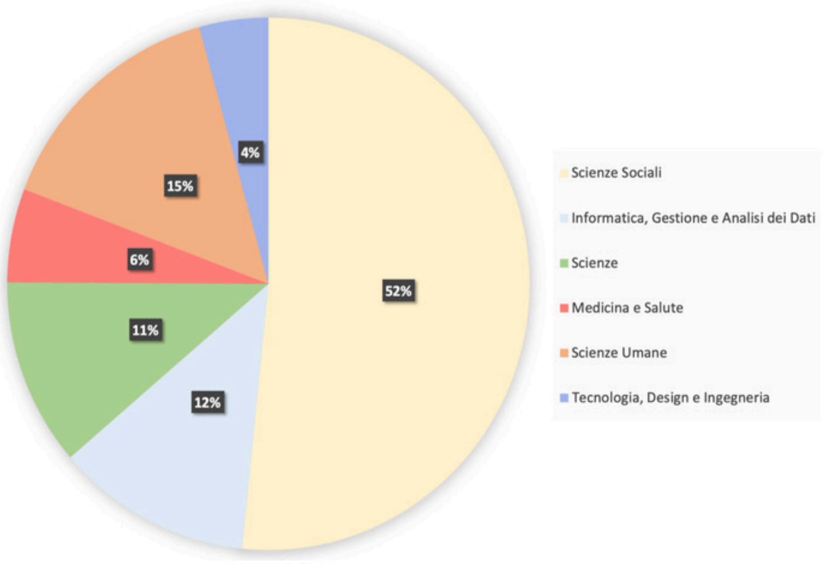

Fig. 2 – Disciplinary categories of EduOpen course catalogue (July 2019)

The situation is quite different if we analyse the disciplinary offer of the pathways, which have a wider and more complex structure (Figure 3). The two categories Science and Technology, Design and Engineering are not present at all in a pathway catalogue, while 58% of the offer belong to the Social Sciences category and 26% to Computer and Data Sciences.

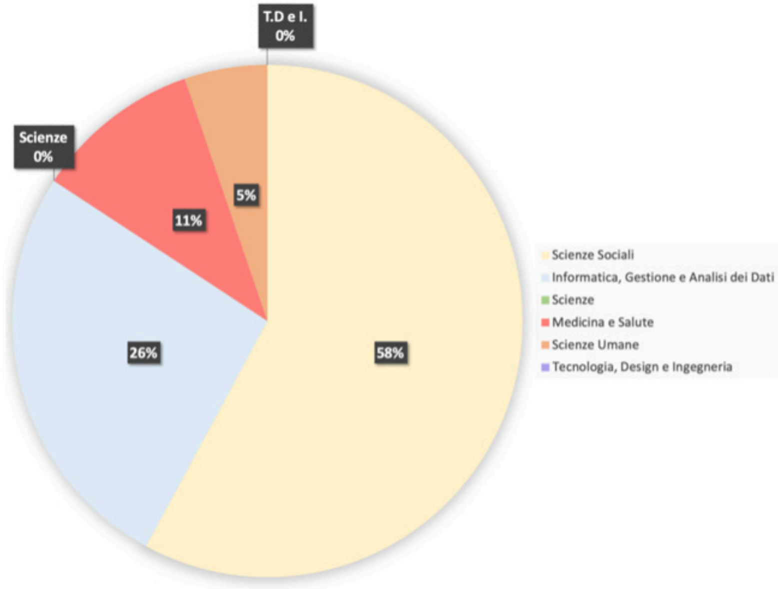

Fig. 3 – Distribution of EduOpen pathways by content category

Figure 4 shows the distribution of the MOOC enrolment by content category. Almost half of the participants in EduOpen MOOCs (49%) chose to enrol in courses belonging to the Social Sciences category, while the remaining enrolment choices were distributed as follows: 17% chose courses in the Computer and Data Sciences category, 14% chose courses in the Science category, 12% chose courses in the Arts and Humanities category, and finally, the Health and Pharmacology category was chosen by 6% of the students and the Technology, Design and Engineering category only by 2%.

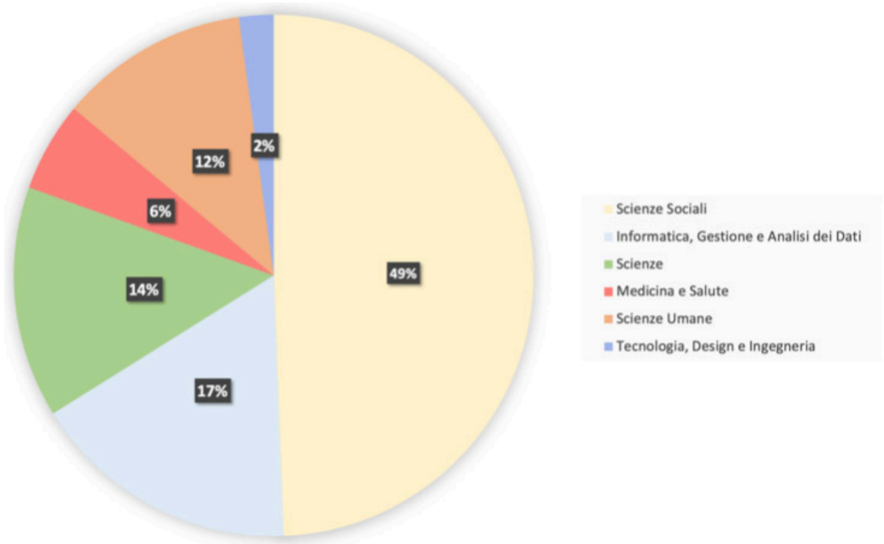

Fig. 4 – Distribution of member enrolment by content category

Table 4
DISTRIBUTION OF MOOCS AND MEMBERS BY CONTENT CATEGORY (JULY 2019)

Content Categories	% of MOOCs	% of members
Social Sciences	52%	49%
Arts and Humanities	15%	12%
Computer and Data Sciences	12%	17%
Science	11%	14%
Health and Pharmacology	6%	6%
Technology, Design and Engineering	4%	2%

Table 4 summarises the data presented in Figures 2 and 4. With all due caution, we may consider the data in the second column of Table 4 to refer to the educational offer and the third column as referring to the demand/request. The need for caution mainly concerns the demand-side, because it is very likely that it has been conditioned by the academic nature of the offered courses. Even if, as we have seen before, university students represent only 25% of the total members of the EduOpen network, we are not sure that the remaining 75% do not belong to a university. In other words, the demand would be very close to the university departments that produced the offered courses. The proximity of the values of columns 2 and 3 seems to confirm this hypothesis. The fact that in two cases (Computer and Data Sciences and Science) the percentage of students enrolled in a given category is higher than the percentage of the same category for the total EduOpen offer could simply tell us that the courses in that category are the most populated by students.

This conclusion could be corroborated by additional data that concerns the number of visits (i.e. the data that can be obtained once a user has logged into a course followed by the subsequent opening of a specific activity or resource) for each course.

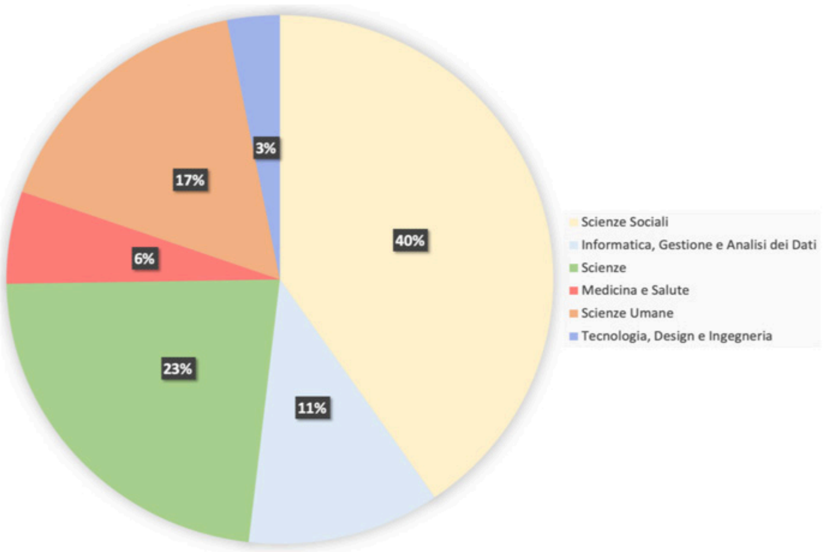

Fig. 5 – Distribution of user course visits divided by category

Courses belonging to the Social Sciences category, which represent 52% of the EduOpen catalogue (Offer), received only 40% of visits, while courses in the two categories Computer and Data Sciences and Science, which together account for 23% of the catalogue, collectively collected 34% of visits.

Structuring of didactic/teaching models

While noting that "empirical evidence on the effectiveness of MOOC's pedagogy is hard to find" (Swan *et al.*, 2014), when referring to this type of online course, we cannot avoid reflecting on the themes of didactic planning and evaluation. The elements of design and evaluation are linked in a self-feeding circle: the characteristics that make online courses for a wide audience more interesting and effective can become key elements of the didactic design of new models, and quality evaluations can confirm the correctness of the theoretical hypotheses resulting in variations in the field of learning design.

As far as the structuring of the EduOpen MOOC offer didactic models is concerned, it is primarily centred on the EduOpen Didactic Design Guidelines (see also Limone *et al.*, 2016), as well as on the validation checklist, which is a series of indicators that helps verify that the standard quality elements required by the EduOpen guidelines have been respected. The definition of the Guidelines for the EduOpen MOOC Educational Design was developed starting from the sharing of best practices, indications derived from scientific research and regulations provided by Italian bodies for the evaluation of academic activities. The definition of a unitary didactic planning style, although respecting the specificities of each university, the didactic preferences of each instructor and the teaching needs of each discipline, was followed by the clarification of course validation criteria developed for online publishing. According to EduOpen network guidelines, course validation is the seventh step in the production flow and is intended to verify the adhesion of the courses to the EduOpen consortium guidelines and to the technical settings of the portal (De Santis *et al.*, 2017).

In an in-depth study to detect key elements of didactic design and the structuring levels of MOOC didactic models on the EduOpen platform, it is useful to first dwell on the very concept of structuring and its meaning in this context. Intended as a didactic model, a scheme allows the planning, realisation and evaluation of the process of teaching and learning in a specific environment to achieve certain goals; the structuring of the scheme, in the context of EduOpen training courses, refers to a specific subset of the didactic design. More precisely, structuring is where the didactic planning takes into consideration aspects such as the definition and organisation of objectives, methods and didactic activities; the choice of content; the choice and preparation of materials and tools; and the didactic and communicative needs. Structuring in the context of EduOpen responds to the question of what is intended to bind the student to a specific educational path designed and implemented during didactic planning. The identification of the structuring level of the didactic model is therefore a part of the design or an organisational choice about the didactic model and marked by two distinct extremes: high structuring and low structuring.

High structuring is defined as linear educational pathways that bind learners along a well-defined learning sequence. For example, a course or pathway may require students to follow a certain sequence of educational activities by applying conditioning criteria governing the availability of a given activity or resource based on the completion of a prior activity or resource that can reflect propaedeutic requirements or simple organisational needs. Alternatively, course designers may provide time periods within which a resource is available or during which it is obligatory to complete an activity, thereby binding students to precise time limits. As the course advances, students may be required to overcome certain activities which, in turn, may require a minimum score (sufficiency), thereby confronting students with obligatory assessment tests. A typical example of highly structured programmes in the EduOpen catalogue are the pathways that provide a constraint on the learning sequence, as learning progression is monitored by passing intermediate ("milestone" courses) and final knowledge checks ("capstone" courses), as well as a constraint focused on passing the assessment tests (intermediate and final).

Low structuring refers to didactic models that do not impose constraints on learning sequence, knowledge assessment or time periods. For instance, in a low-structure course it is not necessary for a student to view all of the video lectures before obtaining the certificate, or there is no knowledge verification through assessment tests with a minimum necessary score (sufficiency). In the EduOpen context, the lowest structure that appears in the catalogue is represented by the courses called courseware – that is, all of those areas designed as aggregators of content (videos, materials, documents, or evaluations) that are not fully structured, and therefore cannot be aggregated into a real training course, but are equally useful for deepening the subject of study, but which do not include evaluation tests or any constraints on the learning sequence or time limits. Low structuring is therefore reflected in the impossibility of achieving a participation certificate and the open badge. What, then, are the criteria that determine the level of structuring in the EduOpen educational model?

Identification of structuring level criteria

The EduOpen platform, based on the Moodle LMS core, in addition to the complex system of conditional display of resources and completion criteria for activities, allows the setting of course start and enrolment times, course publication and the availability of activities. The technical solutions adopted in the design phase represent an indication of the model and, at the same time, a support for certain educational/didactic decisions.

This study sought to identify key elements useful in defining the structuring levels of the educational model of the EduOpen platform based on:

- analysis of the Guidelines, in particular the presence of elements considered essential by the network for the implementation of courses and pathways; and
- analysis of the course and pathway validation checklist concerning didactic, graphic and technical aspects related to the description, structure, activities and resources, evaluation and certification.

The analysis has highlighted a series of useful indicators, which can be divided into three distinct dimensions. The first of which is T, the time dimension, which consists of T1, the presence and definition of a time period for the fruition of the course; T2, the presence and definition of a "tutored"[9] phase; and T3, the presence and definition of deadlines for the completion of activities or evaluation methods. The second dimension is S, space, which consists of S1, the presence and definition of restrictions in the articulation sequence of course topics/weeks; S2, the presence and definition of the materials, activities or resources that it is necessary to use or implement; and S3, the presence and definition of the conditional access criteria between the video lectures. The third and final dimension is V, evaluative, which consists of V1, the presence and definition of tools (quizzes, tests, etc.) or activities (projects, drafts, discussions, online interviews, etc.) to evaluate learning and explain the main evaluation criteria applied; V2, the presence and definition of "intermediate" evaluation tools; and V3, the presence and definition of "final" evaluation tools. The obtained indicators, which can be declined in the temporal (T), spatial (S) and evaluative (V) dimensions, allow analysis of courses with a binomial evaluation (presence/absence) for each single element.

Analysis of structuring levels of educational models

Given the extent of EduOpen's educational offer, this analysis focused on a limited number of courses. Based on analysis of the offer content categories, it seemed useful to investigate the set of courses belonging to the Science category and the possible differences with those in the Social Sciences category.

The analysis randomly selected (simple random selection) 15 active courses from the EduOpen catalogue (not courseware and not archived) belonging to these two categories with no other selection filter[10]. The courses (marked by ID number) were then analysed through the checklist of structuring indicators, assigning a value for correspondence to each single item of the three dimensions (T, S and V).

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[9] The EduOpen guidelines assume a standardised life cycle for the entire educational offer. The course/pathway is initially published in the catalogue in a pre-enrolment mode (a simple overview with no option to enrol or access the course), followed by the enrolment phase (allows course subscription, but not access). On the course opening date, if scheduled, the tutoring phase begins (teachers are present and available to support students in the forums in a predetermined time period), followed by the self-paced phase (no stable instructor presence or interaction and no deadlines) and finally the archived phase (limited access only for enrolled students).

[10] The applicable filters for searching the EduOpen catalogue include: channel (distinction between courses and courseware); category; institution (list of the 20 institutions belonging to the network that have produced the courses); language (English, French and Italian); status (active, ongoing, soon to be published and archived) and objective (curricular courses, knowledge retrieval, input orientation, teacher training, scientific dissemination and lifelong learning).

5 Results

The randomly courses from the Sciences and Social Sciences categories were evaluated by assigning a point for each item of the checklist when the existence of such a feature was noted. Although such a small number of selected elements cannot represent the population of the EduOpen courses and the level of significance for an analysis of 30 elements is often not adequate to effectively explain the resulting data, we observed that the analysis of the data enabled us to highlight a series of elements that emerged despite the small sample.

Table 5
COURSE STRUCTURING LEVELS (SCIENCES AND SOCIAL SCIENCES)

SCIENCE	325	307	308	223	229	208	209	179	182	183	169	168	163	164	165	dimension weight
T 1																
T 2					1	1		1		1	1	1	1	1		10
T 3							1					1				
S 1				1							1	1	1	1		
S 2				1	1	1			1	1	1	1		1		18
S 3				1					1	1		1	1			
V 1	1	1	1	1	1		1	1	1	1	1	1		1	1	
V 2	1	1	1													27
V 3				1	1		1	1	1	1	1	1	1	1	1	
Struct. Level	2	2	2	5	4	2	3	3	4	5	5	7	4	5	2	→3.6

SOCIAL SCIENCE	352	348	289	341	343	306	322	310	311	297	294	288	286	276	284	dimension weight
T 1																
T 2					1					1	1					4
T 3		1														
S 1		1														
S 2	1	1		1	1		1	1	1	1	1	1	1	1		20
S 3					1			1	1	1	1	1	1			
V 1	1	1	1	1	1	1	1	1		1	1	1		1	1	
V 2		1		1					1	1				1	1	27
V 3	1		1		1	1	1	1			1	1				
Struct. Level	3	5	2	3	5	2	3	4	3	5	5	4	2	3	2	→3.4

The two data sets, Science and Social Sciences, exhibited a distribution of the individual courses that tended to lie between the values of 3 and 4 (out of a maximum obtainable of 9). For the Science set, the average structuring level value was 3.6, while for the Social Sciences it was 3.4. This squeezing down of the value of didactic structuring can be explained by two considerations. The first concerns the fact that the T1 indicator (presence and definition of a time period for the completion of the course) was not found to be positive in any of the 30 cases, and the T3 indicator (presence and definition of deadlines for completion of activities or evaluation methods) was found to be positive only three times. The second consideration, a direct consequence of the first, concerns the whole temporal dimension. The time dimension in the Science set yielded a value of 10 out of a total of 55 (18%), while for the Social Sciences it accounted for only 4 points out of a total of 51 (7.8%). Neither data set seemed to differ from the other in terms of data variance (Fig. 6).

It therefore appears that some indicators considered important by the EduOpen Guidelines have not been transformed into procedural choices (time dimension) or real didactic actions (T1, T3).

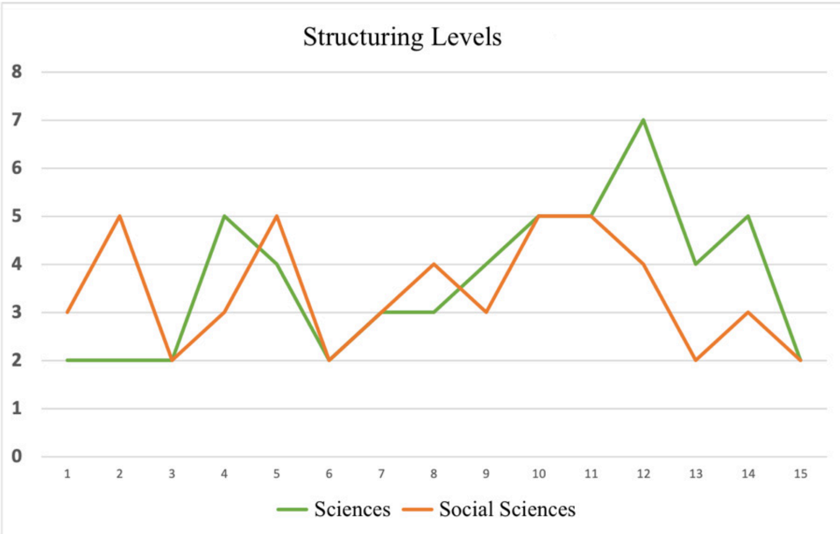

Fig. 6 – Distribution of structuring levels

The two sets of data do not show a particular trend, which suggests that the two categories do not at first sight have different structuring levels. The peak value of 7 and the fact that a lower number of courses belonging to the category of Sciences stands at the minimum value of 2 cannot be considered significant, given the limited sample, as highlighted by the average values for the structuring levels of the two categories.

Concerning the analysis of the structuring levels of the pathways, these, for purely practical reasons (as they just a series of MOOCs, reflect, as a minimum), possessed the same structuring levels as the individual courses of which they are composed. There is also an over-structure intrinsic to the type of modular process corresponding to pathways that binds access to a given course to the completion of the previous one. Access to the final course, called the capstone, is conditioned by the completion of the courses belonging to that same pathway.

Conclusion

While speaking about learning analytics we generally refer to data which benefits learners and faculty and which are focused at the level of courses and department, speaking about the academic analytics we notice a shift in interest towards the level of funders, administrators and marketing at institutional level; funders and administrators at regional level; and governments and education authorities at (inter)national level Long and Siemens (2011).

Analysis of the disciplinary profiles offered in the EduOpen catalogue showed a predominance of courses belonging to Social Sciences category, which covered more than half of the catalogue, to the disadvantage of the categories Health and Pharmacology (6%) and Technology, Design and Engineering (2%). Looking for an answer at the second research question these data indicate the need to rebalance the educational offer through awareness-raising actions and methodological support for the partner universities in the network in the planning and design of new MOOCs in weak categories. It should be noted, however, that the Social Sciences category represents a wide umbrella that includes many different fields (e.g. economics, law, pedagogy and psychology), so that a general review of the EduOpen's catalogue categories could lead to greater representativeness of knowledge and a more precise and recognisable offer. Because the results of the demand-side analysis (enrolment) showed a more consistent flow of users towards courses in the Science and Computer and Data Sciences categories, action should be taken to enlarge the offer of courses related to these categories.

The analysis of the didactic models began with analysis of an already existing and shared MOOC design and validation model through the EduOpen network – that is, the EduOpen didactic design guidelines and the validation checklist. The results of the analysis indicate the importance and role of the evaluative dimension, although the sample considered may be unrepresentative.

The first search question can be answered by the assesment tools, which are useful both to maintain contact between users and the structure of the course and to counter the dropout phenomenon, have proved to be the most followed design indication in EduOpen MOOCs. This is a positive indication and also a reason for satisfaction in the EduOpen network. Analysis of the other dimensions considered shows, however, that it is necessary to act on the resources of the individual universities within the network to encourage greater alignment between didactic practices (the reality of the active MOOCs) and the EduOpen Guidelines (the set of recommendations to ensure the pedagogical quality and effectiveness of the currently active MOOCs and of those that will come in the near future to enrich the EduOpen catalogue).

Finally, concerning the last research question the results of the analysis thus obtained can be helpful in a study and development process of a new dashboard that takes into account the degree of student engagement and the elements could be “really” useful to monitor their progress in the course such as assessment tools.

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THE DESIGN OF A LEARNING ANALYTICS DASHBOARD: EDUOPEN MOOC PLATFORM REDEFINITION PROCEDURES

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Keywords: Time spent, learning analytics, mooc dashboard, dashboard design

The current EduOpen dashboard is not capable of monitoring performances and trends over the medium to long term both for the students as for the instructors; summarising and synthesising the adequate information; allowing implementation of any sort of predictive actions and functions (learning prediction). The article aims to expose the process of innovation and redefinition of a learning analytics dashboard in the EduOpen MOOC platform in order to define a model to design it accurately in terms of productivity for all users (teachers and students above all). From the literature analysis, main MOOC platform comparisons and the insights from the round tables a time spent variable is identified as at the basis of the entire user experience in online training paths. A concrete experimentation, through the design of a learning timeline and a constructive feedback system of an upcoming course in the EduOpen catalogue, is designed and explained relaying on the hypothesis of the existence of a correlation between the "time spent" (time value) and the final performance of the student.

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1 Introduction

This contribution connects three fields: the area of Learning Analytics, the area of Massive Open Online Courses and the area of Dashboards in digital learning environments. The discussion about these three areas is presented through the analysis of EduOpen case study.

Namely, learning analytics is the measurement, collection, analysis and reporting of data about students and the contexts they learn through. The aim of learning analytics is to understand, personalize and optimize learning and the environments in which it occurs. Learning analytics are mainly used in learning contexts mediated by the use of digital environments, since they can produce an amount of data about the traces each student or entire groups of learners leave online, successful activities, difficult experiences, and so on (Rienties & Rivers, 2014, in Dipace *et al.*, 2018).

Learning analytics and Massive Open Online Courses (MOOCs) are two of the most relevant emerging topics in the domain of Educational Technology that can be represented as an umbrella that includes a wide range of engaging online environments and fields. Speaking of Mooc means referring to a well-structured course and not a whole of OERs. As such, a MOOC presents a syllabus with explicit educational objectives and therefore provides a learning assessment system and one or more teachers and tutors responsible for the educational path (Sancassani *et al.*, 2019). Due to their openness, MOOCs attract many participants from all over the world and due to their massiveness, the huge datasets of MOOC platforms need advanced and innovative tools and methodologies for extra examination and analysis.

The extensive amount of data provided by MOOCs platforms concerning students' usage information is a gold mine for Learning Analytics field, but it is important to underline that it is quite difficult extracting meaning from raw data and metrics without being able to visualize it in the form of tables, graphs and other graphical representations (Sclater, 2017). Dashboards are suitable for this purpose as they are systems developed for helping researchers, learners and teachers being extremely useful as a visual overview of their activities and how they relate to those (Duval, 2011).

EduOpen[1] is a project funded and supported by the Ministry of Education, University and Research aimed at creating a digital platform for the provision of online courses defined as MOOC (Massive Open Online Courses) by a network of Italian universities and institutions and a set of selected partners of particular scientific and cultural importance. The EduOpen convention to initiate the project was signed in April 2015, and the kick-off is dated 21st April 2016.

In November 2018, the EduOpen portal was subjected to a major update

[1] learn.eduopen.org

since the launch of the platform where a large number of elements of the LMS have seen a profound update: new general interface, new course formats, adoption of the multilingual system, new parameters and search engine in the catalog, and much more.

The EduOpen innovation process has in a first place introduced a series of questions and definitions regarding the context (state of the art) of the EduOpen platform. In particular, focusing on the the EduOpen dashboard, evident, and in some cases, critical issues emerged from the confrontation with instructors, tutors, course developers (content editors[2]) and instructional/learning managers, highlighting some significant margins for improvement.

The use of dashboards to support sense-making from learning and teaching data, especially speaking about the online education, is not a new concept. The purpose of a dashboard, on the teaching side, is to offer tools for instructors at monitoring the course and student progress in real time, and for educational designers and content editors allowing the visual exploration of data to help understand better the way in which learners engage with particular elements of a course and provide some valuable information able to inform future course designs.

It is important to point out that EduOpen, as a MOOCs delivering portal, seeks in a dashboard a core tool able of guiding users through a whole online experience during the learning pathways, which should effectively synthesize the key data, information and notifications for both the students (learners), who often follow or are enrolled in high number of courses and courses (pathway) whose representation and synthesis becomes fundamental, and, at the same time, the instructors who frequently encounter a high number of enrolled learners, therefore needing synthetic and immediate synthesis and reporting tools.

One of the key aspects that led the process of innovation and redesign of the platform refers to the feedbacks provided by the users, both teachers and students, during the two years of moocs provisions under the 1.0 version of the platform. The so provided feedbacks ware generally pointing out the emerging needs for a move to a newer version of the platform able of taking into account the aspects and demands gradually emerged.

[2] The EduOpen platform has different "roles" that can be assigned to the users depending on which are their "offline/real world" profiles and objectives. The most common role, and the lowest in terms of function permissions, is a "student" which is often referred as "learner". The role assigned to teachers is known as "instructor" and as much as the "tutor" role this guarantees editing permissions on the course contents and some of the main course settings. "Content editors", which is the role assigned to the course developers have even some more editing and setting permissions compared with "instructors". Finally, the "instructional managers" have editing permissions in addition to a course setting and are able to control and edit some aspects related to the platform (outside the course) functionality such as: data extraction, their own institution's settings etc.

2 Background

Learner dashboard:

The current EduOpen architecture does not expose in real time (neither for the students or the instructors) any type of data regarding the learners trends or performance; if we exclude a graphical percentage representation of a course completion displayed in the dashboard list view (Fig. 1) no other indicators are available to summarise the progress and progress of the student within a course.

Fig.1 - EduOpen Dashboard Course representation (list view)

One of the main features, which is present since the launch day, refers to a possibility to distinguishes courses and pathways in three main categories: currently in progress; to be opened soon and completed courses.

Fig.2 - The main EduOpen course dashboard classification

Instructor-side dashboard:

Looking at the instructor dashboard side the learners trends and progress information are summarized through a set of "default" reporting tools provided from the Moodle LMS, which, notoriously, are considered not easily readable.

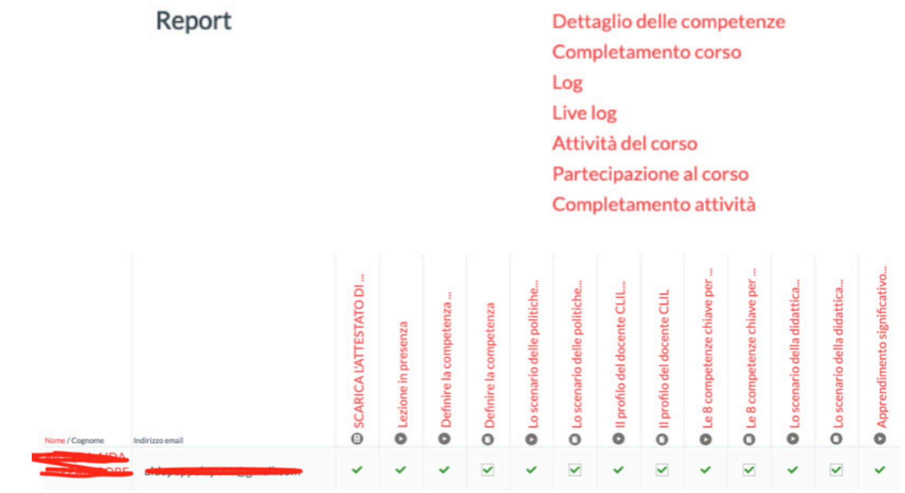

Fig. 3 - EduOpen course progress for a single users report

The need for a general "rethinking" and "redesign" of the platform user experience and the set of available tools, particularly the dashboard, gradually emerged through the first two years after the kick-off. Both the content editors as instructors reached out to the EduOpen staff quite often during that time interval, as the first version of the platform presented more than a few critical issues from a functional point of view. For example, the inability for the instructors to filter the enrolled students list by some basic parameters such as name, mail or id. On the other side, also the learning managers and course editors encountered problems both during the course design phase as during the monitoring one. These "spontaneous" feedbacks structured over time in suggestions and proposals delineating some more concrete objectives of the EduOpen innovation process.

3 Methodology

The innovation process has been structured in three main phases:

a. *Confrontation between instructors and learning managers*:
 The EduOpen team, aware of the critical issues that emerged in the early years of the project, assumed that the innovation process should have been extended to a wider audience right from the beginning of earliest development stages, including not only the developers and the staff members, but, most importantly, all the different types of the platform users such as *instructors*, *students* and *content creators*. The

underlying objective of the extension of the work group at this phase was mainly aimed at gathering as much information as possible on the critical aspects of the EduOpen user experience from multiple points of view based on which role the users ware fulfilling in the platform. A teacher (*instructor*) of a MOOC expresses different needs and goals compared to a *learner* with respect to some basic summary information, functions and filters on what should be more or less clearly visible in the dashboard.

Two different data collection methods have been hypothesised, in order to gather the needed information:

- a profiled questionnaire according to the user "role" in the platform containing questions regarding the most critical issues, proposals or desired features and levels of satisfaction of the adopted tools;
- the establishment of "round tables" with the EduOpen staff and developers.

The two approaches reveal significant differences in terms of information structuring and implementation times.

The final choice fell on the second option following the need to accelerate the innovation process and its implementation given the tight deadlines at that phase, moreover not only it was possible to save time that would have been required for an accurate design and implementation of the questionnaires, but it was also possible to gain time where the "meetings" with the professors and users were in most cases carried out directly "online" in virtual classrooms with evident organisational time and procedure savings. The "round tables" were held, and also recorded, with the Blackboard Collaborate video-conferencing platform focusing on the development of the new version of the platform with a monthly frequency over the 4 months developing period. The adopted procedure saw the developers and staff propose new solutions followed by feedbacks and considerations by the instructors, tutors and learners. The results of the periodic meetings were than structured in concrete *suggestions and indications list* aimed at improving the so proposed and developed tools, which consequently gave rise to the development of guidelines and indicators capable of representing and measuring the strengths and weaknesses according to the needs of different actors. The variety of ideas and proposals were classified into four main categories/ indicators:

- Key Performance Indicators (KPI);
- Data hierarchy;
- Dashboard Design;
- Filters;

The so constructed indicators were then applied in a second development phase focused on a direct comparison with the major/main MOOC platforms.

b. *Literature analysis*:

The monitoring of teaching and learning activities is a fundamental element of any training initiative in order to ensure the control and management of interventions, particularly in online learning environments. In fact, in these online platforms, a timely visualization of the students' activity status allows teachers to provide useful warnings and suggestions to facilitate the learning process.

Monitoring the student's behavior in online learning environments does not only mean collecting data, but it is also essential to take action to maximize the effectiveness of the learning pathway through monitoring. Studies and research on Learning Analytics go exactly in this direction as they focus on how to collect, analyze and present the data produced online to provide rapid feedback and allow the formulation of appropriate, personalized and timely interventions.

Learning Analytics, as claimed by Siemens & Baker (2012), provides new data reading techniques by bringing the focus of educational research closer to the science of data driven decision-making and by integrating the technical and socio-pedagogical dimensions of learning analytics. In this sense, learning analytics allows the analysis of educational processes at the level of assessment and at the level of quality of interactions. Thus, pedagogical research is not limited to the analysis of learning outcomes, but uses data that allow the ongoing monitoring of educational processes by using "current and contextual" data (de Waal, 2017).

Learning analytics focus is on the application of predictive models in education systems through the description of data and results using specific techniques, such as: statistics, SNA visualisation, sentiment analysis, influence analytics, discourse analysis, concept analysis, and sense-making models.

Predictive analytics derives from the use of such data mining practices aimed at using patterns for forecasting purposes. It is a consolidated process that allows to synthesize a large amount of data in powerful decision making capabilities (Baker, 2007).

In academic contexts, learning analytics are mainly used with the intent of encouraging the achievement of an increasing percentage of successes in terms of student learning. Through specific methods of presentation of the educational process, it is possible to stimulate the knowledge, evaluation and self-evaluation of the student. The dashboards of an online learning environment aim exactly at the presentation and representation of learning data for both teachers and students in order to promote effective and targeted pathways. Therefore, in order to set up tools for the timely visualisation of the students' learning status, it is necessary to refer to learning analytics and dashboards.

The process of designing applications using Learning Analytics involves a number of different phases.

The first phase involves the essential selection of data to be used as predictors and indicators of students' progress in terms of educational success. This selection has an effect on the accuracy of the forecasts and also on the validity of the entire analysis.

Indicators can be distinguished in (Brown, 2012):

- *Predisposition* indicators (they refer to the student's background: age, gender, previous assessments, etc.);
- *Activity* and *Performance* indicators (they refer to the performed activities and the traces of those);
- Student's artifacts (refer to works/artifacts produced by the student)

Also in the next phase there is a process of selection, but in this case the most appropriate techniques of analysis are chosen in order to identify the significant patterns hidden within the data sets; in this case, it is possible to apply different techniques that refer to the field of statistics, visualisation, data mining and social network analysis (Chatti *et al.*, 2012).

Visualization techniques play a particularly important role in making information accessible to students and teachers (Brown, 2012). These techniques can produce different types of fully automated feedbacks, when they do not require additional interventions, or partially automated when the final choice is delegated to the teacher.

c. *MOOC platform analysis*:

One of the main objectives at realising the EduOpen dashboard redesign guidelines was to allow a subsequent comparison, as much as quantitative possible, regarding the lack or possession of data reporting functions and data summary elements in a comparison with some of the "best-known" MOOC platforms, in particular: Coursera, EdX and FutureLearn.

The dashboards functions and tools analysis of the "leading" platforms was performed according to scheme of indicator categories emerged from the "round tables" (phase a) and in line with the findings of the literature analysis (phase b). The main elements that have been considered are four:

1. What are the *Key Performance Indicators* (KPIs)? That is, what is the synthesis data able to express the achievement of the objectives according to the "role" of the user? A key performance indicator (KPI) is a quantifiable measure that is used to determine to what extent the set objectives are achieved. For example, for a teacher it could be the number of users that completes the course, or the achievement of a certain average of grades, or the number of users that exceed at least 70% of the course etc. For a student, for example, a key indicator could represent the overcoming of a certain threshold of votes, or the temporal progress in the course etc.
2. What is the correct *data hierarchy*? Intended both as structure(levels) of displayed data as access permissions (privileges): for example, speaking about permissions a *learning manager* may need to access to some data set able to explain the overall institution system performance, but a teacher/instructor does not necessarily have to get too much data (information overflow), while a student should be able to see only his/her personal data. Secondary, speaking about some levels of analysis, at analysing for example the progress of a specific student within a course, it would be more significant to highlight the totality of the activities and actions of his/her course progression, or is it more meaningful to synthesise as first the "mandatory" steps?
3. *Dashboard design*: what is the most appropriate way for an effective representation and consultation of the dashboard? Is it able to effectively respond to the increasingly emerging needs of "mobile" consultation and navigation? Is it able to remain synthetic and data effective even if the data expressed are numerous?
4. *Filters*: are they present, and if so are they clear, visible and effective? If present, what type? For example, an instructor frequently expresses the need to search for a specific student by his/her ID number, or in quizzes/assessments to highlight only those students who have not achieved sufficient marks or those who have actually been present on the platform for a certain period of time, etc.

The dashboard analysis of the three main platforms focused as a first at the comparison with the critical issues present in the EduOpen dashboard on the student side, as it was not always possible to get a full "instructor" access to a synthesis and reporting tools on the platforms mentioned above. Most of the instructor side insights came from external studies and analysis: "Coursera Instructor data dashboard"[3]; "Toward the development of a dynamic dashboard for FutureLearn MOOCs" (Chitsaz *et al.*, 2016); "Building and Running an edX Course" guide (Edx, 2017).

The EduOpen dashboard was therefore compared according to the criteria identified with respect to the three reference platforms. The KPI column indicates what were considered to be the most significant summary indicators; the hierarchy column indicates the dataset setting from a hierarchical consultation point of view; the design column was divided into two additional factors that could explain and summarise two often conflicting dimensions:

- *readability*, how easy is to read and capture the needed information;
- *information*, what is the quantity of information provided.

Regarding the student-side dashboard:

Table 1
INSTRUCTOR AND STUDENT DASHBOARD ANALYSIS

Student/Learner Dashboard			
	KPI	**Hierarchy**	**Design**
Coursera	My courses (active, inactive, completed) Updates Course progress Messages	Overview Week Activities	Readability 10/10 Information 9/10
EdX	Courses/Programs (completed, in progress, remaining) Discussion Progress	Course Chapters Activities	Readability 6/10 Information 9/10
FutureLearn	Courses Wishlist Recommendations Achievements	Course Weeks Steps	Readability 9/10 Information 6/10
EduOpen	My courses (active, completed, archived)	NA	Readability 3/10 Information 5/10

[3] Natalie Kim, Instructor data dashboard, http://ny-kim.com/work/dashboard/dashboard.html

As for the instructor-side dashboard:

Instructor Dashboard				
	KPI	**Hierarchy**	**Design**	**Filters**
Coursera	Enrollments Completions Active Learners Student Engagement Payments	Course Overview Ratings Content	Readability 10/10 Information 8/10	10+ e.g.: learner's payments, demographic status, course comparison
EdX	Enrollments/Completions Grades Assignments	Course Learners Activities	Readability 6/10 Information 9/10	10+ e.g.: learner grades, retention
FutureLearn	Enrolments Step Activity Comments Sentiment Peer Review Assignment/ Reviews	NA	Readability NA Information NA	NA
EduOpen	NA	NA	Readability 3/10 Information 5/10	NA

Furthermore, during the analysis process it was found that the presence of a well-designed and accurately planned data and dashboard construction allows future development actions of considerable interest. Coursera, for example (Fig. 4), implements forms of "smart information nudging" when, given a precise monitoring of the viewing lessons time and frequency, "suggests" students to review a specific lesson indicating that 70% of the other learners have viewed it more than one time.

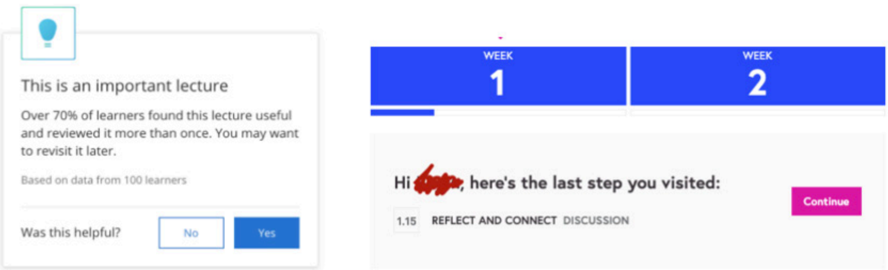

Fig. 4 - Coursera learning path "suggestions" and FutureLearn "resume feature"

In the FutureLearn platform the last visited lecture is shown giving the straight possibility to continue the learning path directly after the course access (Fig. 4).

4 Results

The analysis of the reference platforms and the consequent comparison with the EduOpen portal revealed a general lack of a series of elements which are considered "key" for tools such as dashboards. On the student side dashboard the only key factor that has emerged is the main course dashboard classification (Fig. 2). No clear hierarchy classification was found and the readability and information in the dashboard design scored respectively 3/10 and 5/10. On the other hand instructor side, has proven to be even worse with no clear KPIs, hierarchy and filters and with the same score in a design category.

Given the insights from the three main platform analysis one factor emerges above all: the dashboard tools are dynamic and real-time applications. Coursera provides a dashboard to educators and developers with a live view of their data (Chitsaz *et al.*, 2016). EdX, have analytical plug-in modules to achieve real-time monitoring (Cobos *et al.*, 2016; Fredericks *et al.*, 2016). New time-tracking approaches and technologies are available (Intelliboard, time tracking plugins, xAPI) which allow to collect, process and display this data in a much more effective way than in the past.

4.1 Time spent value

Time-spent value[4] is at the basis of the entire user experience in online training paths as it is a data that transversally affects the entire educational offer and all types of users. The information obtained from the measurement of the time-spent value can be useful both in the monitoring of users, students or teachers, as well as in the analysis of the course activities. Measuring a time-spent value allow the education managers to enhance the students' learning process and to apply an effective and adaptive learning model.

The results and insights of the innovation analysis process came together in a concrete testing proposal. From both literature analysis and the major platforms ones, the variable time-spent, intended as the point measurement of time actively spent on the platform, appears to be a transversal and common element, as well as being particularly useful in the practical process of redefining a dashboard tools.

The role of time in online education is the core of many researches. The Framework for Time Competencies in elearning (Fig. 5) shows both the micro and macro levels to be considered in the online learning and teaching processes, and the variables subordinate to time spent in the considered levels: learner, teaching, institution and technology (Romero & Barberà, 2015). The authors highlight the relationship between the importance of the time factor in online

[4] Indicates the time a user "spent" on a given activity, course or platform section.

education and the importance of developing skills related to its management in teaching and learning processes. In fact, specifically, they consider time competencies not as "individual and preexisting abilities that learners and teachers already have, but to think that the design and the implementation of online education can offer opportunities to increase and refine these competencies through the lifelong learning processes" (Romero & Barberà, 2015, p. 139).

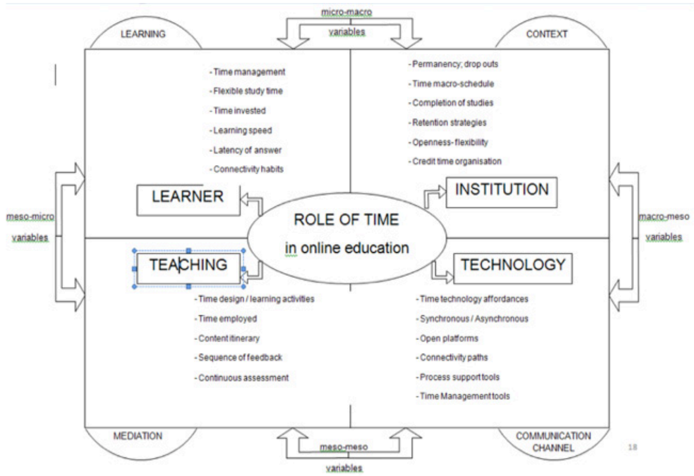

Fig. 5 - Framework for Time Competencies in e-learning, from Romero, M., & Barberà, E. 2015, p. 140.

The current EduOpen dashboard does not expose the time-spent value neither for the instructors or students at any stage or in any format. One of the main reasons why this variable could be effectively implemented is the fact that the core architecture of the system (Moodle LMS) allows us to collect and aggregate this data within a series of minor and additional developments. Secondary, a time-spent value is a traversal element of the learning paths which effects and it's available in all the courses and pathways. Platforms such as Coursera, as experiments available in the literature (Purdue University, Arnold, 2010; Arnold & Pistilli 2012) focus on the time-spent variable to evaluate and therefore also stimulate the student's effort during the learning pathways.

The well-known cited example is Course Signals[5] used at Purdue University

[5] The software product developed at the University, Course Signals is designed to increase student success by using analytics to alert faculties, students, and staff to potential problems. In particular, at the student level, this LA system gives them feedback on the progress of their learning process. At the same time, students do not run the risk of receiving a negative evaluation when it is too late, and accordingly they have enough time to ask for help. In this way, dispersion can be reduced and corrective actions can be promoted through scaffolding strategies and formative feedback that leads students to improve

in Indiana to prevent drop-out (Arnold & Pistilli, 2012). The system adopted consists of a traffic-light signal used for all students to indicate their possible risk of failure. This tool represents a device that acts as an ongoing assessment tool for students, but it also assesses the quality of the processes for the institution (Author et al., 2019 in press).

The time-spent variable allows to measure accurately the "progress" of the student within a specific learning path and therefore to relate this value to the educational objectives and goals. For example, by measuring the time spent by the students in a particular activity, if it turns out to be abandoned and viewed considerably less than the design approach, an indication could be that the resource/lecture is not particularly meaningful, weak or not inherent within the course thematics.

Given this consideration the concrete experimentation will be carried out within the course of Scientific Calculus in Python - Optimisation and differential equations for modelling (University of Padova, opening 16 September 2019).

4.2 Design of experimentation

Design of the EduOpen Learning Timeline:

Given the premises a precise indication of the temporal value of each single resource/activity of an EduOpen course is required. In particular, each section/week will be expressed in a given time "n", and the sum of all sections/weeks will indicate the "course length" value.

More in detail, this sum will represent an "EduOpen Learning Timeline" which reflects generically a "course length" value (student side), through segmentation of course training path into 4 basic elements:

1. time video resources (***t***v)
2. time reading resources (***t***r)
3. time training resources (***t***e)
4. time social interaction resources (***t***s)

These 4 timings constitute together a learning timeline, but will be stored in a separate tables which will be then updated following the student time progression during the course. Each mandatory activity/resource will have time value to be completed. Completing an activity subtracts that specific activity

their learning and their final grade. At the institutional level, the goal is to improve overall retention and the academic success rate and, consequently, the number of students who graduate (Sclater, 2017). This device represents a traffic-light signal, which depending on the light (whether red, yellow or green), indicates the level of risk run by each student is at a certain point in his or her course of study. The predictive algorithm takes into account four components (Sclater, 2017, p.38): Performance (based on the grades obtained during the course up to a certain point); Effort (the level of interaction with the LMS environment compared to other students); Academic background (including the students' average grades from high school and the standardized grades); Characteristics of the student (i.e. age).

time from the total amount of time. That means that a timeline table is updated after every user interaction and updating the data after the activity completion.

In a nutshell:

A total course time left will be divided into 4 time categories.

*course **time left**/course length* = ***t***v + ***t***r + ***t***e + ***t***s

At the ***t***0 the *time left* is ***max*** (***t***v + ***t***r + ***t***e + ***t***s).

At the ***t***1 the *time left* is (***t***v + ***t***r + ***t***e + ***t***s) - ***t***1*

and so on…

*1. Video lectures time (**t**v)*:

The time of video resources (***t***v) is automatically calculated from the "video length" duration which is already stored for the video seek feature, and displayed in the course page as in figure:

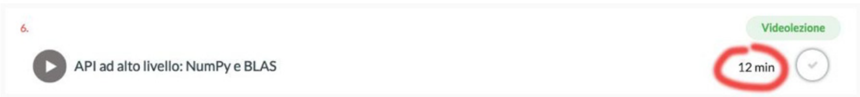

Fig. 6 - Video lecture time indication

*2. Time reading resources (**t**r)*:

"Reading resources" are all mandatory materials that must be read in order to complete the course. Not all files are mandatory, and not all files are "reading type files".

To distinguish between different type of files in the file resource settings (modedit.php?add=resource) a selector will be added for the instructors and content editors to select which type of file/material is being uploaded:

- *Other* (default selection, no time tracking)
- *Reading*
- *Training*

The time duration for the "reading resources" will have to be manually added by the course managers. In order to achieve so, a new field will be added ("type=time field") in the settings.

*3. Time training resources (**t**e)*:

Will be developed same as the above reading time (***t***r).

*4. Social interaction time (**t**s):*

This value refers to a user time spent during social or interactive resources. At the moment this time tracking is meant only for the forum activity and virtual classroom (Blackboard collaborate meetings).

Section/Card/Week time left:

The section/week time will be separately stored and then specified as a time left value for each card/section/week.

card/section 1 = *card 1 time left*

card/section 2 = *card 2 time left*

card/section n = *card n time left*

This value will be displayed on every single card and will be updated according with the user progress.

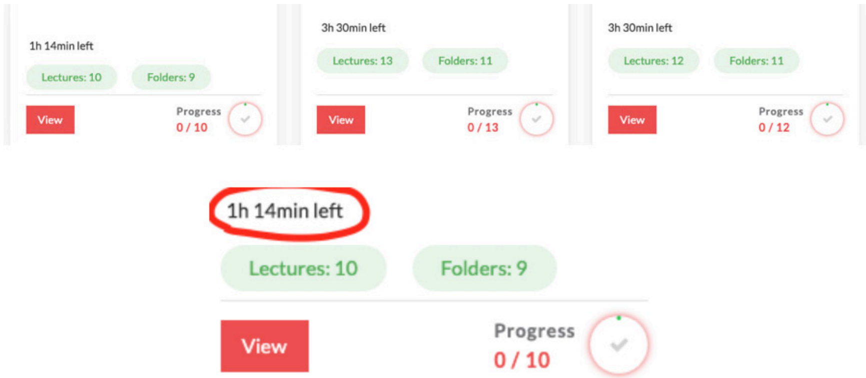

Fig. 7 - Week/section time indication

The time/progress tracking so obtained allow us to "place" a precise position of the student in what is considered a full or total timeline of the course/pathway, which will be displayed in a visual timeline for the student (Fig. 8).

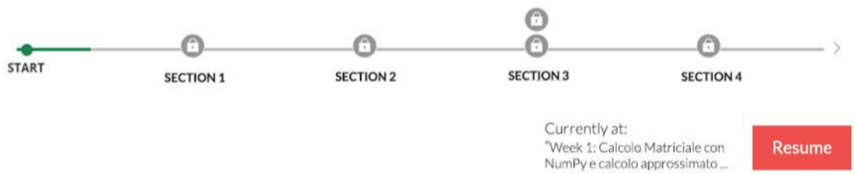

Fig. 8 - Visual timeline for the student

Finally, a "Resume" feature will be added in the section 0: The resume function links to a next single activity after the "last" completed (Fig. 8).

5 Study limitations and future implications

Future developments will be directed towards assessing the impact of using tools that allow monitoring of time-spent value in online learning. In particular, the following hypothesis will be investigated:

H¹: Is there any correlation between the time-spent value and the student's final grade/performance?

For a more exhaustive study, we propose to start from the quantitative data obtained from the analysis of time spent value, combining it with a series of additional data as those obtained through the implementation of a feedback tool for the student. Each video lecture, at the end of the vision, will provide the opportunity to express an evaluation (from 1 to 5) in three distinct categories:

1. *Video* quality (technical)
2. *Communicative* quality
3. *Teaching* quality

Thus collected data will be cross-referenced with quantitative data obtained from learning analytics and will be subject to further analysis and study.

Conclusions

Both literature and analyses conducted highlight the importance of implementing activity monitoring processes that take place in online learning environments. By default, e-learning platforms are equipped with systems that are often not adequate to meet the needs of the various stakeholders involved in the training processes. The major challenge is frequently linked to the numerous difficulties encountered in trying to interpret these data. For such reasons, it is essential that e-learning platforms are equipped with dashboards that are properly designed and able to provide useful data for the definition of effective, user-centered training paths.

By definition, a dashboard is an interactive tool for collecting, monitoring and displaying data and information which, in the case of e-learning platforms, is a valuable contribution to providing both teachers and students with a complete picture of learning activities.

The literature and context analysis that has been developed and described in this paper has shown that time-spent value can be useful for teachers to identify students at risk and for students to compare their own efforts with those of their peers (Klerkx et al., 2017).

The correlation between the time-spent variable and the performance of the students can therefore be an important starting point in the design of the EduOpen dashboard.

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BOOSTING UP DATA COLLECTION AND ANALYSIS TO LEARNING ANALYTICS IN OPEN ONLINE CONTEXTS: AN ASSESSMENT METHODOLOGY

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Keywords: Data analysis, learning analytics, learning management system, open online courses, start@unito

Nowadays learning analytics has been growing as a science, and at the University of Turin we are interested in its potential to enhance both the teaching and the learning experience. In the last few years we have gathered data from two projects: Orient@mente, and start@unito, with the latter offering open online university courses in various disciplines. In addition, we have also studied and analysed the results of the teacher training experience carried out for the start@unito project, as well as those obtained from a survey involving secondary school teachers and the possible employment of the start@unito OERs in their everyday teaching. Our sources of data are students' activity online, the results of formative automatic assessment, and the questionnaires given to the learners; the types of questions range from Likert scale evaluations to multiple choice, yes/no and a few open questions. In this paper we discuss the different tasks we completed in our projects and evaluate their adherence with the learning analytics techniques

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in terms of structure, availability, statistics, outcomes, interventions and, in general, their usefulness and effectiveness. In this way, the insights gained from both usage tracking and questionnaires can be used whenever possible to make interventions to improve the teaching and the learning experience; at the same time, when such interventions were not possible, we reflected on why this happened and how we can change and improve our approach.

1 Introduction

Learning Analytics (LA) techniques, according to the definition provided by SoLAR (Society for Learning Analytical Research) in 2011, include the measurement, the analysis and the communication of data relating to students and their learning contexts, in order to understand and optimize learning and the context in which this happens. The use of these techniques concerns different disciplines, such as education, psychology, pedagogy, statistics and computational sciences. Despite knowing that there is no universal agreement on an LA definition, the one provided by SoLAR best describes our approach and is in line with the learning-centred approach in which we believe. Moreover, George Siemens (2012) underlines how LA techniques concern a series of training activities, as they refer to the whole student learning experience, such as university pre-enrolment, learning design, teaching/learning processes, assessment and evaluation. At the University of Turin, our Data Collection and Analysis (DCA) tasks are devoted to profile users in order to accommodate diverse population, take data-driven decisions, build better pedagogies and structures, build adaptive formative assessment, improve academic performance, reduce the dropout rate and discover new patterns. Our main projects are start@unito (Bruschi *et al.*, 2018) and Orient@mente (Barana *et al.*, 2017). The first one aims to promote and facilitate the transition from secondary school to the university system through the creation and dissemination of a series of open online courses, related to all the main disciplines; the second one has been designed to help students make a responsible choice about academic studies by offering interactive paths for university guidance, preparation for admission tests, OOCs (Open Online Courses) for revision of basic knowledge, and e-tutoring. Both projects offer open online courses delivered on a Moodle platform integrated with an Automatic Assessment System (AAS), a Web Conference System and an Advanced Computing Environment (ACE). Moreover, we dealt with two non-traditional type of learners, namely university professors (Marchisio *et al.*, 2019b) and high school teachers (Marchisio *et al.*, 2019a). These non-standard learner groups present considerably smaller numbers than the traditional student population. The present paper will be devoted to the analysis provided in the context of the start@unito project, considering the differences between different categories of learners. More specifically, our data come from three main sources. First, students' activity online: subscriptions, clicks, testing and assessment, time spent online. Second, questionnaires given to high school and university students, high school and university teachers, grant holders and generic users. Third, information and data gathered during individual and group meetings. It is also important to mention that the courses offered on our online platform are tutorless, therefore besides a central coordination service there is no expert staff who manages individual courses. The data obtained are analysed by technical staff supporting the scientific committee of the project.

Learners are students of a given subject, and generally we think about university students. In our experience managing the start@unito project, we encountered many different types of users who, at one time or another, acted as learners attending one of the courses offered on our platform: students, university professors, grant holders, high school teachers, generic users.

Even though it may seem that these characters have different features, they have one thing in common: they are learners, and their difference is precisely what drove us to focus on understanding the learners' contexts.

Since the field of LA is relatively new to our research team, with this paper we intend to understand and evaluate the quality and relevance of our DCA. After an outline of the theoretical framework, the research question and methodology will be presented, along with the results and discussion.

2 Theoretical framework

According to the NMC Horizon Report 2016, one of the trends in higher education nowadays is the measurement of learning. Especially when dealing with online learning, a huge amount of data is available which, if used wisely, can provide vital information on learners' habits and performance. Given that, the paradigm of higher education has shifted in favour of a more student-centred approach, the insights gathered from the data can be used to improve learning (Doug, 2013) and generate actionable intelligence (Campbell *et al.*, 2007). After all, the focus of learning analytics should always be, indeed, learning (Gasevic & Siemes, 2015). In the present paper we assume that LA can be carried out on data generated by learners in a broader sense, since we are not only considering university students but anyone who is in a learning position, including university professors participating in a training course. In fact, the aim of our research group is to analyse, improve and perfect the online learning experience not only for the average student, but for a wider range of professional figures. As far as the students are concerned, the data gathered from LMSs such as Moodle include "institutional information such as student demographics and course selections, pace of program completion, learning platform engagement statistics, and concept mastery" (Horizon Report 2016). According to the literature, data gathering techniques raise the question of which data are useful for advancing learning outcomes, as well as issues of privacy and ethics. Moreover, learning analytics and adaptive analytics manage to bridge the gap between traditional classroom learning and the more solitary online learning by offering students feedback and personalization which, according to recent studies and reports, is something students crave constantly during the process of learning (Hanover Research, 2016). Although some models for the use of LA have been proposed (predictive modelling, social network analysis and SNAPP method, usage tracking, content and semantic analysis, recommendation engines), there is no standardized methodology, therefore LAs have been implemented using various approaches tailored for different objectives. (Papamitsiou & Economides, 2014) studied the impacts of LA and educational data mining on adaptive learning. Among the benefits of LA we can find "targeted course offerings, curriculum development, student learning outcomes, personalized learning, […] improvements in instructor performance, post-educational employment opportunities, and enhancement of educational research" (Hanover Research, 2016), which are coherent with the objectives of the Orient@mente and start@unito projects. Among the models for the use of LA, two in particular are worth mentioning: the first one is Campbell and Oblinger's five-step process (Campbell & Oblinger, 2007): Capturing, Reporting, Predicting, Acting, Refining. The second one is Clow's learning analytics cycle (Clow, 2012). The cycle is composed of four phases. First, learners: the category of learners is defined and analysed. Second, data: the generation and capture of the data about or by the learners. Third, metrics: processing of data to obtain insights into the learning process. Fourth, interventions: the data gathered are used to make improvements.

3 Research questions

We focused our attention on how we construct and adopt analytics and general DCAs related to the learning process in our projects. We asked ourselves the following questions:

- Which of the DCA we adopted are coherent with good practices provided in the literature about LA? Which of these DCA can be considered LA?
- Can we devise an evaluation framework to assess the quality of DCA and their adherence to the definition and models of LA?

4 Methodology

Considering the theoretical framework presented, the analysis we carried out followed the following steps:

- Recognition: understanding and recognizing which of the measures we adopted can be close to the definition of LA;
- Search: scanning the literature in order to understand and compare the quality of the DCA we adopted in comparison to other experiences and standards.
- Evaluation: evaluating each DCA in terms of outcomes and interventions. On a scale 0-5, the outcomes criterion refers to how relevant the data gathered are, and the interventions one to the actions taken to improve the learning experience.

After a short description of the DCA we adopted, we evaluated its quality according to the following criteria:

- Structure: a short description of the main features of the DCA;
- Population: the number and the typology of learners involved;
- Availability: are the data easy to gather and interpret? Are the data in real time?
- Statistic methods: did we apply the right statistics to the data?
- Outcomes: what did the DCA accomplish?
- Interventions: what actions were taken to improve learning experience? Does the insight derived from DCA impacted positively on the learn path of majority of the learners?

5 Evaluation phase

Our DCA are based on data mining, tracking and collection techniques, which seem to be the most popular form of LA methods (Khalil & Ebner, 2016).

5.1 DCA 1

The first type of learners we analysed with DCA1 are high school and university students. They had the opportunity to attend some of the courses in the subjects they study fully online. This is nowadays quite a general learning context; most universities provide online and distance learning options. In this case, the courses are open and, until they subscribe to university, without tutoring. After attending the online course and passing a final test, students must submit a questionnaire about their learning experience. Thus, the sample of students is provided by those who attended and completed the whole course, exercises and self-evaluation tests.

Structure: the questionnaire asks the students to evaluate the main features of the course. Our aim is for the users to reflect on their online experience and evaluate the course effectiveness and the usability of the automatic assessment system. Questions regard the usefulness, the clarity of the structure, the preferred types of resources, the time spent engaging with the course, the devices used to access it and the general difficulties encountered. Since the questionnaire contains a section for comments, we considered for our DCA comments by students provided by email or via helpdesk, too.

Population: the population so far is made up by almost 900 students who completed one of the online courses of the start@unito project.

Availability: the data are easy to gather due to the potentialities of the Moodle Learning Management System (LMS). However, some issues arose since the data are stored into a single database. It is possible to filter them course by course, but this process is more time-consuming. Setting up different databases for each course would have been possible, but in this case the merging of all the data would have required a similar kind of effort.

Statistic methods: we applied standard statistics (median, average) provided by the system only from the descriptive point of view. A validation of the data via other indices or tests, like Student's t-test, Fisher's test, analysis of variation (ANOVA) may be applied in the future.

Outcomes: we obtained a general description of the users who attended online courses. Users said that the course was useful, the structure clear and the assessment contained enough questions for learning (median 4 out of a 5-point Likert scale, in which 1 was "not useful" and 5 was "very useful"). Two main remarks: textual resources were more appreciated than videos: the course is a full university module, so it requires a deep understanding of the concepts, typical of textual resources. Despite the widespread use of portable devices, most users attended the courses via PC (71%).

Interventions: Even though the students rated the learning experience as good, some interventions were felt to be useful. Since the project is only at the very beginning, so far, we have provided more indications in order to reach the desired resources and activities, especially close to the final test, which contains useful information for sitting the exam. Even though students' questionnaires generated a significant quantity of data, the action we took to improve their learning experience was still minimal.

5.2 DCA 2

Data from students were analysed with DCA2, through the tracked online activity, too.

Structure: the information was gathered from the databases of the platform and the user activity log (update 24th July 2019), using SQL queries.

Population: the platform hosts more than 10000 users; thus, the population size is quite large.

Availability: when requested, administrators can run the query, anytime. Some of the queries we implemented scan the database of all logs more than one time, providing a non-immediate result (anyway less than a minute).

Statistic methods: the amount of data is quite large; therefore, it is very difficult to filter with the proper information to understand and improve the learning environment.

Outcomes: out of 34 active courses, we counted the amount of resources and activities which are delivered by the platform: 1201 files, 847 video resources (without counting the embedded ones), 561 web pages, 410 tests, 237 books, 167 folders, 71 lessons, 48 Maple worksheets. In August 2019 we had on average more than 60000 monthly logins, corresponding to around 900 distinct users, in a single month.

Interventions: we reported to the scientific committee of the project, which sets the pace for the future development of the platform with new courses, taking advantage of the analytics. This intervention did not have a direct impact on the learning experience: this is mainly due to the large amount of data, which makes it hard to extract information.

5.3 DCA 3

University professors and grant holders were considered with DCA3. In order to prepare online courses for the start@unito project, university professors were trained in all topics related to the design and implementation of an online course, from the pedagogical to the technical issues. Professors were accompanied by grant holders (master students or PhDs) who acted as technical and academic support. The training programme consisted mainly in two parts: in-person meetings and online contents. Before and after these programmes, grant holders were requested to submit a questionnaire, in order to evaluate their previous experience about e-learning and the overall progress after the training. The results arising from these data have been discussed in (Marchisio *et al.*, 2019b).

Structure: we obtained feedback and data from grant holders both from questionnaires, and meetings. The aim of the two questionnaires is an evaluation of the quality of the training course (in-person and online). We previously asked about the experience of the grant holders with e-learning in three main areas (didactic, organizational and technical). After the course, they evaluated the same aspects, together with the usefulness of the meetings and of the online resources. Moreover, we organized monthly group meetings and individual sessions on request where we discussed the main issues grant holders were facing and found solutions together.

Population: 29 over 30 grant holders who participated in the development of an online course of the project start@unito submitted the questionnaire.

Availability: the data are reserved, but easily available by manager of the training course, who publish only aggregated data.

Statistic methods: the amount of data is related to a small group of people, thus we applied standard descriptive statistics.

Outcomes: we obtained a general view of the improvement in the confidence of grant holders, from a score to low/average to good (out of a 5-point Likert scale). The usefulness of each meeting was evaluated, with medians 4 and 5 of a 5-point Likert scale. Due to the blended nature of the training programme, the online materials were not widely used by all people involved, but they all stated that the online resources were quite useful (5 out of a 6-Point Likert scale).

Interventions: since the numbers are small, we received specific feedback from grant holders, and took specific actions in order to provide them with resources and utilities they needed. Since we obtained very good results, we will not apply important interventions on the eventual future training course. The online discussion forum, another tool we adopted, was mostly employed by us for remarks of general interest, but it was scarcely used by grant holders, despite our efforts to encourage them to post their questions for everyone to see and reflect upon. This may be because most issues with which grant holders needed our help were very specific and subject-related. However, we noticed a certain amount of resistance towards the use of the forum even for problems related to the correct use of features of the Moodle platform or the integrated Maple TA automatic assessment system, which everyone had to deal with throughout the creation of the course.

5.4 DCA 4

DCA4 considers high school teachers, which are involved in the learning process because they are the main interface with education for high school students who will probably enrol in a university course. Teachers can take advantage of the open feature of the start@unito courses and use the online materials for their regular classroom activities, for self-study and improvement, to help students with special educational needs or for students' autonomous review and practice (Marchisio *et al.*, 2019a). We asked high school teachers to evaluate the online materials they consulted.

Structure: we asked teachers to open and browse the online courses of the project start@unito in order to evaluate the quality of the materials, the possibility to use them in their daily didactics and the overall experience. The feedback from teachers was provided by a questionnaire that contained Likert-scale, multiple choice and open questions.

Population: 136 Italian high school teachers.

Availability: the reserved data are easily available by project managers, who publish only aggregated data. The variety of subjects taught by the teachers involved in the survey and the different types of high school provided an added value to our research.

Statistic methods: the amount of data is related to a not-so-large group of people, thus we applied standard descriptive statistics.

Outcomes: statistics provided us with a general description of teachers (Italian, of all ages) who answered and a view of the situation of OERs in high schools. It emerged that not all teachers are fully aware of what OERs are and their potential and that the ones provided by the start@unito platform are suitable for high school students and useful for teaching.

Interventions: we encouraged teachers to use the OERs with students. The evaluation by teachers was good, so this DCA produced no intervention.

6 Discussion

Through a careful study and analysis of the vast, however not very specific, LA literature, we realized that we had already been practicing LA. However, not all the data collecting and analysis we performed can be considered LA, since data per se are not meaningful if the interpretation of such data is lacking or does prompt the necessary interventions. Evaluating DCA1, we realized that we would obtain more useful insight if the questions about the contents of the course were more detailed and that the questionnaire may be expanded in order to understand better how students relate to this kind of learning environment (fully online, without tutoring), and whether the student profile (working student, student with disabilities, etc.) influences the answer. Evaluating DCA2, we came to understand that the middle-up approach adopted by our research group so far only produces learning analytics if the numbers are small. When the numbers are more consistent, a top-down approach is more advisable, finding objective criteria that will allow us to analyse and interpret data both quantitatively and qualitatively, and act promptly and coherently according to the results. DCA3 and DCA4 both concern small numbers and thus allow for qualitative analysis as well as quantitative analysis. Nevertheless, while in DCA3 we were to make meaningful interventions by catering to professors' individual needs and personalizing the learning experience, in DCA4 we did not manage to make such interventions, due to the totality of positive feedbacks. The following table summarizes the evaluation phase and reflect on the comparison with literature about LA.

Table 1
ARE THE DCA WE ADOPTED ADHERENT TO WELL-KNOWN LA TECHNIQUES?

DCA	Outcomes	Interventions	Adherence to an LA technique
DCA 1	4	3	Yes
DCA 2	3	1	No
DCA 3	4	3	Yes
DCA 4	4	0	No

Conclusion

In the present paper we have attempted an analysis of the DCA employed at the University of Turin in various projects on which our research group has been working, and we tried to define a methodology to evaluate the adherence of these amorphous practices to well-known LA techniques as defined in the literature of LA. Although our DCAs are not methodologically fully refined yet, we can report some interesting findings: first, the idea that LA can enhance the learning experience in a broader sense, considering also teacher training as such. Secondly, the questionnaire methodology, which we have largely employed, has proved a source of reliable data, both quantitative and qualitative. However, data extraction techniques still must be improved, especially when dealing with huge amounts of data. Large data requires more design and more awareness of how to deal with them. We firmly believe in the fact that open online education can provide unique opportunities to learners, and so far we have enacted out tasks to improve course design and teacher training on the one hand, reflecting on our own practices and gathering experts' feedback; on the other hand, they are helping us understand the learner's experience in the online environment, and we plan to use the insights gained thanks to the data to make it an even more stimulating and rewarding experience.

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THE PRESENCE AND ROLE OF ASSESSMENT IN UNIMORE MOOCS

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Keywords: MOOCs, dropout rate, completion rate, assessment tools

This contribution presents a reflection on the relationship between the use of assessment tools and the two-sided phenomenon of the completion rate and dropout rate in MOOCs. In support of this reflection, the experience of the MOOCs proposed by the University of Modena and Reggio Emilia (UNIMORE) within the EduOpen network is described. In particular, data relating to the quantity and quality of the assessment tools used in the MOOCs UNIMORE and data on the completion rates of the five pathways currently active in the training offer on EduOpen, specifically of an MOOC with a complex evaluation system and high completion rates, are reported.

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1 Introduction

UNIMORE's participation in the EduOpen network has prompted both the inter-athenaeum structure dedicated to e-learning (Centro Edunova) and the teachers individually involved in the process of didactic innovation (blended courses and MOOCs) to address problems of a different nature, which are often unprecedented.

The Edunova Centre, for example, had to face and manage the transition from the season in which it provided blended and online courses, reserved only for enrolled students, to a new season in which the learning offer was characterized by a) the MOOCs model, which was also open to non-enrolled students and therefore at least potentially extended to a much wider population of users, and b) the need to define common criteria, both from the technological point of view and from the methodological and didactic points of view to be shared with other universities in the network for the design, development, and delivery of MOOCs. All this has led in a short time to making choices, equipping oneself with resources, and implementing actions concerning two areas: on one hand, the structure of the Learning Management System and the production of video and live streaming, and on the other hand, the creation of a staff of designers and methodologists able to support the teachers in different disciplinary areas, engaged in the redesign of the teachings according to the guidelines prepared by the network. This process, carried out in forced stages, has also led UNIMORE to build a didactic offer that, even if it does not reach the massive dimensions typical of MOOCs, is still characterized by a remarkable openness, if only within the network that involves 17 Italian universities with a student population of over 400,000.

This process, which is still in full development, has led to some choices of priorities that have temporarily marginalized some important issues such as the management of learning analytics within the LMS of EduOpen.

2 A New Priority

Sometimes, some aspects of reality are given priority only after having experienced them, even if awareness of their existence and importance had existed for some time. Although the UNIMORE community was aware of the literature and experiences on learning analytics and on the positive role that these can play in assessment processes, the focus on these issues and the decision to devote resources for in-depth study—and, above all, to develop ad hoc tools—came only after the first three years of experimentation of MOOCs (2016–2018). This is how, in February 2019, the DELAC (Digital Education and Learning Analitycs Center) of UNIMORE was born, an example of priorities acquired ex post, of which psychologists, jurists, pedagogists, statisticians, and linguists are parts. The relationship between learning analytics and assessment is one of the themes that DELAC intends to deepen in the different disciplinary areas involved in the didactic offer of EduOpen, and it is precisely on this theme that this contribution focuses. It collects in written form one of the speeches made by the members of DELAC at the "Conference on Learning Analytics: For a dialogue between teaching practices and educational research" jointly promoted by SIRD (Italian Society of Educational Research) and SIe-L (Italian Society of e-Learning) and held at the Sapienza University of Rome on 9–10 May 2019.

The questions from which the reflection proposed in this paper starts are the following:

- How can the data produced by the EduOpen LMS help to understand the role played by assessment methods and tools in MOOC courses and pathways?
- Does this role play a positive role in ensuring the quality of the courses and, above all, their completion by the students?

These are the numbers of MOOCs UNIMORE (May 2019):

Table 1
DATA ON UNIMORE MOOCS

Courses	67
Pathways	12
Students	14.000
Instructors and tutors	73

2.1 Assessment in MOOCs

The assessment of student learning in MOOCs is unanimously considered a topic of great interest that depends (among other things) on the credibility and future development of this model within formal learning contexts such as academic ones. The most relevant elements of this interest are two: a) the role of assessment in determining the pedagogical quality of a course and b) the difficulty of using traditional methods and tools of assessment in MOOCs, especially when considering the massive participation of students.

The first element, the presence of evaluation in all its functions (formative and summative), is fundamental in all training proposals, but it is even more so in those at a distance because, on one hand, it helps to activate that feedback toward the student that is so important in distance interactions, and on the other hand, the same feedback provides the teacher and the training organisation with very important information on the progress and difficulties of the students and therefore on the possibility of actively supporting them. It should be remembered that many MOOCs, based essentially on the delivery of video lessons, are devoid of any assessment apparatus. Its presence, therefore, is a good indicator of the pedagogical quality of a course. If this assessment is also well done, then the quality of the whole MOOC will benefit even more.

The second element indicates a structural criticality of the assessment in MOOCs, at least as we know it today. The massive participation in MOOCs makes it extremely difficult if not impossible to proceed to a direct evaluation of learning. However, even the use of well-established online testing techniques based on Multiple Choice Questions (MCQs) can sometimes compromise the quality of MOOCs when the test items are not properly constructed and therefore compromise the reliability and validity of the test (Costello *et al.*, 2018). The growing interest in experimenting with new evaluation methods and tools specifically designed for MOOCs is therefore justified.

2.2 Assessment tools and dropout

The dropout rate of participants in distance learning courses has always been one of the most critical and investigated aspects of the research. Recently, alerts on dropout rates have increased due to the success of MOOCs mainly because of their massive participation and the significant increase in dropout rates.

In line with a more constructive view, some recent surveys have focused more on the dropout rate of MOOCs than on the completion rate and the perception of the students completing the courses. Coursera, one of the first and most important MOOC platforms, investigated the perceptions of students who completed MOOCs and found that 65% of them believe that MOOCs have contributed positively to their education, while 72% believe that they have brought benefits to their working careers (Zhenghao *et al.*, 2015). From this point of view (i.e., that of those who have completed MOOCs), these data seem to confirm the usefulness of MOOCs. However, it cannot be ignored that students who complete MOOCs are a small minority—for example, on edX (another important MOOCs platform)—who complete the course represents on average 5% of the total (Onah *et al.*, 2014; Kizilcec *et al.*, 2013; Seaton *et al.*, 2014). In this case, the dropout rate is about 95%. Another survey of MOOCs from the Chinese platform XuetangX found a similar dropout rate of 4.5% (Feng *et al.*, 2019). Although users sign up for an MOOC with the intention of following it in whole or in part, for a number of reasons, they leave it early before its completion (Halava *et al.*, 2014).

As a result, the central questions that have inspired most of the recent research are about this huge population of dropouts.

- What are the factors that push MOOC users to drop out of courses?
- Is there a way to identify students at risk and prevent dropouts?

To identify the reasons for the disengagement and abandonment of participants in MOOCs, it is necessary to start from the awareness that the "monolithic" approach adopted by some analysts, who consider participants in MOOCs as a homogeneous body characterized by the same motivations and the same behaviours (like students in an academic course), does not help to find a realistic explanation of the phenomenon. In the reality of MOOCs, participants have individual differences that are sometimes very marked, so it is more useful to consider them as "unique" cases that interact with the platform in different ways (Kizilcec *et al.*, 2013) because their motivations and their ability to resist from the beginning to the end of the course are different. This heterogeneity of characteristics, including a very weak motivation, is also determined by the great ease with which you access and exit an MOOC. As a result, MOOC dropouts are also exceptionally heterogeneous, and their decision to abandon can be caused by any combination of the many factors that characterize their condition (Breslow *et al.*, 2013).

In recent years, many efforts have been devoted to the development of predictive models that are able to identify activities considered possible factors of disengagement and abandonment by students and to keep them constantly under control to identify early risk of abandonment.

Considering the factors that contribute to determine the completion of MOOCs, we can distinguish between: a) persistence, i.e., the set of abilities to manage the learning process and to complete the course; b) abandonment, i.e., the set of elements that lead to the decision to abandon the course. Naturally, the two aspects are linked together; the absence of the abilities indicated in the first point can lead to abandonment, just as the absence of the elements indicated in the second point can increase persistence.

Factors of persistence include the capacities of self-regulation (such as the ability to manage time), the mastery of independent study methods, and the ability to self-evaluate (Halawa *et al.*, 2014). Factors of abandonment include the real intention to conclude the course, the lack of time needed for study, the level of difficulty of the course and lack of support, the lack of digital skills and study skills, negative experiences during the course, unrealistic expectations, and delays in starting the study (Onah *et al.*, 2014).

Activities of an assessing nature such as MCQs, assessed tasks, and reports can be considered both within the first group (persistence) and within the second (abandonment). The ability to evaluate some aspects such as the difficulty of the course, as well as one's own study skills and the results achieved, can increase persistence, as well as the lack of support (therefore also linked to the evaluative feedback) can lead to abandonment.

Based on this conviction, assessment has been assumed in this contribution as a significant indicator of both the pedagogical quality of MOOCs and the probability of course completion and, therefore, of student success.

2.3 Assessment in UNIMORE MOOCs

The assessment system of MOOCs UNIMORE is inspired by the guidelines developed by the EduOpen network, which in several places make an explicit reference to the methods and tools of assessment.

According to these guidelines, the macro-structure of an MOOC must have three levels: headers (all the information concerning the course), sections (set of activities, equivalent to a chapter in paper publishing), activities (real educational activities).

Sections

In describing the macro-structure of an MOOC, the Guidelines suggest that each Section should contain "at least one formative evaluation activity, usually at the end of the same."

Activities

In line with the ANVUR (Italian National Agency for the Evaluation of Universities and Research Institutes) guidelines, they are divided into erogative or transmissive activities and interactive activities or e-activities. It is precisely within the latter that some tools with an evaluative function are mentioned:

"discussion forum on the topics of the course;

- interactive sessions by videoconference;
- formative assessment activities (peer assessment, closed-answer questionnaires, assignments, reports, etc.);
- collaborative activities, possibly in small groups;
- exercises;
- project work."

Among these instruments, in addition to the third of an explicitly evaluative nature, the others can also be used in an evaluative function. Nevertheless, the focus here will be on "formative evaluation activities" such as peer assessments, closed-ended questionnaires, assignments, and reports.

The EduOpen Guidelines also contain an important indication from the evaluation point of view, that of human resources: "The University must provide for the creation of a working group that includes at least the following professionals:

"an expert in instructional design;

- expert in the management of the Mooc platform (EduOpen Manager);
- instructors and tutors;
- multimedia production experts (video and graphics)."

The first professionalism indicated in the list is that of the expert in "instructional design," a professionalism that includes significant skills in the field of evaluation.

Two other important references from the evaluation point of view contained in the Guidelines are those relating to macro and micro instructional design. Among the tasks of macro-design, the definition of "evaluation and verification strategies" and "certification strategies" is explicitly mentioned. Among those of microprojecting, there is an indication of the need for each Activity to define, among other things, the "tools of assessment and collaboration between students."

Finally, in the EduOpen Guidelines, there are attached operational sheets for macro and micro design, which provide more detailed information, including on assessment. In the 11-point macro-design sheet, the last two points concern the "Formative assessment tools" and the "Final assessment":

10. FORMATIVE ASSESSMENT TOOLS It is suggested to plan during the course the development of tests such as closed-ended questionnaires, projects, or reports. For these activities, forms of self-assessment or peer review and discussion in the forums are envisaged.
11. FINAL ASSESSMENT The final assessment can take place online or in the presence and provide for the issue of training credits. Indicate: - the typology of the test (open/closed questionnaire, project work, interview); - the way in which it is carried out (online or in presence); - the possible attribution of CFU/ECTS. In particular, remember that: - after passing an online test, a certificate of attendance or a verified certificate (no CFU/ECTS) can be issued; - after a test in presence, a certificate of completion of the course (with CFU/ECTS) will be issued by the university of reference.

The microproject card is divided into three parts, one of which is reserved for formative assessment:

FORMATIVE ASSESSMENT
Which assessment tool would you like to use? - Closed-ended questionnaire - Project work - Experience/simulation
What form of evaluation do you envisage? - Self-assessment - Peer assessment - Teacher Feedback
If the questionnaires are closed-ended, please indicate: - How many questions does the assessment test consist of? - How many response options are there? - What is the percentage of correct answers required to pass the test?
If it is project work: - provide a trace - provide an assessment rubric

The EduOpen Guidelines recognise an important role for assessment. Given the extreme heterogeneity of teaching methods implemented in academic contexts by individual teachers, it is essential that the implementation of MOOCs is oriented not only on the technological level but also on the pedagogical and didactical levels, of which the assessment is undoubtedly one of the main aspects.

EduOpen's MOOCs offer is developed in

- single courses;
- paths that consist of a sequence of courses that define a single set of learning objectives.

In this framework, the offer of UNIMORE MOOCs (active in May 2019) is composed of 19 courses and 5 pathways.

The 19 courses, which have an average duration of 19.3 hours, have an average of 3.3 assessment tools each, distributed as follows:

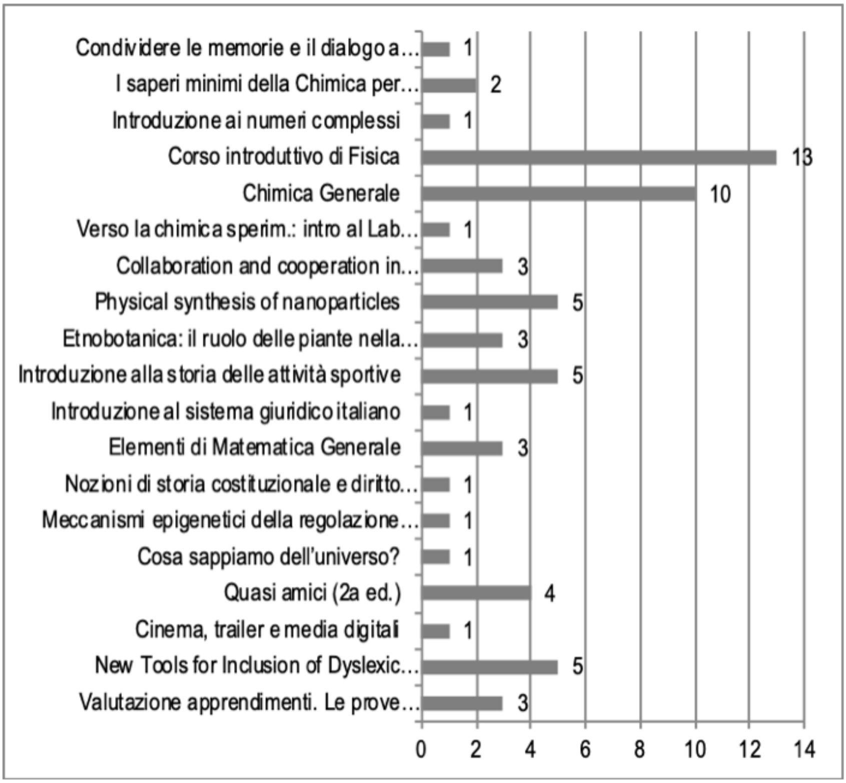

Fig. 1 - Assessment tools in the 19 MOOCs UNIMORE in courses mod

As for the different typologies of assessment tools, in the 19 courses there are: informative questionnaires administered with initial assessment function (5/19); informative questionnaires administered with final assessment function (1/19); MCQs administered with intermediate assessment function (4/19); and MCQs administered with final assessment function (17/19). In one case, the wiki tool with intermediate assessment function was used.

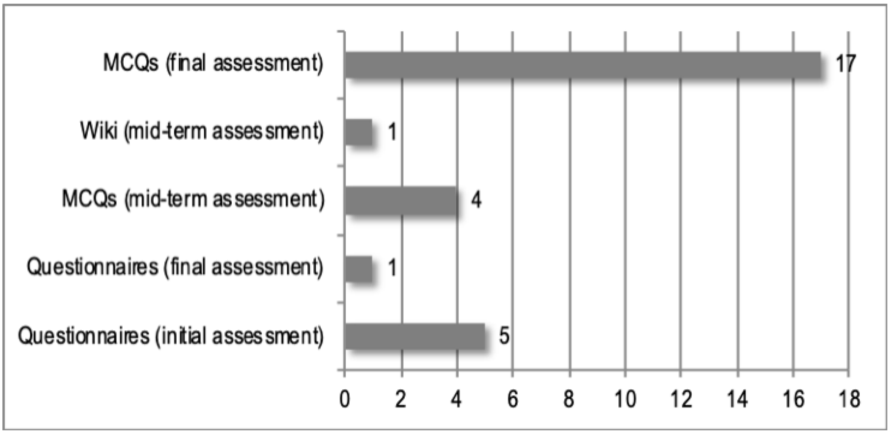

Fig. 2 - Typology of assessment tools in the 19 MOOCs UNIMORE in courses mode.

The 5 UNIMORE pathways have an average duration of 97 hours and use an average of 9 assessment tools each, distributed as follows:

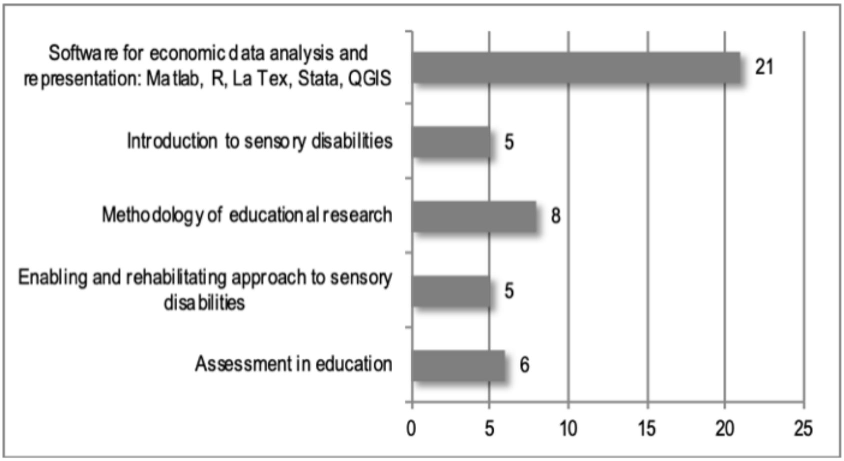

Fig. 3 - Assessment tools in the 5 MOOCs UNIMORE in pathways mode.

The types of assessment tools present in the 5 pathways are: information questionnaires administered with initial evaluation function (2/5); information questionnaires administered with final evaluation function (2/5); MCQs administered with intermediate and final assessment function (5/5); assignments for the final assessment (2/5).

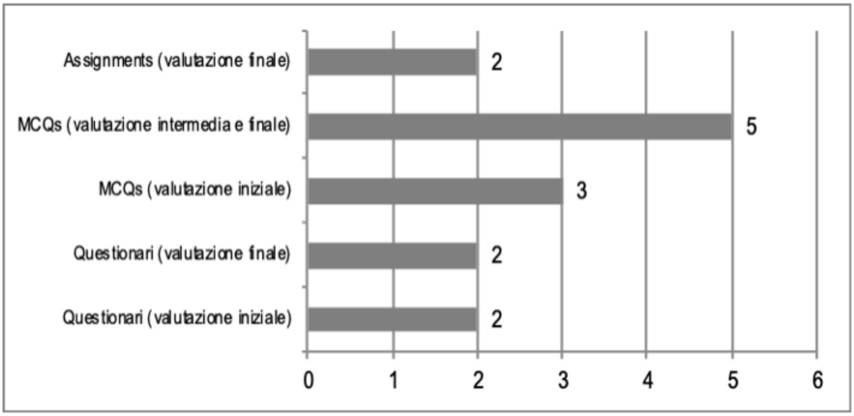

Fig. 4 - Typology of assessment tools in the 5 MOOCs UNIMORE in pathways mode.

As shown in Figure 4, assessment tools are present in all MOOC UNIMORE (at least one is present in all courses). They are mainly used at the end of the courses as final assessment tests; when courses are part of pathways, assessment tools can be considered intermediate tests of pathways (Figure 4). Finally, assessment tools are used, both in courses and in pathways, mostly in the form of MCQs or information and/or approval questionnaires (Figures 2 and 4).

The consideration on the completion rate of the 5 UNIMORE pathways is conditioned by the fact that the participants are almost all UNIMORE registered students. This explains the high completion rates (see Figure 5), certainly higher than the 5% mentioned above.

If, for the 5 UNIMORE pathways, we associate the values relating to the number of assessment tools with the percentages of completion of the path, we obtain the two curves shown in Figure 5:

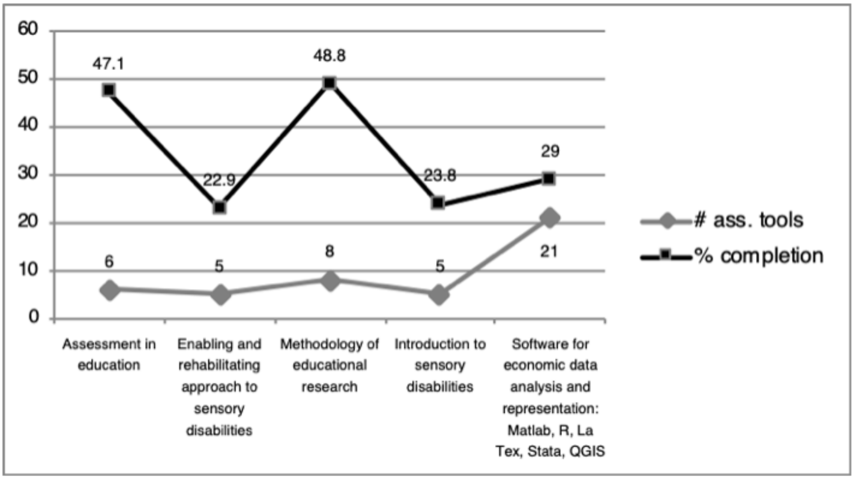

Fig. 5 - Quantity of assessment tools and completion rate in the 5 MOOCs UNIMORE in pathways mode.

The completion rate, which reaches up to 48%, never drops below 22%. The number of assessment tools for each pathway ranges from a minimum of 5 to a maximum of 21. The trend of the two curves is quite similar, as an increase in the number of assessment tools corresponds to an increase in the completion rate, even if not proportionally. The pathway that has the highest number of assessment tools is not the one with the highest completion rate. The two pathways with the lowest completion rates are still those with the fewest of assessment tools. This lack of proportionality can be explained by the fact that there are elements other than the assessment that affect the completion rate, and therefore the assessment tools only partially explain the change in completion rate. Among the determining factors other than the assessment tools, one is present in the two pathways with the highest rates (47.1% and 48.8%)—the mandatory nature of some educational requirements. In particular, the participants in the two pathways are UNIMORE students who must be in compliance with these requirements to take the final exam.

It is useful to see more detailed data regarding the pathway Methodology of Educational Research (MER). In 2018–2019, the cohort consisted of 516 students, and there were 577 registered participants. The excess is mainly made up of teachers in service who use the pathway as a form of updating. Among the eight assessment tools provided with the MER pathway, there are two questionnaires for the collection of personal information, expectations, and satisfaction; three self-assessments in the form of MCQs; and three reports assessed.

Table 2
DATA RELATED TO THE ASSESSMENT TOOLS OF THE PATHWAY METHODOLOGY OF THE EDUCATIONAL RESEARCH
* MANDATORY; ** MANDATORY AND ASSESSED; *** OPTIONAL AND ASSESSED

Assessment tools	Enrolled	Submitted	Completion rate
Initial Questionnaire*	577	439	76,0%
Final Questionnaire*	577	210	36,3%
Self-assessment (MCQs) 1*	577	383	66,3%
Self-assessment (MCQs) 2*	577	401	69,4%
Self-assessment (MCQs) 3*	577	322	55,8%
Assignment (Report) 1*	577	329	57,0%
Assignment (Report) 2*	577	316	54,7%
Assignment (Report) 3**	577	268	46,4%

It should be noted that the data in the table were collected in May 2019 before the end of the pathway. This explains the low completion rate of the final questionnaire (administered at the end of the pathway) and the third self-assessment. In addition, it is important to note that the deadlines for submission remain open for examination appeals after the first until September. Finally, the figure for the third assignment is conditioned by the fact that, unlike the other two, it was optional. All of them exceed (in some cases abundantly) 50% completion just before the end of the course.

Table 3 shows a small historical series. Some data are reported for the first of the three courses in which the pathway Methodology of Educational Research is divided, the Elements of Educational Research (EER) course, the most challenging in terms of duration and complexity of content, in the three-year period from 2016–2018.

Table 3
DATA RELATED TO THE COURSE ELEMENTS OF EDUCATIONAL RESEARCH (EER) FOR THE THREE-YEAR PERIOD 2016-2018.

EER	Completed learners	Total learners	% completion	% open badge
2016-17	270	657	41,1	7,4
2017-18	377	794	47,5	34,2
2018-19	370	698	53	51,8

Conclusion

Systematically acquiring data on the interactions between MOOC students and the LMS platform and carefully reflecting on them can be useful for the monitoring and management of the MOOC, during its development, for the identification after its conclusion of useful elements for its redesign, and for comparisons between different MOOCs at the Department and/or University level for the overall improvement of the training offer—for example, by increasing both the quantity and quality of the assessment tools present in the MOOCs.

In the case of UNIMORE, an analysis has begun aimed firstly at evaluating the experimental three-year period of the MOOCs and secondly at the elaboration of a model that, based on the experiences conducted at an international level and traceable in the literature, is able to identify early cases of students at risk of dropping out. This is just beginning, and there is still a long way to go.

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LEARNING ANALYTICS TO IMPROVE FORMATIVE ASSESSMENT STRATEGIES

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In digital education, learning analytics should support active monitoring and dynamic decision-making during learning processes; they are mainly based on digital assessment, through which it is possible to collect and elaborate data about students' progresses. In this paper we start from Black and Wiliam's theoretical framework on formative assessment, which identified 5 key strategies that 3 agents (student, peers and teacher) pursue when enacting formative practices in a context of traditional learning, and we integrate it in a framework of innovative didactics. In particular, we consider the use of a Digital Learning Environment integrated with an Automatic Assessment System based on the engine of an Advanced Computing Environment to build interactive materials with automatic assessment according to a specific model of formative assessment. In this framework, rooted in activity theory, the Digital Learning Environment plays the role of mediating artifact in the activity of enacting the strategies of formative assessment. Through several

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examples of application of automatic formative assessment in several contexts and modalities, we show how it is possible to use the data gathered by the Digital Learning Environment to improve the enactment of Black and Wiliam's strategies of formative assessment, strengthen and evaluate their action.

1 Introduction

Big data and algorithms are the keywords of modern society: nowadays, even the most traditional workplaces, such as mechanic's or carpenter's workshops, require data analysis expertise to perform market surveys and make decisions about how to manage business (World Economic Forum, 2018). Education is not left out of this panorama: the increasing adoption of learning technologies enables the production of data, which can be used to understand, guide and optimize learning processes. Here the field of learning analytics comes to life. The call of paper of the First Learning Analytics and Knowledge Conference ("LAK 2011" https://tekri.athabascau.ca/analytics/) introduced the definition of learning analytics later adopted by the Society for Learning Analytics Research (SoLAR): "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs". Unlike the general use of statistics to provide evidence of the effectiveness of learning methodologies, learning analytics should support active monitoring and dynamic decision-making during learning processes (de Waal, 2017). The data gathered and elaborated should inform not only teachers and researchers, but also students about their achievements, thus letting them keep control of their learning path.

Learning analytics are based on assessment (Knight & Buckingham Shum, 2017), which is often the main source of data in a digital environment; assessment can be seen both as summative, which is aimed to certify the achievement of knowledge and skills, or formative, that is aimed to support progresses in learning (Black & Wiliam, 1998). Learning analytics are not the mere introduction of algorithms into teaching: it is essential that data collection and analysis are driven by a theoretical framework rooted in pedagogy (Friend Wise & Williamson Schaffer, 2015). The theory has a key role in guiding the researcher in the choice of the variables that should be included in a model, in focusing on some results and drawing relevant conclusions out of large datasets. In this contribution we consider activities of formative assessment in a digital environment. We try to organize existing theories in order to provide a theoretical approach useful to create activities of formative assessment and analyze their results. We start from Black's and Wiliam's theoretical framework of formative assessment, to study the formative assessment strategies and the subjects involved. We present our model of automatic formative assessment with the technologies used and their functionalities. Then we discuss how to move from formative assessment to LA (experimentation and data collection) and from LA to formative assessment (use of data to implement formative assessment strategies), showing examples.

2 Formative Assessment

Black and Wiliam (2009) wrote one of the most acknowledged definition of formative assessment (FA), conceived for a general context of traditional education: "Practice in a classroom is formative to the extent that evidence about student achievement is elicited, interpreted, and used by teachers, learners, or their peers, to make decisions about the next steps in instruction that are likely to be better, or better founded, than the decisions they would have taken in the absence of the evidence that was elicited". This definition entails not only the collection of evidence, which can be gathered through tasks or questions, but also the interpretation and use of the information gathered in order to act on learning. According to this definition, the mere collection of students' answers without using them to make decisions in order to tailor their learning path is not to be considered formative assessment. The abovementioned definition entails three agents: the teacher, the student, and the peers, who are activated during formative practices. Black and Wiliam (2009) further developed a framework, individuating 3 different processes of instruction, that are:

- establishing where the learners are in their learning;
- establishing where they are going;
- establishing what needs to be done to get them there.
- Moreover, the researchers theorized 5 key strategies, enacted by the three subjects during three different processes of instruction:
- clarifying and sharing learning intentions and criteria for success;
- engineering effective classroom discussions and other learning tasks that elicit evidence of student understanding;
- providing feedback that moves learners forward;
- activating students as instructional resources for one another;
- activating students as the owners of their own learning.

3 Technology Enhanced Formative Assessment

When formative assessment is paired with technologies, applying learning analytics techniques is possible, in order to enhance the potentialities of FA. In this paper, when we talk about "learning technologies" we refer to a Digital Learning Environment (DLE) integrated with an Automatic Assessment System

(AAS) (Barana *et al*., 2015) based on an Advanced Computing Environment (ACE), a powerful system for doing Mathematics (Barana *et al*., 2017b). In such a DLE, collaborative or interactive activities can be alternated with automatic assessment; the ACE engine allows questions to be algorithm-based and to accept open mathematical answers independently of the form in which they are provided. Similar systems are flexible enough to be used in several ways and at different educational levels:

- face to face, with students working autonomously or in groups through digital devices, in the classroom or in a computer lab, or solving tasks displayed on the Interactive White Board with pen and paper, especially with classes of lower grades, such as lower secondary school level;
- in a blended approach, that is using online activities to integrate classroom work, asking students to complete them as homework, with students of secondary school or university;
- completely online, using the DLE as a true e-learning platform in online courses in secondary and higher education, proposing automatic assessment activities to help students keep track of their progresses.

The definition of FA that we have mentioned before can be adapted to consider the contribution of the technologies. Pachler *et al*. (2010) define formative e-assessment as "the use of ICT to support the iterative process of gathering and analyzing information about student learning by teachers as well as learners and of evaluating it in relation to prior achievement and attainment of intended, as well as unintended learning outcomes". We adopt this definition as it highlights the role of ICT as a support for the process of formative assessment, and is open to several modalities of using the technologies (face to face, blended and online).

In the perspective of activity theory (AT) (Engeström *et al*., 1999) – a sociocultural theory aimed to study and interpret actions mediated by instruments through a model visible in Fig. 1 – we can consider the activity where the object is performing formative assessment and where the subjects are, in turn, the students, the teachers and the peers. The strategies of formative assessment individuated by Black and Wiliam are mediating artifacts through which the action is completed. In this framework, the technologies are mediating artifacts as well. The outcome is the improvement in learning and, according to AT, it can be the result of the action carried out by at least two activity systems. Rules, community and division of labor are those that are typical of the environment where the action takes place (a classroom, a DLE), which varies on the basis of the modality of use of the technology (face to face, blended or online). When we consider the activity of enacting one of the key strategies of formative assessment, such as providing feedback that moves the learner forward, the strategy is the object of the action and the technology used is the mediating artifact. It is useful to analyze the formative assessment activities according to this model, as it helps to distinguish what causes learning. According to the AT, when the interactions between the elements face some contradictions, the systems modify themselves through expansion and this provides learning (Engeström, 2001).

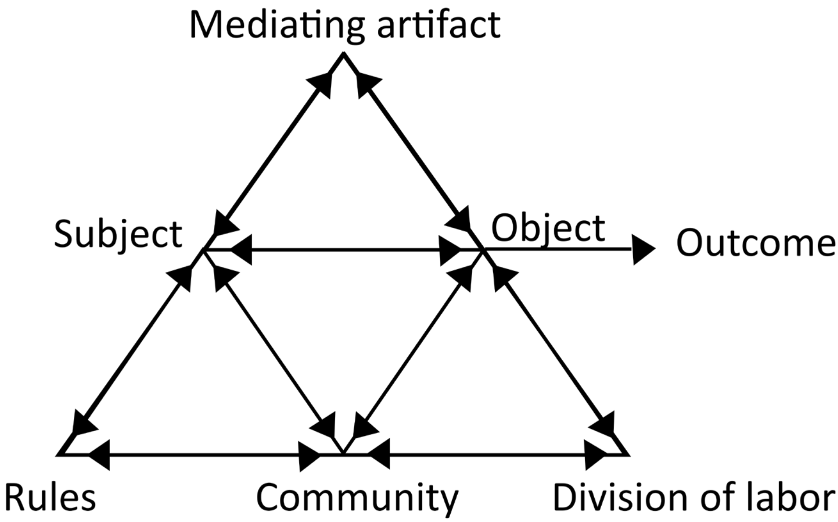

Fig. 1 - One activity system, the unit of analysis of action in activity theory.

From this perspective, a DLE integrated with an AAS has therefore a mediating role in the practice of formative assessment. After years of use of DLEs, we have come to identify as essential the following functions through which a DLE can support the activities:

- creating: to support the creation of materials (interactive files, theoretical lessons, glossaries, videos, etc.) and activities (tests, chats for synchronous discussions, forums for asynchronous discussions, questionnaires, submission of tasks, etc.) by teachers, but also by students or peers;
- delivering: to make the materials and activities available to users;
- collecting: to collect all the quantitative and qualitative data concerning the actions of the students, the use of materials (for example if a material has been viewed or not and how many times) and the participation in the activities (for example number of interventions in a forum, number of tasks delivered, number of times a test has been performed, evaluation achieved, etc.);
- analyzing: to analyze and elaborate the data inserted by the students in the learning activities, possibly using a Mathematical engine to assess

answers formulated in a scientific language;
- providing feedback: to give the student feedback on the activity carried out;
- providing elaboration of data: to provide an elaboration of all these data to the teacher, but also to the students.
- Through these functions it is possible to achieve the following outcomes:
- to create an interactive learning environment;
- to support collaborative learning;
- to share materials in a single environment, making them accessible at any time;
- to offer immediate feedback to students about their results, the knowledge and skills acquired and their level of learning;
- to offer immediate feedback to the teachers on the students' results and the activities they perform.

The identification and classification of the functions of a DLE can allow us to analyze the contribute of the technology during the formative assessment process; it is necessary to separate the functions from the outcomes in order to have a clear frame and find causal connections when analyzing large quantities of data.

Using an AAS based on an ACE, the Department of Mathematics of the University of Turin has designed a model for the creation of activities for the automatic formative assessment of Mathematics (Barana *et al*., 2018c). The model is based on the following principles:
1. availability of the assignments to the students, who can work at their own pace;
2. algorithm-based questions and answers, so that at every attempt the students are expected to repeat solving processes on different values;
3. open-ended answers, going beyond the multiple-choice modality;
4. immediate feedback, provided to the students at a moment that is useful to identify and correct mistakes;
5. contextualization of problems in the real world, to make tasks relevant to students;
6. interactive feedback, which appears when students give the wrong answer to a problem. It has the form of a step-by step guided resolution that interactively shows a possible process for solving the task.

The last one consists in a step-by-step approach to problem solving with automatic assessment, but it is conceptualized in terms of feedback, highlighting the formative function that the sub-questions fulfil for a student who failed the main task. For example, after the first section the student receives a first feedback in a form of green tick or a red cross depending on whether s/he answered correctly or not; the following sections give interactive feedback about how s/he was supposed to develop his/her reasoning in order to reach the solution. The interactive nature of this feedback and its immediacy prevent students from not processing it, a risk well-known in literature that causes formative feedback to lose all of its powerful effects (Sadler, 1989). Moreover, students are rewarded with partial grading, which improves motivation (Barana *et al*., 2019a). This kind of formative activities are mainly conceived to be individual; however, they can be integrated in a DLE with other interactive resources and used in collaborative situations or coupled with different activities of collective discussion and collaborative work.

4 From Formative Assessment to Learning Analytics

Our research group has used formative assessment activities developed through our model, using these kinds of technologies and their functions several times and in different ways and contexts. As DLE we have mainly adopted Moodle platforms, integrated with Moebius Assessment, an AAS based on the engine of Maple ACE. For example, at lower secondary school level in a face to face modality (Barana *et al.*, 2018a), at lower and upper secondary school level in a blended modality (Barana *et al*., 2017c; Brancaccio *et al*., 2015), in online modality at upper secondary school level (Barana & Marchisio, 2016; Barana *et al*., 2019b) or in a university context (Bruschi *et al*., 2018; Marchisio *et al*., 2019).

Through the "collecting" function of these technologies, it is possible to collect many different types of data about the activities carried out by students: evaluate the use of the DLE (such as number and time of logins), qualitative data concerning the use of materials (such as the completion of activities) and specific quantitative data for each type of activity. Evaluation data, elaborated through the "analyzing" function, is automatically saved in the AAS gradebook, also integrated within the grader report. All these data can provide a description of the activity carried out by the student and the possibility of keeping these data in memory can allow to obtain an overview of the student's learning path over time. These data can be made available to students and teachers through the "providing elaboration of data" function, via different tools: for example, progress bars provide students with visual information about their completed activities, while the grader report allows teachers to see the activities carried out by the students, their progress and thus highlighting the students at risk. Data can be combined and analyzed with various Learning Analytics techniques (such as dashboards, recommender systems, predictive analytics, and alerts/warnings/interventions) in order to address concerns related to a broad range of teaching and learning areas. These areas include: retention and student success; improvement of learning design, units, courses and teaching practice; the development of personalized learning pathways; and student support (West *et al*., 2018). In order for LA to help improve formative assessment, it is important to refer to an exact pedagogical framework for the interpretation of the data and to be able to use them for future actions. In our case, we used the framework described above for FA with technologies.

5 From Learning Analytics to Formative Assessment

In this section we focus on how the extensive data that can be collected in a DLE can be useful to "go back" to the previously mentioned FA strategies and support their implementation. Taking in account the reference to the LA definition of Solar (2011), we show some examples of collection and analysis of different types of data relating to students and their activities, to support formative assessment strategies and consequently to optimize DLE and learning. The examples described below reflect the theoretical framework of AT in which technologies are the tool that mediates the action of the subject (student, teacher or peers) towards the object (implementing or improving the FA strategy).

Clarifying and sharing learning intentions and criteria for success

For this strategy, the data on the use of materials and interactive activities by the students can be analyzed and related to their assessment data, to evaluate the effectiveness of the materials and activities. In this way, it is possible to improve the teaching materials and increase the internal coherence of the contents of the platform often organized in Learning Objects, that are a collection of content items, practice items, and assessment items that are combined based on a single learning objective. An analysis of this type has been carried out on the Realignment Course in Mathematics of Orient@mente (Barana *et al.*, 2017a), a platform of self-paced open online courses aimed to guide students in the choice of a scientific university program of our University (Barana *et al*., 2018b). The lessons in the course have many activities, such as online readable books; interactive activities of exploration or simulation; pages with theory applications and curiosities; automatically assessed online tests; exercises with their solutions. The evaluation data have been related to the completion data of the various resources (viewed/not viewed) to understand if the student had completed the other activities or used the other resources before trying the test. Our analysis showed that the students who used the activities before the test did better than those who completed the test based only on their knowledge. This shows that the materials made available were effective and consistent with the test. Different results would have been a clue of the need for a redesign of the course contents, to make materials more effective, or the tests more coherent with the learning activities.

Engineering effective classroom discussions and other learning tasks that elicit evidence of student understanding

For this strategy of formative assessment, it is possible to use the gradebook to view assessment data organized by test, by student, or by question item, and the gradebook statistics. In this way it is possible to analyze indexes such as the discrimination index of the items, the rate of correct answer and the common mistakes made by students. The teacher can identify the topics that are not clear, in order to improve the existing Learning Objects, create new ones or prepare activities in the classroom to clarify the unclear points. An example of this FA strategy was carried out within MATE-BOOSTER, a project conceived to strengthen the mathematical competences of students attending the first year of a technical upper secondary school through an online course (Barana *et al.*, 2019a). The analysis of the learning needs, which preceded the development of an online course, was carried out through an entry test to assess the initial competence and a questionnaire to understand students' motivations. Results of the entry test aggregated by content areas showed the most difficult topics; moreover, the questions with low discrimination indexes identified common misunderstandings and areas for improvement. In light of the results of the entry test and of the questionnaire, researchers and teachers listed the learning outcomes of the course. The design of the teaching materials was made considering the frequent mistakes of the students, emerged both from the entry test and the teachers' experience.

Providing feedback that moves learners forward

To provide more detailed and therefore more effective feedback that moves learners forward, the data collected in the gradebook can be used, in particular the percentage of correct answers to a question in subsequent attempts with interactive feedback. In this way, it is possible to evaluate the effectiveness of interactive feedback, to improve feedback itself and provide useful activities for learning. In (Barana *et al.*, 2018c), some examples of this strategy are presented. The results showed that there was a high trend to make more than one attempt on the assignments developed according to the model of automatic formative assessment and containing interactive feedback. This means that letting students repeat the assignments is an effective way to make them aware that the information from the feedback was useful to improve their performance, as well as to make teachers and researchers sure that the feedback was well built. From the analysis, it emerged that the feedback effectively made students improve their results. In fact, for each student, the average of their grades considering only their first attempt on every assignment was compared with the average of the grades considering only their last attempts through a pairwise student t-test. It resulted that the activities were effective for making students use the information obtained through the feedback to persevere and improve.

Activating students as instructional resources for one another

To activate the students as instructional resources for one other, it is possible to consult the grader report to analyze the relationships and interactions between the students, in order to verify that the activities supported learning. In this way it is possible to study the effectiveness of the collaborative activities and eventually improve them.

An example of this strategy was used in the Digital Math Training project (Barana & Marchisio, 2016) and presented in (Barana & Marchisio, 2017). We analyzed the resolutions of the same problem by two groups of students, one in a context of individual work during a competition, and the other in a context of online collaborative work in the Project's platform. In the second group, the students could discuss their resolution though an asynchronous forum. The analysis of the scores of the second group of students, which were better than those of the first group, and of the interventions in the forum showed that the collaborative activities supported learning and the development of mathematical, problem solving, computer, digital and collaborative work skills.

Activating students as the owners of their own learning

For this FA strategy, it is possible to use the data of the interactive activities and the questionnaires in the grader report to study the relationship between students' performance and engagement. The objective is to evaluate the effects of interactive activities on engagement, one of the most powerful driving forces that pushes students forward into a learning experience. Some examples where presented in (Barana *et al.*, in press) and in (Barana *et al.*, 2018a). These papers are focused on an experimentation where interactive technologies were used in order to improve students' engagement in Mathematics at grade 8. For the whole school-year, all students involved in the project with their teachers had access to an online platform populated with interactive worksheets with real-life mathematical problems coupled with automatically assessed quizzes. According to the results of initial and final questionnaire, the level of engagement increased in particular in students that initially showed low levels of engagement. It is believed that engagement was elicited by the nature of interaction enabled by the interactive files and by automatic assessment, which supported the exploration and the understanding of complex concepts, facilitated teachers' explanations in the classroom, and allowed students to self-correct and understand mistakes. Increasing students' engagement in such environments is an outstanding goal. The online activities managed to catch students' attention thanks to the use of the computer and the interactive feedback, which opens a dialogue between students and the system and encourages them to understand solving processes.

6 Challenges

Being a new approach to formative assessment, the application of LA techniques is not free from risks and challenges. Firstly, the creation of tasks and activities in a DLE to be used with formative purposes requires technical skills and knowledge of the tools, as well as a pedagogical preparation in the strategies and models of formative assessment, otherwise there is the risk to merely replicate traditional instruction with digital tools without reap the benefits that can be gained from a correct, informed and conscious use of these technologies. This can be tackled through a specific training dedicated to the teachers or the instructors that will author the learning activities. Our research group has designed and experimented a model of teacher training that involves face-to-face and online training sessions through which many secondary school teachers became skilled in the adoption of automatic formative assessment through a DLE (Brancaccio *et al.*, 2015). The teacher training is flanked sharing the produced materials in a virtual community of practice, where the contribution of the trainees and the control of tutors from the University assures that high quality materials are proposed to students.

But this is only a part of the risk mitigation: as Black and Wiliam stress (Black & Wiliam, 2009), it is not the mere use of proper tasks at the appropriate time that makes assessment formative: data from the assessment need to be used to take decisions in the instruction process. Here the learning analytics techniques can facilitate the visualization and analysis of learning data. However, it is not easy, especially for school teachers, to do the analyses and to use the results just in time to influence next steps in instruction. Sometimes they need the help of researchers to complete the analyses, some time is required to gather the data and start the analyses, and the results are not immediately available, so that they can undermine the dynamism of the decision-making process that takes place in a classroom (De Waal, 2017). In order to tackle these difficulties, it is possible to act on the automatization of the analyses processes and on the improvement of the visualization of the results directly into the DLE; teachers and instructors need to be trained to read these results and use them in their daily practices.

Conclusion

In this paper we have illustrated and discussed a possible theoretical framework for the creation and analysis of formative assessment activities using a DLE, connecting frameworks on Activity Theory, Formative Assessment and Automatic Formative Assessment. In particular, starting from Black and Wiliam's theoretical framework on formative assessment to study the formative strategies in a context of traditional learning, our research group proposed a model of formative automatic assessment with technologies (DLE integrated with an AAS based on an ACE), in accordance with the theoretical framework of AT. With these technologies one can create materials with automatic formative assessment according to our model and it is possible to add other interactive and collaborative activities for students, resources, questionnaires etc. These materials and activities have been tested on multiple occasions and the numerous and various data obtained have been analyzed with various learning analytics techniques. When formative assessment is paired with technologies, applying learning analytics techniques is possible, in order to enhance the potentialities of FA. The examples discussed show how the data coming from the use of a DLE and the evaluation data can be used in order to improve the enactment of strategies of formative assessment, strengthen and evaluate their action. Certainly, it may be significant to carry out new research on the use of LA to improve formative assessment strategies and learning processes in general.

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USE OF LEARNING ANALYTICS BETWEEN FORMATIVE AND SUMMATIVE ASSESSMENT

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The field of study within which this work is placed is that of data produced within digital learning environments, a field of research now known as Learning Analytics (LA). In particular, the aim is to investigate the relationship between the standard psychometric properties of the test questions and the information obtained from the log files produced during its administration, on a large scale, by computer. The results of this type of survey can help to make visible the intersections between formative assessment and summative assessment and to renew, in this way, the evaluation practices of a rapidly expanding sector such as digital education.

[1] The opinions expressed are to be attributed to the author and do not engage the responsibility of the Institute to which they belong.

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1 Process data: a new research frontier

The use of computers, or other digital tools (tablets, smartphones, etc.), to conduct large-scale assessment tests offers new opportunities, including for educational research, to acquire otherwise inaccessible information on how students learn. Changing the tool with which students carry out assessment tests, from paper to digital supports, has implications not only on the technological level but also on that of knowledge of the cognitive processes underlying learning.

The administration of large-scale computer-based testing (hereinafter referred to as CBT) makes it possible to collect information that cannot be retrieved when evidence is administered in paper form. In principle, CBT mode allows all interactions between the respondent and the testing platform to be recorded in so-called log files (LFs). This information, called process data literature (PD), allows to study the processes that lead the student to provide a certain response and, therefore, more generally can contribute to the observation of learning processes implemented by the respondent. They allow, for example, to trace the ways in which a student relates to a task (time of reading the task, time elapsing between reading and the first or last interaction with the task, number of attempts made to solve the task, etc.), thus providing much information on different cognitive styles and approaches to the task. It is clear that there has been a change of perspective with respect to the traditional evaluations, which are more focused on the observation of the final outcome than on the process that determined that outcome. PDs therefore become one of the most important subjects of study in a discipline that has only become internationally established in the last decade and is known as Learning Analytics (LA). The results produced so far by this new field of research have, on the one hand, contributed to raising the awareness of designers, teachers and managers of what is happening within digital learning environments and, on the other hand, have made more evident the need to involve the world of pedagogy in this field of research (Lang *et al*., 2017).

The study of PD allows to identify proximity variables (proxy) able to provide information on the respondent's motivation, his involvement in the task (engagement), his perseverance, etc.. Thanks to this information and its analysis, it is possible to deepen the knowledge of so-called soft skills, the importance of which is widely shared, but on whose observation and measurement methods many open and controversial issues still need to be clarified (Heckman *et al*., 2017). In fact, PDs can provide proxies for the respondent's behaviour styles in dealing with the proposed task. PDs can provide indications, albeit partial, of the processes activated and the character traits mobilized to reach a solution.

In this perspective, the use of PD makes the boundary between formative and summative evaluation less clear since the evaluation process, whatever it may be, tends to become a process of continuous observation and thus provides feedback that is beneficial to both students and teachers.

However, the interpretation of LFs is not easy, both from a technical and, above all, from a theoretical point of view. At present, LFs are often structured around the technical characteristics of the platform used to deliver CBT tests and are not designed, engineered or developed as an integral part of the assessment action. Although, over the last decade, LA applications have taken very important steps, it is crucial to define theoretical reference frameworks that can give them an adequate systematic approach, thus making them functional to the cognitive instances on learning processes and on the factors that can produce the rise.

PDs can provide a lot of information relevant for both formative and summative assessment; in fact, they allow a new point of observation on student behaviour, whose importance was long known in the literature (Bunderson *et al.*, 1989), but which current technological developments finally make accessible. Until now, the attention of teachers and researchers has been mainly, if not exclusively, focused on summative assessment, i.e. on the product. Today, the opportunities offered by the PDs to acquire information in real time on all the interactions that the student establishes not only with the evaluation tests but also with all the didactic activities (e-activities) that take place through the learning management systems (LMS), are an additional tool in the hands of those who want to start a process of profound renewal of the assessment (Hill *et al.* 2014; DiCerbo *et al.*, 2014), a renewal that places at the centre of the assessment actions the process-oriented dimension of the learning paths. A dimension that is much more congenial to the assessment than those complex skills that can hardly be detected and assessed only with the methods and tools of product assessment (summative assessment). The same summative assessment of complex products needs much more information to integrate those found with traditional assessment tools (tests, standardized tests, etc.), so a different interaction with the formative assessment may be useful.

2 The log files: use and potentiality

The CBT mode of large-scale measurement testing, on which this contribution is focused, is increasingly becoming the reference standard in more advanced countries (Parshall *et al.*, 2002). Since 2018, Italy has been one of the most innovative examples both from the technological point of view and in terms of the number of students involved (INVALSI, 2018). The INVALSI tests of the secondary school are in fact administered to all the students of the third class of the first grade secondary school, of the second grade secondary school and of the second grade secondary school. According to a modern CBT design, students carry out item bank tests based on rigorous psychometric principles that allow them to obtain results for each student on longitudinally comparable Rasch metrics (1980). CBT tests increase the efficiency of administration, the ability to monitor the entire process and reduce errors in the design, implementation and correction phases.

The most important aspect of CBT administration is that it enables the collection of process data (PD), which can acquire information on any interaction between the respondent and the platform that delivers the test (Greiff *et al.*, 2015, p. 92). This is an opportunity that can also prove very useful in the measurement of complex skills, such as soft skills, increasingly cited in schools and universities. However, the problems related to the development and measurement of soft skills are very relevant, because of their obvious intersection with areas from which the school has retracted over the past decades. Several soft skills are related to the sphere of character or aspects very linked to cultural, political, religious visions, from which the mass school in complex and heterogeneous societies has deliberately withdrawn. Some examples are conscientiousness, persistence, openness towards the other. However, their indirect observation using PDs, such as problem solving, can open up very interesting research and application scenarios.

The availability of PDs allows the point of observation to be shifted from the respondent's outcome with respect to a task (the response to a stimulus, open or closed) to the entire process leading to the production of that outcome. The positive aspects of this change of perspective are evident, especially if we consider this change from the point of view of those who observe the individual behaviour of the individual respondent to identify where their learning difficulties lie and to prepare, therefore, appropriate compensation interventions.

PD-based research is still in its infancy, both from the technological point of view and from the more properly theoretical-methodological one. Currently, LFs containing PDs are almost exclusively defined on the basis of the technical characteristics of the platform delivering the CBT tests. This leads to considerable difficulties in their use, but especially in their analysis and interpretation. The development of a general theory that can affect the structuring of PDs, but above all that defines what is important to observe and in what perspective, is almost completely lacking. In this respect, pedagogy, which sees the teaching-learning process as the centre of its interests, can make a very important contribution to the development of LA research.

Even today, PDs are still very much linked to the specific characteristics of the questions to which they refer. This is both an advantage and a limit.

The positive aspect is certainly represented by the fact that the data provide a rather precise and articulated representation of the respondent's behaviour with respect to a given task. However, the information drawn from PDs so linked to a specific type of question is difficult to generalize and compare.

From what has been briefly explained, it is clear that it is appropriate to move from LF, which are, in fact, a sort of technological sub-product, to LF, which become an integral part of the design of the assessment test, whether formative or summative. In this way it is possible to improve the accuracy of the outcome measures by introducing innovative question typologies, after having actually verified their impact on the respondent's behaviour. But above all, it is possible to assess the behaviour of the person who faces a task, observing the processes followed and the resources mobilised in the situation, thus also opening up the possibility of observing competences not strictly related to the construct being measured.

These new scenarios may also trigger new paths of research in other scientific fields, which are crucial for a full understanding of any evaluation process, on a large scale or on a smaller scale. Think, first of all, of educational research and its possible contribution to the definition of the conceptual framework of reference, which is essential to guide the basic decision-making processes for the analysis and exploitation of results. But also in the psychometric field, which can be used of PD to define multidimensional models and not simply multivariate for the definition of the results of a test (Ercikan & Olivieri, 2016, p. 310).

2.1 The value of the log files

It has been said that LFs are generated by the respondent's interaction with the platform that manages the CBT test. The data contained in them, the so called PD, are assimilable to the big data and therefore they are easy to process through the typical methods of the Artificial Intelligence (AI). This opens the way to many opportunities, but also to significant risks. A predominantly exploratory and non-confirming approach, if on the one hand it can open up new horizons of knowledge that cannot be identified a priori, on the other hand it sees a reduction in the methodological, but also ethical control that can be exercised by the pedagogical theories that are involved (Harari, 2018).

The typical structure that LFs have today makes them difficult to understand without the intervention of specific software to facilitate their inspection and analysis. On this aspect, the LA scientific community is producing several open source resources, such as platforms to deliver evidence capable of collecting PDs. However, this is not enough. It is increasingly important that the structure of the LF and the nature of the PDs are defined in the design phase of an assessment test.

PDs can provide a set of information that goes far beyond the final outcome of the respondent's activity with respect to a task (e.g., task reading time, time between reading and the first or last interaction with the task, number of attempts made to solve the task). They would allow to better know the processes that are activated during the performance of the task, to improve the quality of the questions, to customize the analysis of the answers. In addition, PDs would allow to identify more appropriate procedures to prevent unwanted phenomena such as cheating[1] and data fabrication[2], phenomena that are increasingly relevant in the use of CBT tests.

3 Time indicators to investigate respondent behaviour

The first large-scale uses of PDs mainly concerned time indicators. It is still a limited use and, in some ways, only exploratory, but still able to make much more rich and informative the use of PD in the near future.

In this contribution, reference is made to data from the Programme for International Assessment of Adult Competencies (PIAAC) with the aim of showing some of the potential of PDs.

The PIAAC study is conducted periodically by the OECD on a sample basis in the adult population aged between 16 and 64 years. The research is carried out in a sample of about 5,000 adults in each participating country. Data are freely available from OECD website. The aim of the research is to verify the literacy and numeracy skills of adults of working age. The questionnaire consists of literacy and numeracy tasks. The survey is carried out in the presence of a specially trained interviewer. The interviewer has the responsibility of assessing whether the interviewee has basic knowledge in the use of computers. If the verification is successful, the rest of the survey is done by computer, otherwise it continues in paper and pencil format. The PIAAC research is particularly interesting for the purposes of this paper. As these are basic skills of an adult population no longer in school, the strategies and processes activated by the respondents to address the tasks are even more relevant to interpret the answers provided.

PIAAC provides three time indicators:

1. total time spent on an item (time on task);
2. reaction time to the item, i.e. the time between the item being displayed and the respondent's first action on the platform (time to first interaction);
3. time elapsed between the last action on the item and the final confirmation

[1] A set of fraudulent behaviours of the student or teacher in which the correct answer is given or drawn from illegal sources or following the suggestion or direct intervention of the teacher.

[2] Automatic data/response production process capable of delivering hundreds of thousands of tests in a short time.

of the response (time since last action).

The interpretation of time indicators may not be easy and, above all, may lead to very different conclusions. Once again the need emerges for the definition of a theoretical framework of reference that allows the introduction of a confirming dimension in the analysis and interpretation of PD.

Another very important aspect in which PDs can make a significant contribution is the study of missing data. They can represent the epiphenomenon of cognitive and motivational aspects of extreme informative and interpretative relevance. PDs allow you to begin to shed light on how and, potentially, why this missing data is produced.

The PIAAC data show different behaviours with respect to the three above-mentioned indicators based on the level of test result, with respect to the country of origin and the personal background of the respondent. These first and provisional indications seem to encourage the deepening of the study of PD to identify the implementation of different processes, depending on the characteristics of the respondent, for the performance of the same task. Enormous study opportunities would open up for the promotion of positive actions, based on solid and relevant empirical evidence, aimed at improving learning levels. This is a field of research and action perfectly in line with one of the most important functions of LA, that of predicting difficult situations or situations at risk of failure.

Of the three time indicators, the first (TOT) is the easiest to interpret and the most informative. With all due caution, TOT can be considered as a proxy for the respondent's commitment to the task they are facing. This indicator is produced by the interaction of several factors, the most important of which are: a) the level of competence of the respondent, b) the involvement and commitment of the respondent, c) the psychometric characteristics of the question, d) external events of various kinds (distractions, unforeseen events, etc.).

Figure 1 shows a strong variability in the distribution of TOTs between the different questions.

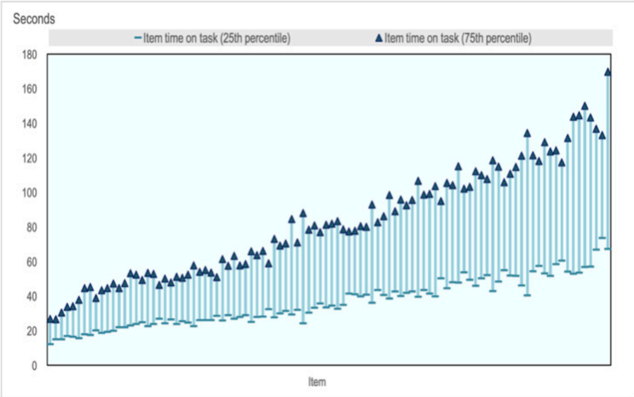

Fig. 1 - Distribution by item of TOT. Source: OECD (2017). PIAAC Log Files.

You can see that there is a large variation in TOT both within and between items. It is therefore clear that the study of the distribution of TOT opens up multiple lines of investigation that allow different assessments to be made on the characteristics of respondents.

Even more interesting is to evaluate the interaction between the median value of TOT of each question according to the type of answer (correct, wrong and missing).

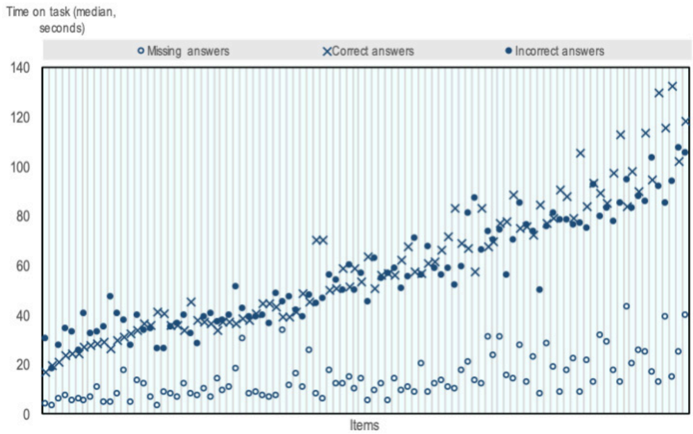

Fig. 2 - Distribution by item[3] and typology of response of TOT. Source: OECD (2017). PIAAC Log Files.

[3] Numeracy and literacy items. The lower end represents the 25th percentile in the TOT distribution aggregating the data of all the countries that performed the PIAAC CBT test and the upper end the 75th percentile.

Figure 2 shows that for each item the respondent providing the correct answer does not stay on the task for a very different time than the respondent providing the wrong answer. This seems to be further proof of the fact that TOT is strongly linked to the characteristic of the item, even more than to that of the respondent. On the other hand, a much lower variability than TOT can be observed in the case of missing answers. This seems to indicate that the decision whether or not to answer is more related to the respondent's characteristics than to those of the question.

Concluding remarks

The technological transformations of recent decades have been so profound that they have ended up influencing the very organisation of our societies, much more than other changes, such as cultural and political changes, have influenced them. However, some authoritative scholars have argued that digital technologies have not produced, in the educational field, those "mega-movers" that instead have produced in other sectors such as medicine, telecommunications, transport or the entertainment industry (Papert, 1993) and that investments in technologies have not been aimed at changing the educational system but only to increase sales of products (Laurillard, 2012; Fullan *et al*., 2013, p. 310). As in all transition phases, even today it happens that while some solutions are proving less and less suitable to solve the problems, there are still no alternative solutions or substitutes for the former. In short, a deadlock between what is no longer appropriate and what is not yet fully available, not by chance called "the swamp" (Fullan *et al.*, 2013, *Ibidem*). Evaluation, within the educational processes, is one of the areas most affected by this stalemate. Many people have seen the development of digital technologies as an important opportunity to renew the evaluation deeply. In 2014, Hill and Barber said: "Next-generation learning systems, however, will create an explosion in data because they track learning and teaching at the individual student and lesson level every day in order to personalise and thus optimise learning. In an online world with intelligent software and a range of devices that facilitate unobtrusive classroom data collection in real time, the big challenges will lie not so much in obtaining data but in managing it and protecting privacy while turning it into powerful knowledge, something that data warehouses built just a few years ago were never designed to support" (Hill *et al.*, 2014, p. 55).

Well, the next-generation learning systems is among us, the explosion of data is in full swing (Hill & Barber, 2014) the real challenge is to be able to manage the huge amount of data made available by digital technologies and ask the right questions. Another important challenge is to be able to give the right importance and the most suitable tools to the evaluation of the process, in a system that has always favoured the evaluation of the product, the final results.

Education and training are affected by changes that need to be addressed in a constructive and balanced way, resisting both past temptations and impulses that, influenced by a kind of technological determinism, emphasize the innovative capabilities of technologies. The objective must be to restore to the educational system that centrality which is progressively losing, using all the resources made available by technological innovations. Artificial intelligence and, in particular, LA will increasingly be the subject of research in the field of education, the results of which may become important information supports for policy makers and for those responsible, at different levels, for educational institutions.

In this contribution we have tried to highlight some aspects related to LA and their potential. If LA, and therefore also PD, are used within a framework that is also pedagogically connoted, then they can become an integral part of the evaluation processes of education systems, contributing significantly to improvement, both at the micro level (the classroom, the school) and at the macro level (the whole system). In this perspective it is therefore possible to make the formative evaluation and the summative evaluation interact, determining a reciprocal and positive contamination, for the benefit of the learner, but also of those who plan the formative actions at various levels.

LA finally seems to offer a concrete way to implement what has always been hoped for, but which has so far proved almost impossible to implement on a large scale. LA can in fact be useful for personalisation, for a more careful evaluation of processes, understood not as a scale down of the importance of goals, but as a decisive factor in them.

All this will be possible, however, if the LAs do not follow only what in the statistical sciences is a clear exploratory approach, i.e. to search in the data for criteria and principles that are not desired or can be established on the basis of a theoretical framework. There is a need for in-depth methodological and theoretical reflection, which certainly finds its natural, though not exclusive, place in the sciences of education.

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LEARNING ANALYTICS TO SUPPORT LEARNERS AND TEACHERS: THE NAVIGATION AMONG CONTENTS AS A MODEL TO ADOPT

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Learners have different needs and abilities; teachers have the ambition to intervene before it is too late. How may e-learning systems support this? Learning Analytics may be the answer but there is not a general-purpose model to adopt. Many learning analytics tools examine data related to the activities of learners in on-line systems. Research efforts in learning analytics tried to examine data coming from LMS tracks in order to define predictive model of students' performances and failure risks and to intervene to improve the learning outcomes. The analytical methods are widely used but no theoretical references are clear.
In this paper, we tried to define a prediction model for learning analytics. In particular, we adopted a Moodle-based LMS in a blended course and collected all data of more than 400 undergraduate students in terms of resource accesses and exam performances. The model we defined was able to identify the learners at risk during their learning processes only by analysing their navigation paths among the contents.

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1 Introduction

The information and communications technologies are changing the teaching and learning approaches adopted into the higher education. This is happening mainly because Internet offers the possibility to gather more content that is open and it is transforming traditional courses into richer online experiences (Hoic-Bozic *et al.*, 2009). Moreover, Learning Management Systems (LMSs) easily allow teachers giving their students additional resources and activities as animation, slides, exercises, quizzes, collaborative components (Piña, 2012). Since all the actions tracked by the LMSs are information about the behaviour of the learners, they become the mean to improve learning and teaching. The analysis of this kind of data is what everybody thinks about the learning analytics (Siemens & Baker, 2012).

Learning analytics are defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Baker, 2012). There are two main approaches for making decisions based on learning analytics techniques. First approach takes into consideration visual analytics in order to provide students with insights on their own progress and teachers with easy to comprehend information about student's competency and decision making on the education context. The second approach of learning analytics refers to collecting and analysing student data to provide a recommending or adaptive system.

Teachers need better insights from the systems about the interaction among students and technologies. To provide them, systems should be more efficient in processing the large amount of data. Since the traditional approaches analyse structured data to provide feedback to the tutors, learning analytics should examine patterns, correlations and try to transform data in a way to support decision-making, or to give benefits to the Intelligent Tutoring Systems themselves.

Many learning analytics tools examine data related to the activities of learners in on-line systems. Some of them analyse the number of user clicks (Siemens, 2013), others investigate the participation into forums (Agudo-Peregrina *et al.*, 2014), some others consider the time spent and the number of email messages sent (Macfadyen & Dawson, 2010). Another approach (Virvou *et al.*, 2015) analyse logs of user actions and, moreover, collects and analyses feedbacks of learners about level of understanding, satisfactory level, emotion and interaction on each learning object in order to correlate actions done by learners to what they perceive about the adopted content. The system itself process all data to support on-line tutors and give them early warnings about progresses of students.

Research efforts in learning analytics tried to examine data coming from LMS tracks in order to define predictive model of students' performances and failure risks and to intervene by providing personalized injections able to change the learning outcomes (Shum & Ferguson, 2012). The analytical methods are widely used but no mention to theoretical argumentation. Moreover, it is very hard to compare studies and draw overall conclusions because the analysis involve usually few institutions, few courses or only special cases (Gasevic *et al.*, 2016). In fact, many studies have examined similar LMS data, have used similar models and predictors but they have found different results (Gaeta *et al.*, 2016).

In this paper, we describe what we have observed and which kind of prediction model we could apply on learning analytics. In particular, we adopted a Moodle-based LMS in a blended course and collected all data of more than 400 undergraduate students in terms of resource accesses and exam performances in order to define a model able to identify students at risk and eventually to create personalized and target actions.

2 Reference scenario

Since the learning analytics examine data, they are, of course, widely data-driven and they do not refer to some specific theories. Their analysis usually refer to raw data coming from the LMS logs and their interpretation has no direct connection to theoretical or methodological models (Marzano & Notti, 2014).

Nevertheless, some recent studies tried to orient the learning analytics approaches versus the interaction theory of Moore (1989), the self-regulated learning (Agudo-Peregrina *et al.*, 2014) or the constructivist theory (Gasevic *et al.*, 2016). Students during their activities may reach different performance although they use the same resources and follow the same suggestions. These theories serve to explain these differences. The measurements adopted in learning analytics do not reflect exactly these theories, thus, other theories such as the situated learning (Brown *et al.*, 1989) or the connectivism (Siemens, 2005) should be considered.

Predicting the students' performance seems to be the principal target of the learning analytics approaches. They should be able to forecast whether a student pass the exam and receive a good final grade. The main models adopt data related to the student features. Recent studies abandoned these features to apply predictive analytical techniques only to data coming from the LMSs. The main problem is that there is a wide variety of systems, variables to consider and techniques, thus, it is hard to point out the best approaches, or in particular, the most effective predictors (Tempelaar *et al.*, 2015).

Rafaeli and Ravid (1997) were the first to use LMS data for learning analytics. They analysed the amount of pages read by the users and compared with their results. They are able to explain only the 22% of the variance of final grades.

Morris, Finnegan, and Wu (2005) found that the number of content pages viewed was a significant predictor, but they examined also posts and time spent on viewing discussions. They reach the 31% in the estimation.

Macfadyen and Dawson (2010) correlated the number of links and files viewed with the final grade. Their researches reached a 33% in the prediction. Moreover, they provided better predictions for "at risk students" by analysing posts, messages and assessments. Their predictions were around the 74% of this kind of students.

In following studies (Nandi *et al.*, 2011), the analysis of the participation of students to forum discussions gave only a 40% of accuracy in the predictions of final grades.

Yu and Jo (2014) examined logs, times, regularities of study intervals, downloads, interactions with peers and with the instructors. They found that only the total time online and the interaction with peers has significant correlation with final grades, but the accuracy of their predictions, however, is around the 34% of the variance.

Zacharis (2015) analysed 29 variables. He found that only 14 of which correlated significantly with final grades. In particular, he found that total time online and the amount of files and links viewed has a significant correlation with the final grades.

On the contrary, Macfadyen and Dawson (2010) did not considered these data in their final prediction model of students' performance, but only the number of viewed files, the interactions and the contributions to content. They reached the accuracy of 52% of the variance of the final grades of their students.

All these researches reached not so much significant percentages of estimation and considered few numbers of learners (around some hundreds). Some wider studies conducted on different platforms considering a more significant number of students (around some thousands) (Beer *et al.*, 2010), showed as their main result, that the higher correlation with the final grades is on the number of clicks.

Recent studies underlined that is still unclear how to use data coming from LMSs for predictive modelling and, in case there is a model, its portability is a crucial step because its effectiveness depends on the learning design approach used to create the course (Miranda *et al.*, 2017). By collecting all the variables considered by the most effective learning analytics approaches, the researchers recommended to consider the following parameters: total number of clicks, number of online sessions, total time online (min), number of course page views, irregularity of study time, irregularity of study interval, largest period of inactivity (min), time until first activity (min), average time per session (min), number of resources viewed, numbers of links viewed, number of content page views, number of discussion posts views, total number of discussion posts, number of quizzes started, number of attempts per quiz, number of quizzes passed, number of quiz views, number of assignments submitted, number of assignment views, number of wiki edits, number of wiki views, average assessment grade.

As alternative and holistic methodologies are starting to get interest the Multimodal Learning Analytics (MMLA) systems. They include multiple data sources and the data organization and the data processing they need is very complex. For this reason, the creation of MMLA software architectures is quite complicated and their adoption is not so wide.

We hope the issues raised in this paper are useful for the growing community of MMLA researchers. We believe that the short- and medium-term MMLA agenda should encourage researchers to pay special attention to the design of flexible infrastructures that support the whole data value chain, enabling the scalable adoption of MMLA, in real scenarios, and in a sustainable way (Shankar *et al.*, 2018).

Nowadays, the LMSs are widely adopted by institutions and they are generating large amounts of data that are indicative of the interactions of learners with the systems. The goal of the Learning Analytics is being proactive in order to mitigate the risks, to improve the engagement and to increase the performances of learners. In fact, Learning Analytics allow institutions improving the quality of their e-learning courses, fine tuning learning strategies and ensuring better interventions (Mothukuri *et al.*, 2017).

In particular, researches in Learning Analytics are going on to face the well-known problems in MOOC (Massive Open Online Course) environments, such as reducing the high dropout ratios, predicting the student performance or gauging the effectiveness of educational resources and activities on learners (Munoz-Merino *et al.*, 2015).

Elaborating all this data is quite difficult and expensive. Often, LMSs do not allow accessing all of them in order to apply deeper learning analytics (Sergis & Sampson, 2017). Therefore, the goal of this paper is to find a model simpler and effective as well that could be applied in e-learning platforms and support MOOC environments.

3 Methodological approach

In line with the reference scenario, we are trying to define a model that should have a good predictive accuracy and that allows teachers monitoring their students and intervene on their learning processes before it is too late.

We started this research in the cohort 2017-2018 by involving 140 students in the undergraduate courses of Computer science basics for the bachelor degree in Educational Sciences, at the University of Salerno (Miranda *et al.*, 2019). The experiments went on in the following cohort 2018-2019 by involving 267 other students.

We collected data from the Moodle LMS of students that took the final exam on the first round in June immediately after the in-presence activities. Thus, we are going to analyse the data tracked for the total amount of 407 student.

The course has 37 resources: 19 lessons, 11 exercises and 7 formative assessments.

1. Introduction
2. Lesson 1.1: Introduction on computers
3. Lesson 1.2: Basic notions
4. Lesson 1.3: Representation of Information
5. Assessment n.1
6. Lesson 2.1: Sound coding
7. Lesson 2.2: Character encoding standard
8. Lesson 2.3: The coding of numbers
9. Assessment n.2
10. Lesson 3.1: Computer architecture
11. Lesson 3.2: Programming concepts
12. Lesson 3.3: CPU operation
13. Assessment n.3
14. Lesson 4.1: Algorithms
15. Lesson 4.2: Basic programming concepts
16. Assessment n.4
17. Lesson 5.1: Sorting algorithms
18. Lesson 5.2: Animations sorting algorithms
19. Lesson 5.3: Operating system
20. Assessment n.5
21. Lesson 6: Computer networks
22. Assessment n.6
23. Lesson 7.1: Scratch Off line Environment
24. Lesson 7.2: Scratch On Line Environment
25. Lesson 7.3: Scratch script foundations
26. Scratch Exercise 1
27. Scratch Exercise 2
28. Scratch Exercise 3
29. Scratch Exercise 4

30. Scratch Exercise 5
31. Scratch Exercise 6
32. Scratch Exercise 7
33. Scratch Exercise 8
34. Scratch Exercise 9
35. Scratch Exercise 10
36. Scratch Exercise 11
37. Assessment n.7.

The final exam was an online quiz on the same Moodle platform. The students that gained more than 5.75 points out of 10, passed the exam, the others that did not reach this threshold, failed it.

Learning analytics directly available on Moodle may identify students at risk of abandon or may raise warnings for the absence of the teachers and tutors, but they are not able to provide any kind of forecasting about the final learning outcomes.

Since we gave to the students the maximum flexibility in the use of resources, we started analysing the way the learners navigate among them. In particular, we observed that, among the variables considered in the reference scenario, there is no mention of the navigation path. This means that the order the learners navigate among the content has not been considered as a possible predictor of the learning outcomes. In fact, from the analyses conducted in our first experimentation (Miranda *et al.*, 2019), we understood there is no significant correlation between the exam grade and the number of contents seen. Moreover, there is no significant correlation between the exam grade and the visualizations of specific contents or even the time spent online.

Since we observed that chaotic navigation rarely leads to good results, the navigation path itself could be the only indicative element that could represent a variable to consider in the prediction. Consequently, we would show that the students that follow the most orderly paths achieve the better learning outcomes. First, we should define what we mean by an "orderly path". We identified the resources in the course as the previous numbered list from n.1 to n.37. Thus, the orderly path is the following sequence:

"1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37".

The resources and the assessments are in this order because they respect the requirements of the topics they treat. In other words, for instance, we suggest studying the content n.3 before studying the content n.4 because it will be easier to understand the concepts in the content n.4 if you have some knowledge about the content n.3.

Second, we should define some criteria able to measure the distance between the "orderly path" and the student path.

This problem seems a problem occurring in computational biology and in coding theory: comparing and finding common features in sequences or, more in general, measuring distances between two strings.

This theory named "String metric" has a wide variety of solutions including Hamming distance and similar measures. A good criterion for measuring the distances between the two paths is those of Levenshtein (1966). In information theory and language theory, the Levenshtein distance, or edit distance, is a measure for the difference between two strings. It serves to determine how two strings are similar. It is applied, for example, to simple spelling check algorithms and to search for similarities between images, sounds, texts, etc. The Levenshtein distance between two strings X and Y is the minimum number of elementary modifications that allow transforming X into Y. By elementary modification, we mean the deletion of a character, the substitution of one character with another or the insertion of a character. In our case, the characters are the number corresponding to the learning resources and the Levenshtein distance between the "orderly path" and the student path is the similarity between them. This means that the lower the Levenshtein distance, the more the path of the student is close to the right order.

4 Learning analytics results

The data we got from the Moodle LMS are those related to the completion of the students. The "completion report" includes all dates and times in which the students completed each learning activity: when they read a document, watched a video or submitted a test. This allows us understanding which content has been shown before other ones and which activity has been completed before other ones (Fig.1).

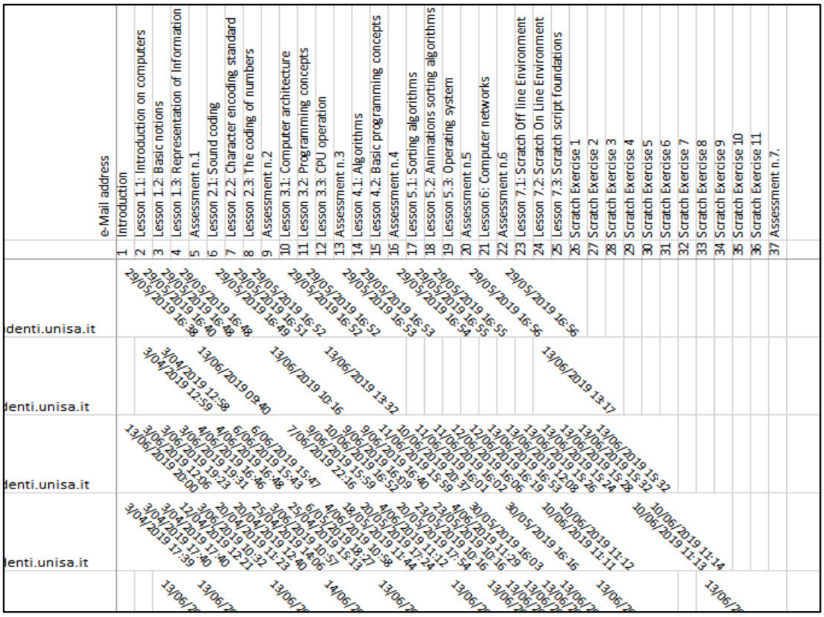

Fig. 1 - The "Completion report" shows all dates and times in which students completed learning activities.

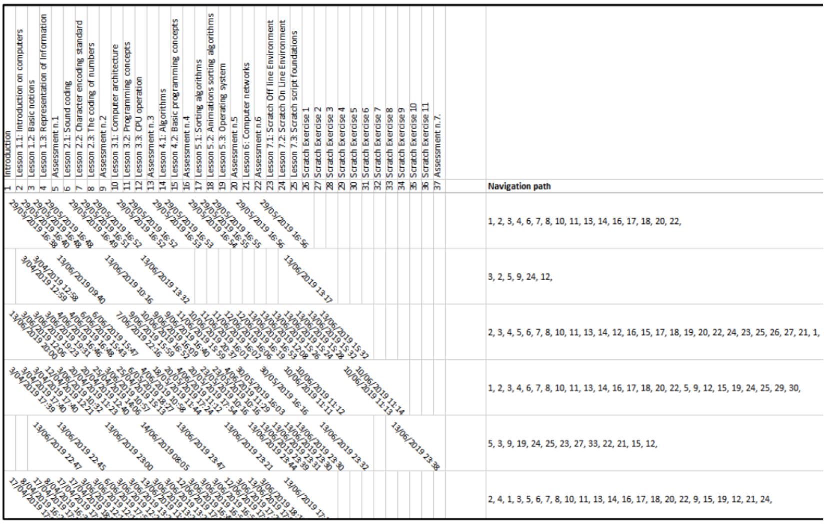

Fig.2 - The navigation paths shows the order the learners followed during their learning experience in the LMS.

We supposed this distance could be indicative of the results. Therefore, we tried to define a sort of prediction of learning outcomes by analysing navigation paths and comparing them with the reference “orderly path”.

The easiest way to do it is to define a threshold on the distance and try to do some estimations.

The estimation algorithm we used is very simple and it is in the following:

- IF the Levenshtein Distance is under the Threshold, THEN the Student will pass the final Exam
- ELSE, the Student will not pass the final Exam.

Empirically, we tried all the possible values for the threshold in order to maximize this estimation. The procedure we adopted is in the following:

1. Measure the Levenshtein Distances among the strings relative to the paths of the learners and the string of the “orderly path”
2. Find the maximum M among all the measured distances
3. Try all the possible values of the threshold T between 0 and M
4. For each value of T, estimate by using the pointed out estimation algorithm, which student passes the final Exam and evaluate the total success percentage.

The best results we got are for the threshold equal to 65. In fact, we are able to predict positive results of 313 students out of 407. This means that the percentage of estimation is close to 77% (Table 1, First estimations).

This allowed us forecasting whether a student will pass or will not pass the final exam only by observing his/her navigation path (Fig.3).

This seems to be a good results but it has a poor applicability. In particular, if we think in terms of learning analytics, understanding which will be the learning outcomes at the end of a process could not have a high relevance. Thus, we tried to do the same evaluation by analysing just a half of the learning path of each student. It means that we would try if we were able to predict whether the learning outcomes will be good when the learners are in the middle of their learning processes. This should be relevant because there is time to intervene and eventually fill the gap to move the learners on the right way to reach their goals.

To do it, we considered only a half of the orderly path as a reference and we compared it with the half navigation path of each learner, by measuring, the Levenshtein distance.

Once again, empirically, we tried all the possible values for the threshold in order to maximize this estimation. The best results we got are for the threshold equal to 80. In fact, we are able to predict positive results of 301 students out of 407. This means that the percentage of estimation is close to 74% (Table 1, second estimations). Data and predictions are in Fig.4.

Orderly path			
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37,			
Navigation path	**Lev.D.**	**Exam passed**	**Prediction**
2, 3, 1,	130	0	0
1, 2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 5, 9, 20, 22, 24, 25, 23, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 12, 15, 19, 21,	36	1	1
2, 1, 4, 3, 6, 7, 8, 5, 9, 10, 11, 12, 15, 20, 21, 33, 13, 19, 36, 14, 16, 17, 18, 22, 23, 24, 25, 26, 27, 29, 30, 31, 32, 34, 35, 28,	42	1	1
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 25, 24, 22, 19, 20, 21, 23, 27, 29, 33, 26, 28, 30, 31, 32, 34, 35, 36,	23	1	1
25, 22, 2, 3, 10, 23, 11, 1,	114	0	0
1, 2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 20, 22, 23, 24, 26, 27, 30, 31, 34, 25, 5, 28, 29, 32, 36, 21, 12, 15,	44	0	1
3, 2,	133	0	0
2, 1, 3, 6, 7, 8, 9,	118	0	0
1, 2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 20, 22,	82	0	0
13, 14, 11, 2, 3, 4, 5, 24, 22, 25, 26, 36, 33,	94	0	0
2, 4, 3, 6, 7,	124	0	0
2, 4, 16, 17, 3, 5, 9, 15, 21, 24, 36, 12, 19,	99	1	0
2, 4, 6, 7, 8, 10, 11, 3, 13, 14,	105	0	0
2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 20, 22, 5, 9, 24, 15, 25, 29, 30, 28, 34, 31, 35, 36, 19, 1, 21, 26, 33, 32, 23, 27,	49	1	1
1, 2, 3, 4, 5, 25, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 22, 24, 29,	60	1	1
1, 2, 4, 6, 7, 8, 10, 11, 13, 14, 16, 18, 20, 3, 5,	87	0	0
2,	136	0	0
2, 4, 6, 7, 8, 10, 11, 1, 13, 14, 16, 17, 18, 20, 22, 3, 5,	79	0	1
2, 24, 36, 3, 4, 1, 22, 10, 16, 17, 23, 25, 6, 7, 8, 11, 13, 14, 18, 20, 26, 34, 27, 31, 28, 29, 33, 35, 32, 30, 5, 9, 15, 21, 19, 12,	53	0	1
1, 2, 3, 4, 5, 6, 7, 8, 10,	111	0	0
1, 2, 3, 4, 6, 7, 8, 10,	114	0	0
2, 1, 4, 3, 24, 6, 7, 8, 22, 10, 11, 13, 14, 16, 17, 18, 20, 23,	84	0	0
2, 3, 13, 4, 5, 6, 8, 1, 7, 9, 10, 11, 14, 15, 16, 17, 18, 20, 12, 22, 24, 36, 23, 25, 27, 19, 21,	57	1	1
2, 23, 25, 26, 24, 28, 34, 33, 3, 4, 6, 7, 10, 16, 20, 22, 30, 8, 11, 27, 21, 5, 9, 12, 29, 31, 32, 35, 36, 13, 14, 15, 1, 17, 18, 19,	62	0	1
2, 3,	133	0	0
2, 3, 22, 4, 5, 6, 7, 8, 10, 11, 9, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 32,	61	1	1
2, 3, 4, 1, 25, 5, 6, 7, 8, 10, 9, 11, 12, 13, 15, 16, 19, 20, 21, 22, 23, 24, 33, 34, 26, 27, 28, 29, 30, 31, 32, 35, 36,	40	1	1
2, 1, 3, 4, 6, 7, 8,	118	0	0
2, 3, 4,	130	0	0
1, 2,	133	0	0
1, 2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 20, 22,	82	0	0

Fig.3 - In each raw there is the navigation path of the learner, the Levenshtein distance (Lev.D.) between the navigation path and the orderly path, whether the student passed or not the final exam (1 if passed, 0 if not passed) and the prediction of it.

Table 1
DATA RELATED TO BOTH THE FIRST AND THE SECOND ESTIMATIONS

	First estimations	Second estimations
Threshold value	65	80
Number of good prediction	313	301
Number of bad predictions	94	106
Number of students	407	407
Success percentage	76.9%	73.96%

Half orderly path			
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19			
Half navigation path	**Lev.D.**	**Exam passed**	**Prediction**
2, 3, 1,	130	0	0
1, 2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 5, 9, 20, 22, 24, 25	73	1	1
2, 1, 4, 3, 6, 7, 8, 5, 9, 10, 11, 12, 15, 20, 21, 33, 13, 19, 36, 14	80	1	0
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 25, 24	70	1	1
25, 22, 2, 3, 10, 23, 11, 1,	114	0	0
1, 2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 20, 22, 23, 24, 26,	70	0	1
3, 2,	133	0	0
2, 1, 3, 6, 7, 8, 9,	118	0	0
1, 2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 20, 22,	82	0	0
13, 14, 11, 2, 3, 4, 5, 24, 22, 25, 26, 36, 33,	94	0	0
2, 4, 3, 6, 7,	124	0	0
2, 4, 16, 17, 3, 5, 9, 15, 21, 24, 36, 12, 19,	99	1	0
2, 4, 6, 7, 8, 10, 11, 3, 13, 14,	105	0	0
2, 3, 4, 6, 7, 8, 10, 11, 13, 14, 16, 17, 18, 20, 22, 5, 9, 24, 15, 2	72	1	1
1, 2, 3, 4, 5, 25, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19	78	1	1
1, 2, 4, 6, 7, 8, 10, 11, 13, 14, 16, 18, 20, 3, 5,	87	0	0
2,	136	0	0
2, 4, 6, 7, 8, 10, 11, 1, 13, 14, 16, 17, 18, 20, 22, 3, 5,	79	0	1
2, 24, 36, 3, 4, 1, 22, 10, 16, 17, 23, 25, 6, 7, 8, 11, 13, 14, 18,	81	0	0
1, 2, 3, 4, 5, 6, 7, 8, 10,	111	0	0
1, 2, 3, 4, 6, 7, 8, 10,	114	0	0
2, 1, 4, 3, 24, 6, 7, 8, 22, 10, 11, 13, 14, 16, 17, 18, 20, 23,	84	0	0
2, 3, 13, 4, 5, 6, 8, 1, 7, 9, 10, 11, 14, 15, 16, 17, 18, 20, 12, 22	79	1	1
2, 23, 25, 26, 24, 28, 34, 33, 3, 4, 6, 7, 10, 16, 20, 22, 30, 8, 11,	86	0	0
2, 3,	133	0	0
2, 3, 22, 4, 5, 6, 7, 8, 10, 11, 9, 12, 13, 14, 15, 16, 17, 18, 19, 2	80	1	0
2, 3, 4, 1, 25, 5, 6, 7, 8, 10, 9, 11, 12, 13, 15, 16, 19, 20, 21, 22	82	0	0
2, 1, 3, 4, 6, 7, 8	118	0	0

Fig.4 - In each raw there is the half navigation path of the learner, the Levenshtein distance (Lev.D.) between the half navigation path and the half orderly path, whether the student passed or not the final exam (1 or 0) and the prediction of it.

Conclusions

Learning analytics examine data coming from LMS tracks in order to provide feedbacks to learners and change their learning outcomes, but they have not reference to some specific theoretical argumentation. Many researches have examined similar LMS data and used similar models and predictors but they have found different results. Some researches reached significant percentages of estimation but they considered few numbers of learners. Recent studies underlined that is still unclear how to use data coming from LMSs for predictive modelling and, in case there is a model, its portability is a crucial step because its effectiveness depends on the learning design approach or on the technologies used to create and deliver the course. The best approaches uses much kind of data, but LMSs do not allow accessing all of them in order to apply deeper learning analytics and, generally, elaborating all these data is quite difficult and expensive.

Therefore, the goal of this paper is finding a model simpler and effective as well. We described a prediction approach adopted for learning analytics on data coming from a Moodle-based LMS. In line with the reference scenario, we defined a model that have an interesting predictive accuracy and that allows teachers monitoring their students and intervene on their learning processes before it is too late.

We started this research in the cohort 2017-2018 and went on in the following cohort 2018-2019. We experimented our model on more than 400 students.

Our model refers to navigation path of the learners and is able to provide predictions on the possible learning outcomes when the students are in the middle of their learning processes, so teachers and tutors may have enough time to identify students at risk and, eventually, to create personalized and target actions to improve their performances.

This approach could have some major benefits. From the learner point of view, since it is able to provide predictions on the performances inside an e-learning course, it may be useful to give direct feedbacks and suggest directly to the students some specific order to follow or some particular topic to go in deepening. It could be used also to compare performances among students and creating, by using some gaming approaches, new stimulus for the students themselves. However, it could be able to motivate learners and recommend them resources and activities to reach better results.

In fact, current researches in educational psychology reveals that learners do not use optimal tactics and strategies during their learning processes and, often, they are unaware of the employed study tactics. Just providing them information about the benefits of some of the effective tactics and strategies increases their chances to get better learning outcomes. Moreover, suggestions coming from Learning Analytics are more effective when the learners themselves increase their awareness of the approaches they are following or they should adopt. Therefore, the future work on user-centred learning analytics systems should be on finding the right mechanisms to communicate with the learners by means of complete and effective dashboards able to allow them optimizing their learning processes (Matcha *et al.*, 2019).

From the teacher point of view, the approach we presented in this paper may give an overall picture on the involved learners. It may help teachers monitoring their students' progresses. It may raise warnings on particular contents and activities, on particular students that are at risk of abandon or at risk in reaching their learning goals. It can identify learners needing some helps and provide them support in terms of strategies, learning styles, suggestions or, simply, motivation add-ons in order to increase the quality of teaching and, consequently, the quality of their learning processes. It may also give feedbacks about the instructional design. In fact, the results and, in particular, their relevance even if it is measured at the end of the learning experience, allows getting something about the effectiveness of the course itself, about the quality of its structure, about resources and activities it contains.

Our simple-to-use learning analytics approach may be implemented in a communication dashboard for both learners and teachers. It may become the mean to raise alerts and to lead a learning support system able to visualize information and to show feedbacks and suggestions.

As it is, our model represents a quite good predictor, which could be improved by getting suggestions from other models adopted in the literature. Some of them refer to data complex to get and analyse, some other ones refer to data easier to collect.

In this research, although we did not consider any other parameters different from the navigation paths, the results are encouraging. We are confident that by relating these results with the analysis of some features more, we could define a more effective approach for learning analytics, reach better results in the prediction of learning outcomes and provide a model for support systems useful for MOOCs and any other kind of LMSs.

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HOW TO USE ASSESSMENT DATA COLLECTED THROUGH WRITING ACTIVITIES TO IDENTIFY PARTICIPANTS' CRITICAL THINKING LEVELS

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Keywords: Critical thinking, evaluation, automatic assessment, open-ended questions, writing activities

The present paper aims at presenting the Critical Thinking (CT) Skills assessment results in teachers participating in the Erasmus+ KA203 CRITHINKEDU summit (Critical Thinking Across the European Higher Education Curricula), organised in Leuven in June 2019. Within the summit, a workshop was organized to promote in participants' CT skills knowledge, especially in terms of CT assessment methods through open-ended questions. Based on our theoretical assumptions, description and interpretation activities of written text promote skills such as Analysis, Argumentation, Inference and Critical evaluation, which can also be defined in terms of improvement of language skills. Teachers participating in the workshop were assessed through a test composed by literary text paraphrase and commentary exercises; a prototype for the automatic assessment of CT in open-ended answers was used to evaluate the open-answers. Also three human raters evaluated the answers' texts. The goal of the present research

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was to verify the assessment method reliability and to collect some data useful for the implementation of the automatic prototype.

1 Introduction

The definition of Critical Thinking (CT) in education has been representing a crucial issue of scholarly debate for the last century and still is today. It is a central topic of discussion not only in the field of education, given its significant implications in many areas of knowledge, ranging from philosophy to science and from technological innovation to economics. CT skills are more and more defined by educational policy as pivotal for human and social progress in terms of innovation, economic and knowledge growth (World Economic Forum, 2016; Scott, 2015). The promotion of CT learning and teaching methods and assessment tools should be considered as an urgent need in all the formal educational context, taking into consideration the different dispositions and cognitive skills to be promoted at school and university level. According to Paul and Elder (2006), there is a significant relationship between literature and CT development; moreover, Bloom (2000) highlights that reading literature is fundamental in order to know ourselves: close and individual reading allows for memorization, without which we are not able to think (Poce, 2017). According to Esplugas and colleagues (1996), thanks to an in-depth analysis of literary text, many meaningful actions may be encouraged to develop CT, for example: the identification of multiple meanings in the literary text, the use of background knowledge and the recreation of those processes leading the author to conceive the text in the form we read it. Once the great value of the literary text for the purposes of CT development has been shown, it is necessary to reflect upon the best tools suitable to achieve our teaching objectives and for assessing them.

2 Assessing Critical Thinking

Writing is widely considered to be one of the most effective practices for interpretation, elaboration and argumentation purposes. Moreover, writing activities present positive aspects for collecting data useful in terms of CT monitoring and evaluation (Poce, 2017). However, a general lack of agreement on the definition of CT led to the production of different assessment methods. Indeed, the conceptualization and the assessment of CT are interdependent issues that must be discussed together: the definition of CT determines how to best measure it. The most common measurements fall into four categories (Ku, 2009; Liu, Frankel, & Roohr, 2014): 1. multiple choices (e.g. Watson & Glaser, 1980; Facione, 1990b); 2. open-ended answers (e.g. Ennis & Weir, 1985); 3. Self-report measures (e.g. Facione, Facione & Sanchez, 1994); 4.

mixed methods (e.g. Halpern, 2007).

Although multiple choice tests could guarantee a higher reliability, they present problems in terms of validity (Poce, 2017). Ennis (1993) recommends the adoption of the short essay because it allows to assess the CT underlying dimensions and personalize the assessment tool based on the teachers' educational objectives. Open-ended questions offer the benefit of evaluating CT on the basis of all dimensions (skills and dispositions, defined by Facione, 1990a). Ennis (1993, p.185) suggests the adoption of the short essay for assessment purposes and distinguishes three structure levels: high, medium and low. There are numerous examples for each of the three levels. For instance, Ennis Weir Critical Thinking Test (1985) was created for the most advanced structure, while the Illinois Critical Thinking Essay Contest (Powers, 1989) was created for the lowest level. Despite these positive aspects, essays and open-ended measures could present problems related with inter-rater reliability and high-cost of scoring. Automated scoring could be a viable solution to these concerns (Liu, Frankel, & Roohr, 2014).

Starting from these assumptions, the Center for Museum Studies – CDM research group autonomously developed a prototype for CT assessment on the basis of the studies carried out by Ennis and Newman, Webb and Cochrane (1995) which aims at meeting validity and reliability criteria to gain relevant information for future data collection.

The prototype is based on a rubric developed in previous research by Poce (2017) aimed at evaluating CT through short essays or open-ended answers and overcoming the problems of reliability related to CT assessment in open-ended questions. The rubric is composed by six different indicators: *Use of Language*, *Justification*, *Relevance*, *Importance*, *Critical Evaluation* and *Novelty* (Poce, 2017). The prototype has been adopted to automatically assess four of the six CT macro-indicators: *Use of Language*, *Relevance*, *Importance*, and *Novelty*.

In the present paper we will present the results of CT skills in professor participating in the workshop *How to assess critical thinking skills through writing?* organised in June 2019 within the CRITHINKEDU project. The assessment data has been analysed by involving expert human evaluators together with the automatic assessment method in order to collect preliminary validity evidence regarding the use of our CT assessment method. More specifically, the research here presented is aimed at answering to the following research questions:

Which level of CT are shown by participants in the sample analysed?

Which level of reliability are shown respectively by the manual and the automatic assessment methods?

2.1 Context of the research: the CRITHINKEDU Project

The CRITHINKEDU project (Critical Thinking Across the European Higher Education Curricula) is an Erasmus+ KA203 Strategic Partnership project started in September 2017 and lasted 36 months. The universities participating in the project are 10 from 9 different countries: Universidade de Trás-Os-Montes e Alto Douro (coordinator, Portugal), Universidad de Santiago de Compostela (Spain), University of Roma TRE (Italy), University of Wester Macedonia (Greece), University of Thessaly (Greece), National University of Ireland (Ireland), UC Leuven (Belgium), Siuolaikiniu Didaktiku Centras (Lithuania), Vysoka Skola Ekonomicka V Praze (Czech Republic) and Academia de Studii Economice din Bucuresti (Romania).

The project arises from the background and the experience of European Higher Education Institutions, business corporations and Non-Governmental Organizations, and their ongoing concern to improve the quality of learning in universities and across different sectors, which converge in a common need on how to better support the development of CT according to labour market needs and social challenges.

The main objective of the project is to design a model of CT university teaching and learning activities to be adopted at transnational level and in the various partners' courses, promoting CT education around Europe and providing an academic environment that supports the diverse cultural learning needs of international students.

After a first analysis of CT disposition and skills needed in different fields of work and an analysis of the university learning and teaching context in terms of CT promotion, the CRITHINKEDU course was designed in order to promote and support quality teaching on CT (Dominguez, 2018). It provides educational resources and practical training activities within different key topics, such as learning design, teaching methods and CT assessment. By engaging teachers with effective instructional design principles, teaching strategies, and assessment criteria for CT, they were encouraged to integrate them in the daily teaching practice. The CRITHINKEDU project realized and published an educational Protocol on CT development (Elen *et al.*, 2019) which reflects a historically situated, operational understanding of the theoretical and empirical research on CT on one hand, and actual experiences with developing CT on the other.

2.2 Methodology

As part of the CRITHINKEDU research and dissemination activities, the *First European Summit of Critical Thinking* was organized in Leuven in June

3rd, 2019 at KU Leuven in Belgium. The Summit involved higher education researchers and educators, deans, student support agencies, policymakers and employers eager to invest in CT education. During the Summit, different workshops were organized in order to support a deeper analysis on CT learning and teaching methods at university level: teachers from different fields of study had the possibility to enhance their knowledge on the topic.

In particular, the workshop "*How to assess critical thinking skills through writing?"* was aimed at presenting different tools for assessing CT and analysing them from a pedagogical point of view, promoting participants' knowledge acquisition in CT assessment methods context and their critical reflection on the topic. The workshop was composed by the following sections:

1. CT assessment tools presentation: different tools for assessing CT were proposed and analysed from a pedagogical point of view, highlighting the relationship between learning objectives, tools and university teaching methodologies.
2. Text paraphrase and commentary to promote and assess CT skills: the *Verba sequentur* model. The model designed by the research group author of the present paper, within the *Verba sequentur* project, was presented to workshop participants and discussed. The model was designed taking into consideration the research hypothesis by which text description and interpretation through writing led to the development of student CT skills. It was also analysed as an assessment model in different fields of study, from the social sciences to the humanities and STEM. All the indicators of the prototype for CT assessment were in-depth analysed by participants.
3. CT assessment tool design. The prototype for CT assessment was used in order to create new CT tests in different fields of study and teaching. Participants were divided in group taking into consideration their fields of study: Social Sciences, STEM, Humanities, Health, Business and political studies. Each group had to design a teaching activity, addressed to university students and aimed at CT skills promotion, and elaborate the related CT assessment test, taking into consideration the model proposed in the previous section.
4. A final plenary session allowed participants to present the evaluation tools realised and to discuss them together with the workshop presenters.

At the beginning of the workshop, the participants' CT skills level was evaluated through a particular kind of text composed by literary text paraphrase and commentary exercises, elaborated taking into consideration the *Verba sequentur* model.

2.3 How to automatically assess Critical Thinking

In recent years, the idea to support Critical Thinking assessment through automatic scoring has been growing. In a review from Liu, Frankel and Roohr (2014) the authors presented different tools to assess automatically CT both for short-answer and essay questions. Answers' contents (e.g., knowledge accuracy) are mainly assessed in short-answer items. C-rater and c-rater-ML are two tools commonly used to automatically evaluate open answers, both developed by Educational Testing Service (ETS). These two tools utilize natural language processing techniques to score knowledge accuracy (Mao *et al.*, 2018). On the other hand, the writing quality of the responses (e.g., grammar, coherence and argumentation) are usually assessed in short essays. For instance, a functional model to evaluate automatically arguments in dialogical and argumentative contexts was proposed by Gordon, Prakken and Walton (2007). In addition, it was also developed a computational model to identify moments within e-discussion in which students adopted critical and creative thinking (Wegerif *et al.*, 2010). Developing a computational model to identify Critical Thinking levels in students' written comments could provide many advantages. For instance, an automatic program could assist researchers and teachers in finding key aspects of Critical Thinking in big amounts of data in Learning Management System platforms. Results could be used to implement the digital learning environment (Miranda, Marzano, & Lytras, 2017) and students learning engagement (Gaeta *et al.*, 2017). In the field of Learning Analytics (Siemens & Baker, 2012), a growing number of studies have been focusing on the automatic analysis of big corpus of linguistic data (Ezen-Can *et al.*, 2015; McNamara *et al.*, 2017). Nevertheless, before adopting these kinds of tools to automatically assess Critical Thinking, the accuracy of automated scores need to be examined. Indeed, it is necessary to be sure they achieve an acceptable level of agreement with valid human scores. However, only few studies have evaluated the accuracy of automatic scoring test for Critical Thinking Assessment (Mao *et al.*, 2018). From our perspective, more research is needed in terms of development and validation of automatic tools for Critical Thinking assessment. Within the research group, the idea to develop an automatic tool for Critical Thinking assessment has been recently started. The tool is organized in four main modules that allow to perform all the operations necessary to obtain the experimental results. The four modules are described below:

1. *Authentication Manager*: the module allows online registration via email and provides a secure login form to access the services offered. Every operation within the system is logged anonymously.
2. *Input module*: this module manages the insertion of the questions and

answers to be evaluated. A title, the text of the question and a *golden answer* are required for each question. Users are also asked to include words representing the *concepts* and the *successors* respectively for the evaluation of importance and novelty. Concepts could be defined as the topics that should be covered in a correct and exhaustive answer. Successors represent, instead, deepening or related topics of the given concepts.

3. *Manual evaluator*: through this module, experts can manually evaluate the answers.
4. *Automatic evaluator*: this module is the heart of the system which uses two external tools to perform the automatic evaluation for the four indicators presented.

Use of language: the system uses an external tool that provides a value calculated by normalizing the number of errors considering the number of words contained in the answer.

Relevance: the indicator is assessed carrying out an analysis of the concepts. The text is processed by a Part of Speech Tagger, a software that extracts entities such as nouns and verbs from any kinds of text. After a stemming process that reduce the words to their root, an algorithm is applied on this set of nouns by generating n-grams with a length from one to three. The number of the intersection between the n-grams and the concepts will give the relevance of the answer.

Importance: the system exploits an open source knowledge base. Initially, the text of the answer is sent to an online tagging service through entities pages. The service returns a set of entities pages associated with a given text, in our case the text of the answer. Afterwards, each defined concept is automatically linked to its page. All the outgoing links of this page are considered. The importance indicator is given by the number of known pages that the tagging service system detects respectively from the answers given by the participants and from the concepts defined by the assessor/researcher.

Novelty: the indicator is assessed carrying out an analysis of the successors. As for the relevance indicator, all the nouns and n-grams are extracted from the answers' texts. The frequency of intersections between n-grams and successors results in the novelty dimension of the answer

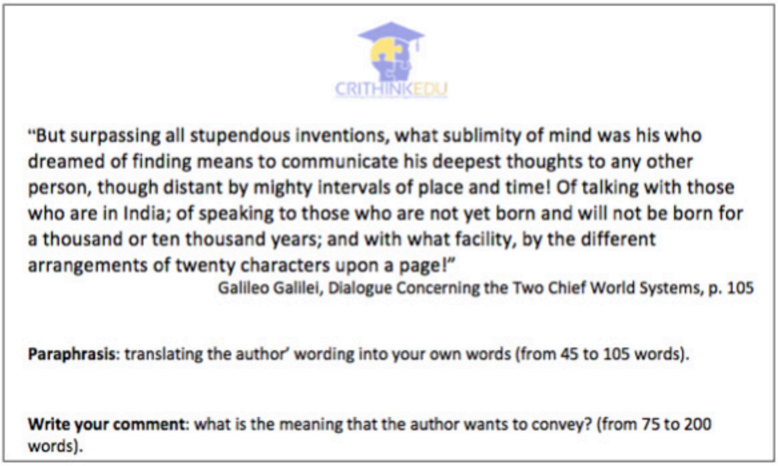
2.4 Data collection: CT assessment test

18 participants took part in the workshop. The participants were mainly European university teachers involved in the field of CT promotion and evaluation in HEI context. For privacy reasons, data were collected

anonymously. The participants were asked to write in 20 minutes a paraphrase and a comment starting from an extract of Galileo Galilei "*Dialogue Concerning the Two Chief World Systems*".

The participants were provided with a template which included the following instructions (Figure 1):

1. Paraphrase: translating the author's wording into your own words (from 45 to 105 words).
2. Write your comment: what is the meaning that the author wants to convey? (from 75 to 200 words).



CRITHINKEDU

"But surpassing all stupendous inventions, what sublimity of mind was his who dreamed of finding means to communicate his deepest thoughts to any other person, though distant by mighty intervals of place and time! Of talking with those who are in India; of speaking to those who are not yet born and will not be born for a thousand or ten thousand years; and with what facility, by the different arrangements of twenty characters upon a page!"

Galileo Galilei, Dialogue Concerning the Two Chief World Systems, p. 105

Paraphrasis: translating the author' wording into your own words (from 45 to 105 words).

Write your comment: what is the meaning that the author wants to convey? (from 75 to 200 words).

Fig. 1 - CT assessment test used during the workshop

After 20 minutes of the writing activities, participants were invited to reflect upon the assessment of CT through the written analysis of literary texts and providing feedback. The use of paraphrase and commentary exercise depended on the workshop objectives: literary text paraphrase and commentary require the simultaneous use of textual, linguistic and expression skills and they also set up and mobilise CT, analysis and argumentation skills. Paraphrase requires participants to rewrite the literary text by reproducing the original meaning and smoothing out the semantic, lexical, syntactic and content difficulties (Serianni *et al.*, 2003). Paraphrase is based on a thorough understanding of the meaning of the source text and favours the skill in making a comprehensible text in a form that differs from the original one chosen by the author. The commentary of the literary text requires workshop participants to provide a single and deep interpretation of the whole text created by the author, stating, elaborating and exemplifying the thesis of the extract, the author' purpose, the most significant information and concepts. Accordingly, commentary "actively" involves workshop participants who, while defining the main text elements, must explain and assign the meaning(s) which characterize(s) the text by discussing their interpretation in a critical manner.

At the end of the workshop, participants' written answers were collected and subsequently transcribed in an electronic format in order to be assessed by our prototype for CT Assessment.

2.5 Data analysis

Three human raters with prior experience in CT evaluation, assessed both paraphrase and comment by using a rubric developed by Poce (2017). Although on the comment all the six macro-indicators were applied, the macro-indicator "novelty" was not applied to assess paraphrase since the task does not require the emergence of new ideas. The prototype assessed the answers by applying three macro-indicators on the paraphrase (*Use of Language*, *Relevance*, *Importance*) and four macro-indicators on the comment (*Use of Language*, *Relevance*, *Importance*, and *Novelty*).

The prototype used *concepts* and *successors* provided by the experts and a *golden text* collected during the workshop. As suggested by Mao and colleagues (2018), this study used the quadratic-weighted kappa (QWK) and Pearson product-moment correlation to evaluate the agreement between the three raters' scores and between human raters and the prototype. QWK is a measure of score agreement between raters beyond that expected by chance (Fleiss & Cohen, 1973). The coefficient is a number between 0 and 1, with 0 indicating agreement no better than that expected by chance and 1 indicating perfect agreement. QWK is statistically equivalent to an interrater reliability coefficient (Fleiss & Cohen, 1973). Pearson correlation is another criterion to evaluate consistency between two raters.

2.6 Results

In figure 2, we compared the participants' performance average scores on the six macro-indicators of CT, respectively in paraphrase and commentary.

It is possible to see that participants achieved higher scores in commentary than in paraphrase and this could be explained by two different reasons. Firstly, international participants during the workshop declared they were not familiar with the paraphrase exercise, that is instead commonly used to teach language and literature in Italy from primary schools[1]. On the other hand, according to the

[1] Italian National Guidelines for Primary and Middle School Education, 2012.
http://www.indicazioninazionali.it/wp-content/uploads/2018/08/Indicazioni_Annali_Definitivo.pdf

Verba Sequentur hypothesis (Poce, 2017) supported by Paul and Elder (2006), paraphrase is an exercise that facilitates the adoption of more sophisticated level of CT. Moreover, participants obtained a good average score only for the macro-indicator *Use of Language*, both in paraphrase and commentary (from 2,9 to 3,4). The average score could be considered sufficient for *Argumentation/ Justification* and *Importance* both in paraphrase and commentary and also for *Critical Evaluation* and *Relevance* but only in the commentary (from 2,3 to 2,8). The average score could be not considered satisfactory for the indicators *Critical Evaluation* and *Relevance* in the paraphrase and for the indicator *Novelty* in the commentary (less than 2,2).

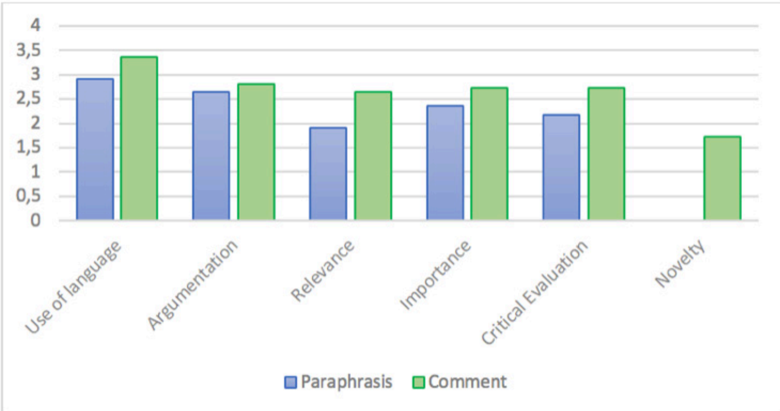


Fig. 2 - A comparison of Critical Thinking performance in paraphrase and commentary.

In order to see whether the prototype could assess CT in a reliable way, we compared the average scores obtained by human raters and prototype respectively in paraphrase and commentary. In figure 3, it is shown that in paraphrase the prototype provides higher score than human raters for the macro-indicators *Use of Language* and *Relevance*. On the other hand, the average score for the indicator *Importance* is slightly higher for human raters than in the prototype. In the commentary, there is a general trend of the prototype to provide lower scores comparing to the human raters. However, it is possible to see that the differences between the average scores for the *Use of Language* scores and *Novelty* in the commentary is quite low.

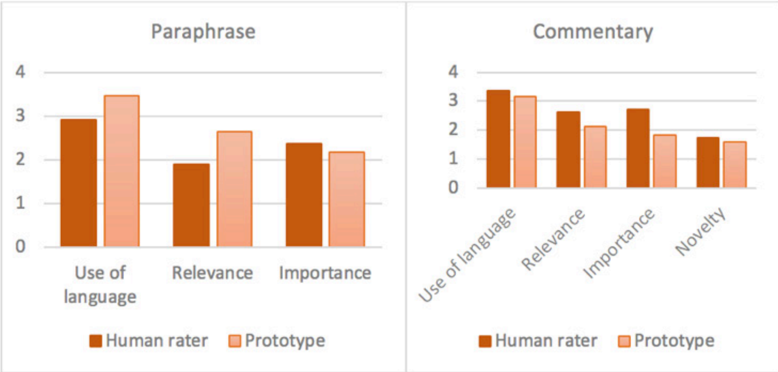


Fig. 3 - A comparison of CT scores calculated by a human rater and the prototype in paraphrase and commentary.

As shown in table 1, the agreement among human raters regarding the indicator *Use of Language* is satisfactory both in the paraphrase and in the commentary, with a higher performance in paraphrase (83% of agreement) comparing to the commentary (approximately 62% of agreement).

Table 1
THE AGREEMENT AMONG HUMAN RATERS REGARDING THE INDICATOR "USE OF LANGUAGE" IN THE PARAPHRASE AND IN THE COMMENTARY. *SIGN. < 0,05 **SIGN < 0,001

Macro-indicator	H-H Correlation	H-H Quadratic Weighted Kappa
Paraphrase_Use of Language	0,911*	0,83*
Commentary_Use of Language	0,745*	0,618*
Paraphrase_Relevance	0,75*	0,682*
Commentary_Relevance	0,881**	0,811*
Paraphrase_Importance	1,000**	1,000*
Commentary_Importance	0,642	0,571

However, there is no correlation among human raters and prototype. These could be explained by at least three factors: firstly, the texts of the answers are quite short (35 words per sentence) and we saw in previous experiences that the prototype achieved better performance with more elaborated texts (Poce *et al.*, 2019). Secondly, participants were not English native speakers and this might have had an impact on their use of language. Thirdly, human raters are Italian and this could affect their assessment of the use of English language by not native speakers. The agreement among human raters regarding the indicator *Relevance* is satisfactory both in the paraphrase and in the commentary (Table

1), with a higher performance in the commentary (81% of agreement) comparing to the paraphrase (68% of agreement). In the commentary, it is possible to see a tendency to a correlation among the prototype and human raters (r = 0,47) for the indicator *Relevance*, but this correlation is not statistically significant. All in all, we can say that the indicator *Relevance* is easier to detect in the commentary than in paraphrase both for human raters and prototype.

The agreement among human raters regarding the indicator *Importance* is 100% in the paraphrase, but the agreement is lower for the commentary (r = 0,64). There is a tendency of the prototype to correlate with human raters both in the paraphrase (r = 0,45) and commentary (r = 0,43) but correlation is not statistically significant in any case.

2.7 Discussion and conclusive remarks

The present contribute aims to present some preliminary results of validity and reliability regarding a prototype for CT assessment developed by the CDM research group. Data collected and presented in this paper are limited to a pilot activity with a small number of participants (18 in total), so any generalization is not possible. In the sample analysed, mainly composed by European university teachers involved in the field of CT, participants achieved generally good results on CT assessment based on their written answers to two kinds of exercise: a paraphrase and a commentary starting from an extract of the work of Galileo Galilei "*Dialogue Concerning the Two Chief World Systems*". Generally, participants achieved higher scores in comments than in the paraphrase exercise. This result could be explained by a low familiarity with the paraphrase exercise in the European sample or by the fact that writing a paraphrase before the commentary could facilitate the adoption of more sophisticated level of CT (Poce, 2017; Paul & Elder, 2006).

The rubric for CT assessment shows good properties, with satisfactory correlation and inter-rater agreement between human raters. However, the results of the prototype validation are not satisfactory yet and the the accuracy of automated scores still has room for improvement. Interviews were organized with human evaluators in order to understand the reasons for the low correlation values between prototype and human. For the macro-indicator *Use of Language* human evaluators did not give the same weight to spelling errors as the prototype, since human evaluators are not English native speakers. In addition, the human raters rewarded the use of a sophisticated language in terms of words and analyzed the diaphasic and diastratic variation present in open answers. Furthermore, human raters consider the coherence of verbal forms within the text whilst the prototype does not. In the future, we will try to reproduce the human decision-making process following the instructions of a human-expert evaluator.

The best correlation among human raters and prototype were obtained for the macro-indicators *Relevance* and *Importance* with correlation higher than 0,43. However, correlation could be not considered statistically significant. As shown in other researches (Liu *et al.*, 2014), human raters tended to assign higher scores than our automatic assessment tool in the commentary. On the other hand, in the paraphrase the prototype assigned higher scores than human raters on the macro-indicators *Relevance* and *Importance.* This result could be explained because the prototype is designed to infer concepts from the questions and answers texts. In the paraphrase, the participants are required to report all the text's topics. In this condition, the prototype easily identifies all the concepts, without the need of further analysis. For these reasons, in paraphrase exercise the macro-indicators *Relevance* and *Importance* could obtain higher scores than the other macro-indicators and, more in general, than commentary or argumentation texts. This data leads us to think that it may be necessary to apply changes to the evaluation of the macro-indicators based on the type of stimulus given to the participants (paraphrase, argumentation, commentary, poetry).

Moreover, in recent years, many researchers rely on open data to give a semantic connotation to their analysis (Bovi, Telesca, & Navigli, 2015; Benedetti, Beneventano, & Bergamaschi, 2016). A study of the relationships existing between entities can help in identifying the concepts associated with *Relevance*, *Importance* and *Novelty* and increase the correlation levels associated with the indicators.

The attempt to automatize CT assessment through open-ended questions is at its beginning but it proves to be a useful support to human evaluation. The use of Natural Language Process techniques seems to be a possible direction according to the first results collected in the study herewith presented (McNamara *et al.*, 2017). The research group feels therefore encouraged to follow up the research described above, through further experimentation, working also on different macro-indicators from the Newman, Webb and Cochrane adapted model used so far. A reliable prototype for CT assessment could support researchers and teachers' understanding regarding learning processes related to CT and the environment in which it occurs (Siemens & Baker, 2012).

In future studies, we are going to expand the textual corpus because our prototype achieved slightly better performances with longer and more elaborated open-answers. We will conduct further validation studies with a larger sample and with different kinds of questions.

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DATA MANAGEMENT IN LEARNING ANALYTICS: TERMS AND PERSPECTIVES

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Online teaching environments acquire extremely high granularity of data, both on users' personal profiles and on their behaviour and results. Learning Analytics (LA) is open to numerous possible research scenarios thanks to the development of technology and the speed of data collection.
One characteristic element is that the data are not anonymous, but they reproduce a personalization and identification of the profiles. Identifiability of the student is implicit in the teaching process, but access to Analytics techniques reveals a fundamental question: "What is the limit?" The answer to this question should be preliminary to any use of data by students, teachers, instructors and managers of the online learning environments.
In the present day, we are also experiencing a particular moment of change: the effects of the European General Data Protection Regulation (GDPR) 679/2016, the general regulation on the protection of personal data that aims to standardize all national legislation and adapt it to the new needs

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dictated by the evolving technological context.
The objective of this work is to propose a three-point checklist of the questions connected to the management and limits of teachers' use of data in Learning Analytics and students' right of transparency in the context of Higher Digital Education, to take into account before conducting research.
To this end, the paper contains an examination of the literature on privacy and ethical debates in LA. Work continues with legislative review, particularly the Italian path, and the discussion about online data management in our current universities' two contexts: technology and legislation.

1 Introduction

According to the definition provided in the first International Conference on Learning Analytics (LA) and Knowledge held in Alberta in 2011, "learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs."

Learning efficacy is a principal goal of Higher Education institution didactic strategies, especially now that their attention is becoming focused on learner-centred pedagogical approaches. Now that they can design whole courses embedded in Learning Analytics, universities are forced to adopt new strategies in the way these goals are achieved, and it must have a clear idea of how to go about doing this.

In the current education context, "this call is gaining a new level of urgency" (Slade & Prinsloo, 2013, p. 31), especially in the last few years with the emergence of educational platforms, mobile-learning, micro-learning, and an increasing use of video resource as didactic tools. Moreover, understanding the potential of Learning Analytics is urgent – "as well as the changes that may be required in data standards, tools, processes, organizations, policies, and institutional culture" (Campbell *et al.*, 2007).

In line with Slade and Prinsloo (2013), "approaches taken to understand the opportunities and ethical challenges of Learning Analytics necessarily depend on a range of ideological assumptions and epistemologies" (p. 3). At the same time, they depends also on who is managing the data: leaders of institutions, teachers and academic staff (database administrators, educational researchers, programmers, instructional designers, and institutional researchers). Each has different interests in collecting data with their particular goals, with consequent privacy and ethical issues concerning the ownership of data and users' consent, etc. What binds them is the fact that everyone is required to have more than traditional digital skills.

Below we propose a scenario in a wide variety of potential cases contained in the 2018 edition of the EU Handbook of privacy with the type of question on which this paper aims to focus:

> "A university research department conducts an experiment analysing changes of mood on 50 subjects. These are required to register in an electronic file their thoughts every hour, at a given time. The 50 persons gave their consent for this particular project, and this specific use of the data by the university. The research department soon discovers that electronically logging thoughts would be very useful for another project focused on mental health, under the coordination of another team in another university." (p. 119)

The first questions that researchers must ask are:

- What must be written in formal consent before data can be collected and/or analysed?
- Do students have the option to "opt out" from the analytics project?
- Is a new student formal consent needed for sharing data with a new team?

This is a short example of how data analytics generates a privacy debate in common situations for Higher Education Institutions.

Our goal is to contribute to this debate by providing suggestions adapted to the General Data Protection Regulation (GDPR). With this aim, we start with a literature review on Learning Analytics, privacy, and ethical issues. We continue our discourse with a focus on the Italian context in these fields. The paper concludes with open questions on privacy policies and learning analytics linking three overlapping categories:

1. management of personal data;
2. limits of teachers' use of students' learning data;
3. students' right of transparency.

2 Related Works

In the debate during the past 10 years on privacy and ethics in education before the GDPR, several authors and pioneers in distance education referred to privacy and ethical issues as parts of a Learning Analytics system (Hoel *et al.*, 2017; Ferguson *et al.*, 2016; Drachsler & Greller, 2016; Slade & Prinsloo, 2013; Pardo & Siemens, 2014; Drachsler *et al.*, 2015; Campbell *et al.*, 2007) that has not yet been influenced by another major debate on privacy coming out of the GDPR. Each one faces the topic from a different point of view and with a different series of principle analyses.

Pardo and Siemens (2014) define ethics in a digital context as "the systematization of correct and incorrect behaviour in virtual spaces according to all stakeholders" (p. 439). In the same context, the concept aligns with the definition of privacy formulated by Drachsler and Geller (2016): "a living concept made out of continuous personal boundary negotiations with the surrounding ethical environment" (p. 91).

In the Learning Analytics scenario, giving a possible reply is not straightforward. As Ferguson and colleagues note in their work, "the ethical and privacy aspects of learning analytics are varied, and they shift as the use of data reveals information that could not be accessed in the past" (2016, p. 5). What is sure is that Higher Education institutions have an obligation to protect students' data on the institutional platform and to inform them of possible risks when research data are sent outside the boundaries of national jurisdiction.

Teachers (and institutions) must know the current responsibility they have if they want to use data collected from students for a specific purpose. At the same time, designers are encouraged to include privacy and security issues in the early stages of their work and to comply with the requirements from both technological and legal aspects (Pardo & Siemens, 2014, p. 444).

Higher education institutions have always collected and analysed data of students in class through assessments and questionnaire. What has changed today is the volume of data that continues to rise along with tools' digital development, the diffuse use of Learning Management Systems (LMS), and the increasing need for the exploitation of data for educational goals (predictive learning, cases of special student, significant learning).

Quantity changes the methods and approaches that we use to interact with students and their data (Siemens & Long, 2011, p. 32) in ways that were not possible in the past without current technology. Google's Mayer (2010) suggested three "S"s (Ivi, p. 33). We propose something similar in an education context:

1. *Speed:* increasing available data in real time. Download speed from LMS allows for a larger range of research in a shorter time span.
2. *Scale:* increase in computing power. The diffusion of digital competence for both teachers and students produces data interaction and types of collaboration that change didactically, predicting the success of students and proposing new methodologies.
3. *Sensors:* new types of data. The information on student learning (analysing discussion messages posted, time spent watching videos, assignments completed, interaction with peers, etc.) serves the purpose of situated teaching and predictive modelling.

As a result of these new possibilities, there are a growing number of ethical issues regarding the collection and analyses of educational data. In this scenario, students (and society in general) are in a delicate situation in which the exchange of personal data is normal, but a balance between control and limits needs to be achieved yet (Pardo & Siemens, 2014, p. 440).

Generally, students know of the growing prevalence of data mining to monitor their behaviour on social media and shopping, but they might not be equally aware of when this occurs within an educational environment. In any case, they should be able to feel safe when they study and learn through an online system for distance education.

3 The Italian Path

"The data that is collected and analysed may be protected by federal, state, and institutional privacy regulations" (Campbell, 2007, p. 8).

As Hoel and colleagues said in their work "The Influence of Data Protection and Privacy Frameworks on the Design of Learning Analytics System" (2017), national data protection acts influence LA tools and systems. They propose an international study in a different context (OECD, APAC, and European GDPR) aimed to design a general privacy framework related to privacy processes and pedagogical LA requirements.

In Italy, the path to digitalization of services began in 2005 with the publication of the Digital Administration Code (CAD), a text that laid the foundations for the digitalization of the Italian public administration. Numerous revisions of the code have taken place over the years, most recently in December 2017. In it, the Agency for Italian Digitalise (AgID) introduced (Annex B) the minimum-security measures for public administrations to better protect the archival heritage and digital data of them. In addition, the AgID has published the three-year plan for the ICT of the Public Administration (PA), indicating the rules for a coherent development of systems.

Regarding the management of data, the Public Administration referred to the Legislative Decree 196/2003 before the GDPR. The privacy code, text that appears original for the period in which it is issued, implements its sanction based on the minimum-security measures contained in an annex.

The annex contains a list of minimum-security measures that all controllers or processors (regardless of size), features, and peculiarities of represented institutions must comply with. However, technological evolution has demonstrated the ineffectiveness of this system, in particular from two points of view: 1) to have imposed equal measures for all, which therefore does not take into account the characteristics of each controller or processor (e.g., the 8-character password for both a small company and a large hospital); and 2) these measures are not in line with the times because they were based on the technological contest of 2004 that has now completely changed (e.g., at that time, a 5-character password could be violated in one minute. After only four years, the time to violate a 6-character password dropped to 0.0224 seconds) (Re Garbagnati, 2012). As a result of this, the GDPR is no longer based on standard measures but on a self-assessment of the owner in accordance with the accountability principle.

The GDPR was issued on 25 May 2016 as a general regulation on the protection of personal data. It has the aim of standardizing all national legislation and adapting to new needs based on the evolution of the technological context. Directly applicable in all member states (as an "self executive" Regulation), each national legislator has had a deadline to adapt to the new European legislation. On 25 May 2018, the two-year time limit expired, and the GDPR began producing its effects concretely.

3.1 What is going on in the Italian universities?

This discourse has emerged in Italian University debates only in recent years, in particular with the National Plan for Digital University edited by the Rectors Conference of Italian University (CRUI). During the Rectors meeting in Udine (2018), they organized a series of "work tables" in which professors and sector experts debated on a specific topic regarding distance education including digital environments for the innovation of teaching, technology and cybersecurity, MOOCs, and so on. This event suggests that university institutions finally understand the critical value of education technology (Siemens & Long, 2011, p.33) in addition to the monetary value (Margoni, 2007). The different scope that exists between *learning analytics* and *academic analytics* affirms this trend[1].

Moreover, the CRUI has turned on a GDPR regulation web page on the national territory aimed at monitoring the development and speed of the digital transition process. The survey involved 60 universities. In most cases (44.29%), the appointment of the Data Protection Officer (DPO) is still ongoing and little more than the Digital Transition Manager (55, 71%). In at least half of the cases (45.71%), the minimum-security measures proposed by the AgID (Agency for Digital Italy) were not activated, nor was the software implemented for the management of the registers related to the processing of personal data (48.57%)[2].

It is evident that Italian universities are in delay with this accountability process. The result is that academic staff could be in trouble without a clear idea of the new regulation and aspects linked to research.

With the purpose to clarify some new approaches and based on research evidence of existing research on Learning Analytics and privacy issues, this paper adds an integrated overview of European GDPR principles from an online

[1] The Academic Analytics focus on political/economically challenge on the potential to create actionable intelligence to improve teaching, learning, and student success. In the first time they were corporate in education sector as "business intelligence".

[2] Data update in July 2019. Direct: http://bit.ly/gdpr-crui

education perspective.

4 The Need for the GDPR in Online Education

Universities are increasingly damaged by cyber-attacks (Cisternino *et al.*, 2018, p. 2). This represents a danger not only for the intellectual property of the contents present in the university databases but also for the personal data recorded about the numerous persons that work in the academic context (students, teachers, administrative staff). Added to this is the sanctioning provide of GDPR that can concern institution that failure to provide high levels of data protection.

The GDPR has as its principal goal to protect the personal data of the subjects (i.e., the natural person to whom those data belong) up to a coherent engineering of the data management system that avoids the need to protect them afterward. With the evolution of digital education, in the field of public infrastructures, the process of transition and review of the functioning of an organization through ICT services and digital management (Sperduti *et al.*, 2018, p. 2) must fall within the current academic policies.

In this scenario, which continues to experience rapid technological evolution (but not as rapidly evolving legislation), the universities are now facing the heavy task of updating administration, guaranteeing compliance, and innovation of services, even with respect to performing consistently toward quality assurance.

In the educational environment, this particularly concerns distance learning issues and those regarding the work done on e-learning platforms in the current need to respect the new legislative provisions.

Whenever a user interfaces with the platform, be it a teacher or a learner, it variously transfers his personal data through multiple actions: registering, uploading a course, sending requests, managing the materials, following a course, and providing its access and use data. On the other hand, technology makes education more personal, and it empowers academic staff and students to make better decisions (Oblinger, 2012).

The data flow in the e-learning platform can be long and complicated to manage. We propose a typical one in Figure 1.

In this flow, the personal data of students, teachers, external users, and operators must always be acquired, managed, processed, and preserved following the principles sanctioned by the GDPR. The distance education distributed by e-learning platforms, as well as the whole traditional didactic context, can no longer avoid it. This leads to the emergence of new "privacy" problems, the use of LMS helps researchers in the design and delivery of learner-centred courses, and students have greater access to more flexible options for engaging with peers and instructors (Macfadyen & Dawson, 2010, p. 589; Drachsler & Geller, 2016). However, every decision in the flow must be made with sufficient information to reduce risk.

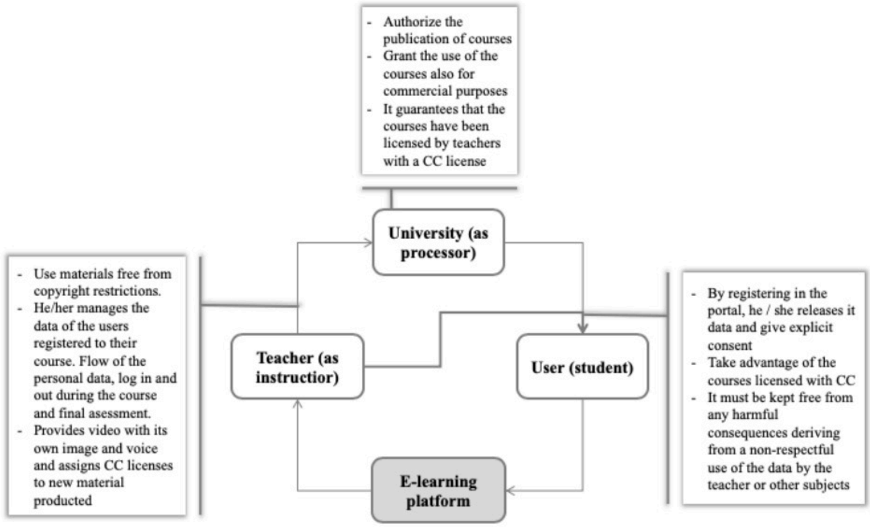

Fig. 1 - *Data flow in e-learning systems.*

To fully understand the scope and the novelties of the new regulation, we must clarify the meaning of "personal data":

> "Personal data' means any information relating to an identified or identifiable natural person ('data subject'); an identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person." (Art.4, GDPR)

It is also important to understand the difference between types of personal data: name and surname, fiscal code, address, e-mail address, telephone number (common data); data revealing racial and ethnic origins, religious beliefs (particular data); data revealing of the quality of a suspect or accused person (judicial data).

The controller or processor who manages the e-learning platform protects personal data in the simplest and most stringent way possible, first by following and respecting the fundamental principles contained in article 5 of the GDPR: lawfulness, transparency, relevance, accuracy, conservation and security, in order to achieve privacy in compliance with the new European regulation.

What establishes the limit of what teachers, Instructional Designers, and Higher Education institutions in general can do with students' learning data depends on which data will be used.

In the process of acquiring personal data, as in the LA survey, it is always necessary to request and subsequently retain the consent of students. Researchers must guarantee the right to the revocation of consent and map the databases to respond promptly and adequately to any requests received. The databases like the servers or Learning Management System must be adequately protected. Exposure to data breach could result in serious losses of trust in the users.

A big challenge for Learning Analytics in this respect is the complexity of the data collection (Drachsler & Greller, 2016) and variety of use for the researchers. The best method to manage data in online education is to be clear and available when explaining the purpose of data collection and to do it in compliance with the existing legal frameworks (Ivi, p.95).

Going beyond these terms, "using analytics requires that we think carefully about what we need to know and what data is most likely to tell us what we need to know" (Siemens & Long, 2011).

Conclusions and future perspectives

In the Learning Analytics process, selected questions, quality data, sound practices, and prudent processes mitigate risks (Oblinger, 2012) that are inherent in making any decisions.

The GDPR introduced a fundamental revolution with respect to the past: the principle of accountability, privacy by design and by default. Those require constant and continuous self-assessment and previous knowledge of the treatment to be activated.

The GDPR today seems to be the more complete law with respect to digital transformation and consequent needs within various sectors (Hoel *et al.*, 2017, p. 3) for these two principles. With the GDPR, we have gone from the typical Italian logic, which permeated the whole regulatory framework of the privacy code, to a more Anglo-Saxon logic oriented to self-assessment. This is the real novelty of the European regulation — no longer a detailed set of rules "dropped from the top" but a series of principles to which the processor must adapt, evaluate, and implement.

Once we overcome the logic of static and equal security measures for all and a dynamic and flexible approach has been inaugurated, a fundamental question emerges: what if I have to know, and what is the limit to manage the personal data in a research project?

A checklist of questions can help teachers who intend to proceed with a treatment to simply and quickly assess the intrinsic criticalities of the treatment itself.

Drachsler and Geller proposed a checklist called "DELICATE" (2016) in order to reach the goal of providing a largely self-explanatory practical tool for designing Learning Analytics surveys within any data-driven educational organisation.

We propose below a short set related to three categories, as indicated in the introduction:

Management of personal data	• What should I do? • Have I carefully evaluated the operations to be undertaken with personal data? • Under which conditions do I want to use these data? • Were the personal data of the interested party (or third party) collected legitimately? • Are there special categories of personal data be processed?
Limit of teachers' use of students' learning data	• To whom will I send the data? • Are there other subjects (colleagues) to whom I will send the data? • Have the purposes of my processing been clearly defined? • Are there purposes that require special additional information (e.g., research, industrialization, data transfer)?
Students' right of transparency	• Have I decided the measures through which individuals' identity will be protected? • Can my processing in any way compromise the interests or fundamental rights and freedoms of the data subjects? • Can data subjects access the data if they wish? • Are there any obstacles to guaranteeing the subjects' right to rectify and/ or delete data or to oppose their processing and their portability?

Based on these three macro-areas, it will be possible to draw up other questions that are common for the activities of Learning Analytics with the critical issues that will need to be resolved before starting the research.

The final part of the case proposed in the Handbook of Privacy is:

> "Even though the university, as controller, could have used the same data for the work of another team without further steps to ensure lawfulness of processing that data, given that the purposes are compatible, the university informed the

> subjects and asked for new consent, following its research ethics code and the principle of fair processing.” (p. 119)

This case demonstrates how sensitive the issue of privacy use on Learning Analytics is, particularly when dealing with other groups. This practical example could also help to understand the difference between the previous legislation on privacy and the GDPR that we can synthesize, saying everything we need to know and do for privacy compliance and what must be done before every decision (privacy by default) for the principle of “prevent, not correct.” The university, as a data controller, puts in place appropriate measures to ensure that only the personal data necessary for each specific purpose of the processing are treated by default.

Reflecting on future directions for this research, we aim to analyse more cases related to Learning Analytics and data management in distance education, to create a comprehensive framework to address all types of data used in possible scenarios and propose a grid and parametres to respond, with an original point of view, to the questions presented in the table.

What we can share now is the consciousness of the need to update university privacy policy, in line with new content introduced by the GDPR, ensuring an effective governance and data management in every work sector, from research to administrative issues.

For teachers, it is important to establish research goals, taking care to associate the relative legal basis of each purpose that makes the processing legitimate.

Numerous questions exist around Learning Analytics, privacy, and ethical issues, so it is important to have full knowledge of the present state of things to be sure of the future. The proposed considerations and questions in this paper provide practical support for higher education actors to clarify the Italian legal context and to increase the quality and effectiveness of Learning Analytics.

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PREDICTIVE MODEL SELECTION FOR COMPLETION RATE IN MASSIVE OPEN ONLINE COURSES

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In this paper we introduce an approach for selecting a linear model to estimate, in a predictive way, the completion rate of massive open online courses (MOOCs). Data are derived from LMS analytics and nominal surveys. The sample comprises 722 observations (users) carried out in seven courses on EduOpen, the Italian MOOCs platform. We used 24 independent variables (predictors), categorised into four groups (User Profile, User Engagement, User Behaviour, Course Profile). As response variables we examined both the course completion status and the completion rate of the learning activities. A first analysis concerned the correlation between the predictors within each group and between the different groups, as well as that between all the dependent variables and the two response variables.
The linear regression analysis was conducted by means of a stepwise approach for model selection using the asymptotic information criterion (AIC). For each of the response variables we estimated predictive models

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using the different groups of predictors both separately and in combination.
The models were validated using the usual statistical tests.
The main results suggest a high degree of dependence of course completion and completion rate on variables measuring the user's behavioural profile in the course and a weak degree of dependence on the user's profile, motivation and course pattern.
In addition, residual analysis indicates the potential occurrence of interaction effects among variables and non-linear dynamics.

1 Introduction

The three major themes comprised by learning analytics are predictors and indicators, visualisations and interventions. Studies belonging to the first theme aim «to establish a predictive model» and «to identify specific correlations between user actions in online tools and academic performance», as well as among skills, self-regulated learning and learning strategies (Gasevic *et al.*, 2019).

Therefore, to carry out such research, we need to identify the data set and analysis methods.

Malcolm Brown (2012) identifies three kinds of data to design an LA application:

- *dispositional indicators*, which are features that students have before the course that can predict his/her involvement in the activities, including age, gender, learning experiences, financial status, psychological measures, "learning power", learning styles and personality types.
- *activities and performance indicators*. The author defines these as «digital breadcrumbs left by learners as they engage in their learning activities and make their way through the course sequence» (p. 2). Some examples of these types of data can be logins, time spent, forum posts, grades and quiz scores.
- *student artefacts*, namely essays, forum posts, media productions and other objects produced by students while attending the course.

In explanatory and predictive modelling, linear regression represents one of the conventional approaches used for building predictive models, together with logistic regression, nearest neighbour classifiers, decision trees, neural networks and so forth (Brooks & Thompson, 2017).

In the analysis of data coming from massive open online courses (MOOCs), linear regression has frequently been used in previous studies to estimate the relationship among data coming from LMS, surveys or students' accounts.

In 4 edX MOOCs, Philip Guo and Katharina Reinecke (2014) have analysed correlations and conducted multiple linear regression among three categories of variables: i) demographics, including age, years of education, country, student-teacher ratio from UNESCO documents (number of students divided by number of teachers); ii) motivation, comprising certificate, grade, coverage (number of learning sequences visited by students), discussion forum events; and iii) navigation, specifically backjumps and textbook events.

«Age, gender, education level, motivation for taking the MOOC, working in groups, and intention of completing the course» (Zhang *et al*., 2019, p.143) are the independent variables in research realised on MOOCs offered on the Coursera platform. This research aimed to identify learners' profiles and their preferences in group working and in attending MOOC, as well as to predict if demographic and motivational elements affect course completion. Other studies have focused on the influence of the instructional design of courses (Jung *et al*., 2019) or on participation and motivation (Brooker *et al*., 2018) across different disciplines (Williams *et al*., 2017).

These investigations tell us, among other things, that countries and age can affect the means of navigating among learning activities. Working in groups does not affect course completion. Motivation varies in courses related to Humanities or STEM, and interaction with course content can help predict student learning.

In this study, we perform a regression model selection to define the relationship between students' and courses' profiles and course completion. We used data from EduOpen, the Italian MOOC platform, and those collected through a survey.

2 Materials and methods

We performed an empirical study to understand how the features of MOOCs and users' profiles, motivation and behaviour affect course completion in order to define a linear model to predict completion rates, starting from analysed phenomena regarding courses and learners.

2.1 Data

The data come from EduOpen, the Italian MOOCs platform, including 22 universities. This project, funded by the Italian Ministry of Education, was launched in 2016. Today, the users registered to the portal number more than 55,000. EduOpen is a Moodle-based platform; the courses published until the present day are more than 250, are divided into six categories and offered in two fruition modalities: self-paced or tutored.

This study involves seven of the courses that show differences in category, level, effort, language and fruition mode. Three of the courses selected belong to the category “Science”, four are tutored, and the same number are in the Italian language and for beginners. 1,508 learners were enrolled in these courses, and the mean completion rate was 23%, a higher value than the usual percentage revealed in other portals and researches. The courses deal with very different themes (from ethnobotany to gender violence, robots, nanoparticles, and history of sports) and provide qualitative and quantitative assessments, as appropriate.

We collected users’ data through:

- Moodle reports that give us information about users’ log, single activity completion and general course completion;
- a questionnaire administered to users before starting the course, composed of 15 closed questions, of which the last two are designed with multiple items. The survey investigates the demographics and motivations of learners.

922 students (61.1% of enrollers) replied to the survey. Removing N/A, we obtained a data set with 722 observations corresponding to 722 users (students).

2.2 Variables

For each student, we collected variables from a survey, courses, and log data.

Independent variables (predictors) were divided into four groups: User Profile, User Engagement, User Behaviour and Course Profile.

As response variables we considered a dichotomic variable (Certificate Download) reporting if the user completed the course and downloaded the course certificate and the completion rate of the tracked activities in the course. The full set of variables, together with their summary statistics, is reported in Table 1.

Table 1
VARIABLES LIST

GROUP	PREDICTOR	NOTES	GROUP	PREDICTOR	NOTES
User Profile	GENDER	The gender of the user	**User Engagement** (all values refer to an individual estimation)	EFFORT	Estimated effort (hours) to complete the course
	DEGREE	The highest level degree		PRE. KNOWLEDGE	Estimated level of knowledge in the field of the course
	LANGUAGE	Native language		DROPOUT_TOT	Level of disposition to abandon the course
	AGE	The age of the user/student		DROPOUT_INT	Level of disposition to abandon the course by lack of interactions with instructors/peers
	MARRIED	Married or common-law partner		DROPOUT_LEA	Level of disposition to abandon the course by lack of learning design
	CHILDREN	Has children		DROPOUT_NAV	Level of disposition to abandon the course by lack of navigation
	TRAINING	Attending an official degree		MOTIVATION	Level of motivation to attend the course
	WORKING	Working status	**Course Profile**	CTUTORED	Whether the course is tutored or self-paced
	SECTOR	Working sector		CCAT	Course category
	DIGITAL	Digital competencies		CLANG	Course language
User Behaviour	CLICKS_TRACKED	Rate of clicks on tracked activities		CHOUR	Estimated effort (from the instructor) to complete the course
	CLICKS_TOTAL	Rate of clicks on overall activities		CLEVEL	Difficulty level of the course
RESPONSE VARIABLES					
CERTIFICATE	The user completed the course AND downloaded the certificate (binary variable)		**CRATE**	Rate of the tracked activities completed by the user	

2.3 Analysis methods

After depicting the data set through conventional descriptive statistical tools, we examined the correlation within each group of predictors and between each predictor and the two response variables. We then conducted a full stepwise analysis to select and fit the linear regression models. We considered two cases, one in which the response variable was certificate download, and the other in which it was completion rate.

The stepwise approach is both backward and forward. The stepwise selection algorithm adds and removes the predictors to obtain a stable set of variables and the optimal final regression model based on the maximisation of the asymptotic information criterion (AIC). AIC is an indicator that balances the number of observations, the number of independent variables introduced and the variance of the residuals in a model with independent variables (Akaike 1969, 1978; Paterlini & Minerva, 2010).

For each stepwise linear regression model, we reported the R-squared adjusted, Residual standard error, F-statistics and model p-value.

Within each linear regression model, we evaluated the value of the intercept and the predictors' coefficients, and for each of them we estimated the standard error, t test, and p-value.

The usual residual analysis was carried out to analyse the model's goodness. We used the Shapiro-Wilk test, the Anderson-Darling test and the Lilliefors (Kolmogorov-Smirnov) test together with the graphical Q-Q plot to test the normal distribution of the model residuals.

In the last part of the study, based on the previous results, further gradual stepwise regression analyses were carried out, including only variables from selected groups or sets of groups.

As a computational environment, we used R/R-Studio and the following R libraries: tidyverse, caret, leaps, MASS, kableExtra, data.table and summarytools.

The full dataset and a R-Markdown script file are available as supplementary material to this paper.

3 Results

3.1 Overview of the sample

The gender representation of the sample contained two groups of almost the same size (55.1% women, 44.9% men). Nearly 90% of students spoke Italian, 42.4% were married/cohabiting and 31.0% had one or more children.

The mean student age in our sample was 38 years; 53.6% of learners had stable work, 22.6% were occasional workers and 13.4% were unemployed. 37.5% had finished secondary school and 58.6% had a tertiary educational qualification (equal or more than a bachelor's degree). At the time of investigation, 41.6% were not attending a university course. Instead, 30.6% were working towards Bachelor's, Master's or doctoral degrees.

Based on these results, we may expect on EduOpen the presence of two different sets of students. The first shows younger university students: occasional workers with no family responsibilities. The second (and larger) contains adults more committed to taking care of family and lifecare issues.

Regarding the engagement variables, the survey respondents indicated their estimated effort to complete the courses as being on average 29 hours. This value was higher than that assigned by the EduOpen instructional designers, ranging from 14 to 25 hours. The mean motivation level to enroll on courses was 23.0 (SD=6.7, Range: 1.0-40.0) and the mean motivation level to drop out was 25.2 (SD=7.6, Range: 3.0-45.0).

Regarding students' behaviour, the mean number of clicks per tracked activities was 3.5 (SD=5.5, range: 0.1-28.3). If we consider all the activities and materials (tracked and not tracked), the mean number of clicks per activity/document was 2.6 (SD=2.3, range: 0.1-14.3), and thus lower, as expected.

Moving to dependent variables, we can pinpoint that 34.5% of learners completed the course and downloaded the certificate.

On the other hand, we can see that more than 44.3% of users completed at least 90% of learning activities. We have about 10% of users/students who completed most of the course but did not finalize it by downloading the certificate. About 38.9% of students covered less than 20% of learning activities. About 16.8% of users completed more than 20% and less than 90% of the course.

The frequency distribution of the completion rate was nearly bimodal. The modal bin was between 90% and 100% (320 obs.), but the option related to a completion rate of less than 10% showed a frequency of 208 users. Therefore, we can distinguish students who even if enrolled did not attend courses at all and users who after completing at least 50% tended to finish their activities and acquire a certificate. A complete description is in supplementary material attached to this paper.

3.2 Intragroup correlation

As expected, the correlation coefficient (ρ) assumes high values between CRATE and CERTIFICATE (0.77), CLICKS_TOTAL and CLICKS_TRACKED (0.92) and among variables of the group about course features that can be common to more than one course in the research.

In the other two groups, the correlation shows few significant associations.

In demographic phenomena, we can observe a correlation between AGE and MARRIED (0.50), CHILDREN (0.51), DEGREE (0.26), WORKING (-0.33), SECTOR (-0.34) and between MARRIED and CHILDREN (0.64), WORKING (-0.18), SECTOR (0.17). This evidence confirms that, as we assumed earlier, older users are more likely to have a stable job, a tertiary education degree and a family.

In the block of engagement variables, correlations are significant among the four variables related to reasons to abandon a MOOC (DROPOUT_TOT, DROPOUT_INT, DROPOUT_LEA, DROPOUT_NAV). The explanation is in the fact that we evaluated these values by the items of the same group of questions in the survey.

However, ρ values deviate from 0 also between the 4 DROPOUT_x variables and MOTIVATION (ρ is between 0.18 and 0.34). Moreover, PRE.KNOWLEDGE of course themes slightly correlates to DROPOUT_INT (0.18) and MOTIVATION (0.32). Even if the ρ values are not far from 0, we can say that:

- the higher students' expectations for participating in a course, the more numerous the reasons for abandoning it;
- the more a student knows the course topics, the more he/she is motivated to enroll and to discuss with teachers and classmates.

3.3 Response vs predictors correlation

We present here the correlation between dependent and independent variables in Table 2.

In most cases, the ρ values are close to 0 and we can observe a weak linear relationship between variables. Except for the group User Behaviour, where the correlation coefficient has values between 0.64 and 0.86 (higher for CLICKS_TRACKED than CLICKS_TOTAL), in the other groups ρ is between -0.20 e 0.17. The correlation with GENDER, DEGREE, AGE and CHILDREN tell us that men, Italian students, adults and people with children have a slightly higher chance of completing courses. The values related to CERTIFICATE for these groups are slightly stronger than CRATE. The highest ρ values in the block User Engagement are recorded by variables PRE.KNOWLEDGE (CRATE -0.09, CERTIFICATE -0.09) and MOTIVATION (CRATE -0.17, CERTIFICATE -0.15).

Table 2
RESPONSES AND PREDICTORS CORRELATION COEFFICIENT (P)

GROUP	PREDICTOR	CERTIFICATE	CRATE	GROUP	PREDICTOR	CERTIFICATE	CRATE
User Profile	GENDER	-0.20	-0.13	**User Engagement**	EFFORT	0.00	0.03
	DEGREE	-0.03	-0.01		PRE. KNOWLEDGE	0.09	0.09
	LANGUAGE	-0.13	-0.09		DROPOUT_TOT	0.04	-0.02
	AGE	0.16	0.12		DROPOUT_INT	0.07	0.04
	MARRIED	0.07	0.04		DROPOUT_LEA	0.02	-0.02
	CHILDREN	0.11	0.10		DROPOUT_NAV	0.05	0.02
	TRAINING	0.04	0.04		MOTIVATION	0.15	0.17
	WORKING	-0.02	-0.01	**Course Profile**	CTUTORED	-0.08	0.02
	SECTOR	0.00	-0.02		CCAT	0.04	0.03
	DIGITAL	0.03	0.01		CLANG	-0.04	-0.03
User Behaviour	CLICKS_TRACKED	0.64	0.77		CHOUR	-0.05	0.03
	CLICKS_TOTAL	0.73	0.86		CLEVEL	-0.04	-0.03

These data show that if a relationship between the dependent and independent variables exists, it seems to be non-linear; the elements that most influence completion seem not to be found in the features of students but in their use of the portal (expressed in clicks).

3.4 Stepwise analysis: the general model

We used a stepwise approach, with AIC as model fitness function, to select the predictor set to consider in fitting a regression model among all examined variables. In this first stage, we performed a selection from the whole set of variables, considering the two cases for CERTIFICATE and CRATE prediction model. The selected models presented different predictors for the two response variables: seven for CERTIFICATE, 16 for CRATE.

Table 3 reports the regression results for the model. We show for each selected predictor the estimated value of the regression coefficient (β), t-test and p-value. The legend in Table 3 indicates that only a subset of variables reaches the required significance levels at 95% (starred).

Both models reached a level of significance of 95%; the CERTIFICATE model explains 57% of variations among variables (adjusted $\mathbf{R}^2$=0.5726), while the CRATE model explains the 75% (adjusted $\mathbf{R}^2$=0.7504).

To validate the two regression models, we performed the analysis of residuals. Normality tests on the residuals are not satisfactory because the p-value in Shapiro-Wilk, Anderson-Darling, Lilliefors (Kolmogorov-Smirnov) normality tests indicated that we can reject the hypothesis of normality.

Table 3
STEPWISE SELECTED REGRESSION MODEL FOR CERTIFICATE AND CRATE

REGRESSION MODEL FOR CERTIFICATE
Residual standard error: 0.311 on 714 DF
Adjusted R-squared: 0.5726
F-statistic: 139 on 7 and 714 DF, p-value: < 2.2e-16

Variable	Coefficient	SE	t-test	p-value
(Intercept)	-0.084	0.069	-1.216	0.224
GENDER *	-0.112	0.024	-4.579	0.000
LANGUAGE *	-0.095	0.040	-2.369	0.018
DIGITAL *	0.027	0.013	2.070	0.039
DROPOUT_TOT *	0.004	0.002	2.536	0.011
CLICKS_TOTAL*	0.151	0.005	29.477	0.000
CTUTORED *	-0.124	0.030	-4.147	0.000
CCAT *	-0.061	0.030	-2.034	0.042

REGRESSION MODEL FOR CRATE
Residual standard error: 0.2165 on 705 DF
Adjusted R-squared: 0.7504
F-statistic: 136.5 on 16 and 705 DF, p-value: < 2.2e-16

Variable	Coefficient	SE	t-test	p-value
(Intercept) *	-0.247	0.085	-2.897	0.004
GENDER *	-0.049	0.017	-2.804	0.005
DEGREE *	0.013	0.006	2.065	0.039
AGE *	-0.011	0.004	-2.446	0.015
CHILDREN	0.031	0.021	1.514	0.130
SECTOR	-0.003	0.002	-1.526	0.127
EFFORT	0.001	0.000	1.715	0.087
DROPOUT_TOT	-0.013	0.007	-1.865	0.063
DROPOUT_INT	0.012	0.008	1.504	0.133
DROPOUT_LEA	0.014	0.008	1.700	0.090
DROPOUT_NAV	0.012	0.008	1.544	0.123
MOTIVATION *	0.003	0.001	2.043	0.041
CLICKS_TRACKED *	-0.042	0.009	-4.802	0.000
CLICKS_TOTAL *	0.220	0.013	16.919	0.000
CTUTORED *	0.064	0.026	2.517	0.012
CCAT *	0.126	0.029	4.288	0.000
CHOUR *	0.016	0.003	4.899	0.000

LEGEND:
DF = Degree of Freedom;
SE = Standard Error
* = variable with p-value < 0.05 at 95% significance level

We obtained the same outcome by graphic display in Q-Q plot (Figure 1). We must refuse the hypothesis that model residuals follow a normal distribution. Consequently, we can assert that a predictive linear regression model can partially explain the completion rate of courses and provide evidence for non-linear or interaction or for missing variables effects.

The fact that the residuals' distribution was not normal and that the regression model does not explain all observations in the data set requires further and in-depth analysis.

The explanations of these results can be seen in one or more factors:

- the variables are not exhaustive of the phenomena described in each block and are not calculated through significant parameters or scales;
- the relationship between the dependent and independent variables is not linear;
- there are interactions among the variables that we have not taken into account and that require further studies.

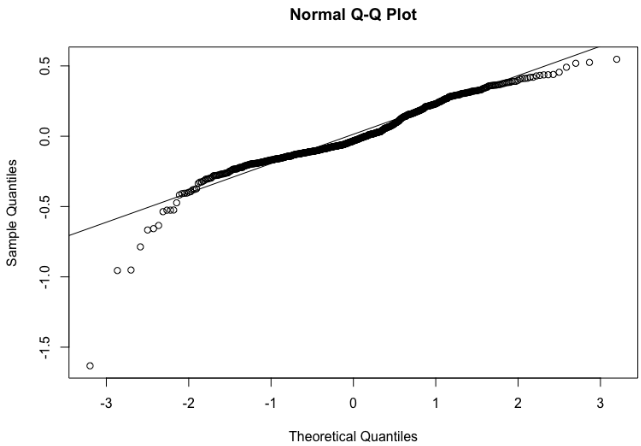

Fig. 1 - Normal Q-Q plot for residuals in CRATE selected model.

3.5 Stepwise analysis: partial models

As a final step and before planning further analysis, we re-ran the regression model selection by including one or more groups of predictors (Table 4). The goal was to better understand the role of each group of variables.

Table 4
PARTIAL REGRESSION MODELS FOR CERTIFICATE AND CRATE

Partial regression models for CERTIFICATE (* = variable p-value < 0.05 at 95% significance level)				**Partial regression models for CRATE** (* = variable p-value < 0.05 at 95% significance level)			
MODEL	**FORMULA**	**Adj-R2**	**F-statistic *(p-value)***	**MODEL**	**FORMULA**	**Adj-R2**	**F-statistic *(p-value)***
I - Target vs Profile + Course	CERTIFICATE ~ GENDER* + LANGUAGE* + AGE* + SECTOR	0.073	15.16 (6.6E-10)	I - Target vs Profile + Course	CRATE ~ GENDER* + LANGUAGE + AGE* + MARRIED + CHILDREN + TRAINING + CTUTORED* + CCAT*	0.044	5.181 (2.6E-03)
II - Target vs Profile + Course + Engagement	CERTIFICATE ~ GENDER* + LANGUAGE* + AGE* + SECTOR + DROPOUT_TOT + DROPOUT_INT + DROPOUT_NAV + MOTIVATION*	0.097	10.73 (2.5E-11)	II - Target vs Profile + Course + Engagement	CRATE ~ GENDER* + LANGUAGE* + AGE* + CTUTORED* + CCAT* + DROPOUT_TOT* + DROPOUT_INT* + DROPOUT_LEA* + DROPOUT_NAV* + MOTIVATION*	0.090	8.171 (1.37E-12)
III - Target vs Engagement + Behaviour	CERTIFICATE ~ CLICKS_TOTAL* + CLICKS_TRACKED* + PRE.KNOWLEDGE* + DROPOUT_TOT*	0.549	220.3 (< 2.2E-16)	III - Target vs Engagement + Behaviour	CRATE ~ CLICKS_TOTAL* + CLICKS_TRACKED* + PRE.KNOWLEDGE + DROPOUT_TOT* + DROPOUT_INT* + DROPOUT_LEA* + DROPOUT_NAV + MOTIVATION	0.737	253.2 (<2.2E-16)
IV - Target vs Engagement	CERTIFICATE ~ MOTIVATION	0.021	16.61 (5.1E-2)	IV - Target vs Engagement	CRATE ~ DROPOUT_TOT* + DROPOUT_INT* + DROPOUT_LEA* + DROPOUT_NAV* + MOTIVATION*	0.046	8.008 (2.3E-07)

V - Target vs Behaviour	CERTIFICATE ~ CLICKS_ TOTAL* + CLICKS_ TRACKED *	0.544	430.8 (<2.2 E-16)	V - Target vs Behaviour	CRATE ~ CLICKS_ TOTAL* + CLICKS_ TRACKED *	0.733	988.9 (<2.2E-16)

We first considered only groups related to variables whose values were known before beginning the courses. In the second row of Table 4, it is possible to see the regression models calculated with User Profile and Course Profile as predictors, while the third row contains results related to models that add the group of User Engagement to the two previous ones. Both the models for CERTIFICATE and CRATE explain a percentage of observations of less than 7%. Including the engagement variables, the value of Adjusted $\mathbf{R}^2$ increases by a very low percentage (2% for CERTIFICATE and 5% for CRATE).

Therefore, excluding the personal features of users and the general characteristics of the courses, we focused on groups related to the engagement and behaviour of users (third model of the tables): the results of Adjusted $\mathbf{R}^2$ show a condition similar to the total regression models described in the previous paragraph. After distinguishing the model contingent on User Engagement by that depending on User Behaviour (fifth and sixth rows), we can see that the last regression model of the tables (the one related to behaviours) explains almost the same completion rate of the model as that considering all the variables in our research.

The only factor that at the end of the analysis of regression models was in a stronger relationship with CERTIFICATE or (better) CRATE is represented by the number of clicks, which can be seen as students' participation in learning activities.

Conclusions

The aim of this study was to define a predictive (and adaptive) system that in a MOOC platform estimates (predicts) the completion of courses and percentage of completed activities according to students' demographics, engagement and behaviours, as well as the courses' features.

We performed an analysis of data collected from a survey and the reports of EduOpen LMS. We identified 24 independent variables in four blocks: User Profile, User Engagement, User Behaviour and Course Profile. The responses measured course completion (binary variable) and learning activities' completion rates (quantitative variable).

The findings of the study suggest that we can outline two learner profiles on EduOpen: on the one hand, young university students and, on the other, adult professionals. This result is confirmed by intragroup correlation, which moreover highlights the relationship between pre-knowledge and motivation. The correlation between responses and predictors tells us that there is a weak linear relationship between variables, except for numbers of clicks (tracked and total), a factor more widely confirmed by stepwise regression run among all predictors and selected groups.

This first step leads us to continue the research with a further selection of variables to be included in the regression models and with an in-depth study of the types of function that express the relationships among variables. The use of genetic algorithms for regression modelling, including genetic algorithms for regressors' selection (GARS), or better yet genetic algorithms for regressors' selection and transformation (GARST) is proposed to determine not only the most adequate variables, but also the most appropriate mathematical transformations (Paterlini & Minerva, 2010). This will allow us to understand if a relationship among phenomena exists and what are its characteristics.

At the same time, this first finding shifts our attention from the profiles of courses and learners to the learning activities and materials within courses. The design of courses, interaction with contents, assessments and time spent represent at this point the elements to investigate in order to gain clearer explanations of the phenomena that data describe and to develop the long-term potential to intervene on the elements that we, as the portal administrators, manage in the production of MOOCs. These may include the audio-video quality and the length of the videolectures, the design of assessments, the automatic reminders, the completion indicators and the tools to support self-regulated learning, among other factors.

Learners usually attend MOOCs following autonomous and independent learning paths, sometimes in the list proposed by teachers, but in other cases according to an order chosen by themselves. The design of this particular typology of online courses must be planned very carefully, paying attention to automatic processes that are necessary for massive courses. However, at the same time and in order to reply to different learning styles, this should permit the students to participate in activities, learning with a high level of freedom.

Therefore, this research places the management and quality of the MOOCs at the centre of the debate.

The next variables to include in future studies are scores and assessments, the number of interactions with different materials in the portal (such as video lectures, documents, links, forums and collaborative activities) and time used to carry out each activity. These new indicators should provide a more comprehensive description of "what happens in our virtual classroom", providing explanations regarding the number of clicks recorded in this study as the fundamental element that can predict MOOC completion.

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UNIVERSITY DROPOUT PREDICTION THROUGH EDUCATIONAL DATA MINING TECHNIQUES: A SYSTEMATIC REVIEW

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The dropout rates in the European countries is one of the major issues to be faced in a near future as stated in the Europe 2020 strategy. In 2017, an average of 10.6% of young people (aged 18-24) in the EU-28 were early leavers from education and training according to Eurostat's statistics. The main aim of this review is to identify studies which uses educational data mining techniques to predict university dropout in traditional courses. In Scopus and Web of Science (WoS) catalogues, we identified 241 studies related to this topic from which we selected 73, focusing on what data mining techniques are used for predicting university dropout. We identified 6 data mining classification techniques, 53 data mining algorithms and 14 data mining tools.

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1 Introduction

One of the goals in the Europe 2020 strategy is to have at least 40% of adult (30-34 years-old) complete higher education (Vossensteyn *et al.*, 2015). Therefore, in several different field of study there is an increasing interest in reducing dropout and improving academic retention in higher education approaches for achieving this goal, which is regarded as crucial for building the high-level skills useful to foster productivity and social justice in Europe. In Europe, according to the 2016 report by the Organization for Economic Cooperation and Development (OECD) dropout rates ranged between 30% and 50%. In Italy, the enrolment rate of 20-24 years-old is one of the lowest among OECD countries (33.7 %, rank 31/40) (OECD, 2016).

Academic *retention* can be defined as the continuous participation of the student in the university's educational path until its end. Retention can be also conceptualized from the point of view of the student (in this case it is called *persistence*) representing the student motivation to achieve his or her academic goals, first of all obtaining of the degree (Hagedorn, 2005). Persistence is also the period of time in which a student remains enrolled at the university and it could be considered as a prerequisite, a necessary condition, even if not sufficient, of university success. When students leave university before achieving their intended goals, they could be labelled as *dropout* students. In this way, retention and dropout phenomena are then described as two side of the same coin; but when "something goes wrong" diverse and more complex failure scenarios may occur, which can be summarized as follows:

- Permanent leaving of studies (*drop-out*), it can be classified into *early* and *late drop-out* (respectively at the second year of enrolment or in subsequent course years).
- Transfer from one bachelor program to another in the same or in another university (*transfer*).
- Different forms of delay (in Italian language *fuoricorsismo*, *out-of-schooling*) that can be defined as a time extension of the forecasted time required to obtain the degree.

The general phenomenon that includes this type of criticalities is defined as *attrition*: "the diminution in numbers of students resulting from lower student retention" (Hagedorn, 2005, p. 6).

The term dropout, unfortunately, is recognized by Astin (1971), Tinto (1987), Bean (1990) and others as one of the more often misused labels for an educational descriptor in literature. Bean (*ibidem*) points out that a dropout student could return and transform his or her status in a "non-dropout" one.

Nevertheless, we will use in this review the university dropout definition by Søgaard Larsen & Dansk Clearinghouse (2013, p. 18): "withdrawal from a university degree program before it has been completed".

In this scenario, there is an increasing interest in the early prediction of student dropout, trying to predict its rates in the most precise manner possible. The main objective of this paper is to provide an overview of the educational data mining techniques that have been used to predict dropout rates in studies of the last decade.

Educational data mining is the use of data mining (also called knowledge discovery in database - KDD) applied in educational field in order to extract meaningful information, patterns and relationships among variables stored in a huge educational data set (Bala & Ojha, 2012; Koedinger, D'Mello, McLaughlin, Pardos, & Rosé, 2015; Mohamad & Tasir, 2013; Romero & Ventura, 2007; Shahiri, Husain, & Rashid, 2015). The useful information may be used to predict dropout causes and finally to improving student persistence preventing identified causes (i.e. providing teachers a dropout student dashboard to improve their teaching approach). Previous literature reviews on educational data mining have covered different topics such as intelligent tutoring systems, learning analytics, student modelling, prediction of student performance and several others. But none of these studied the university dropout except one, but with a limited time frame and only 67 identified papers (Alban & Mauricio, 2019).

2 Methodology

In order to perform this review, we considered the procedures described by Kitchenham in her technical report called "Procedures for Performing Systematic Reviews" (2004). First of all, we proposed three research questions in order to determine the aspects that have been developed to predict university student dropout, stated as follows:

- What data mining techniques have been used to predict university dropout in traditional (face-to-face) courses?
- Which data mining algorithms were used?
- Which data mining tools were used?

Book sections, conference papers and journal articles were reviewed in above mentioned catalogues. To identify relevant documents, we have used the advanced search engines provided by Scopus and WoS respectively. The Scopus query used in *advanced search* function is described in appendix 1.

Through this query we selected all the English documents that had the words: dropout, drop-out, dropping out, attrition, higher education, university, college, data mining, neural network, bayesian, artificial intelligence, AI in the title, abstract and keywords. In addition, with the boolean operators we excluded the documents that did not respond to the research questions. After this step, we applied the selection criteria (Table 1) to refine the final search.

Table 1
SELECTION CRITERIA

Inclusion	Exclusion
Documents including data mining-based university dropout prediction. Documents presenting metrics to assess the quality of predictive models of university dropout. Documents answering research questions.	Documents about dropout's prediction that are not related to the university level in attendance (exclusion of primary, secondary and postgraduate education and all distance learning courses). Documents that do not use data mining techniques. Documents that do not report research data and metrics and where the methodology and techniques used have not been explained

The same methodology has been used for the selection of documents on WoS with small differences in the query due to the different syntax of the search engine. The WoS query used is described in appendix 1.

3 Identified documents

The selection process was completed by deleting the duplicate documents (listed both on Scopus and WoS) with a result of 73 documents selected: 36 documents from Scopus and 37 documents from WoS (Table 2). Figure 1 presents the increasing number of selected studies during timeline (we did not specify any time range in the search query, nether on Scopus or WoS). The first selected document is from 1999, the last one is from 2019.

It is crucial to notice that the number of selected studies has a notable increment since 2014.

Table 2
SELECTED DOCUMENTS

Source	Identified documents	Selected documents
SCOPUS	144	36
WoS	97	37
TOTAL	241	73

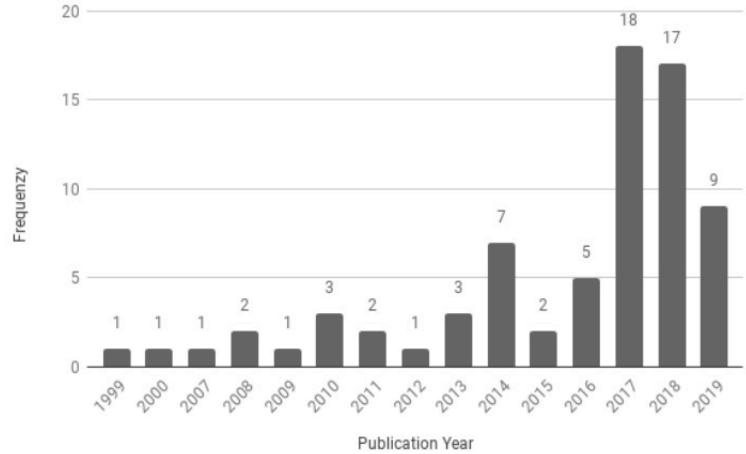

Fig. 1 - Temporal trend of selected publications.

From the selected documents, we identified three aspects regarding university dropout prediction: data mining techniques, algorithms and tools. As stated above, data mining technique is part of the process of converting raw data into useful information, from data pre-processing to postprocessing of data mining results (Tan *et al.*, 2005). We identified six classification techniques: *Decision Tree*, *K-Nearest Neighbor*, *Support Vector Machines*, *Bayesian Classification*, *Neural Networks*, *Logistic regression*, and on *miscellanea* class for other techniques.

3.1 k-Nearest Neighborhood

The *k-Nearest Neighborhood* is a simpler classifier based on the idea that an object O can be classified by taking the class of the object which is most similar to O. First of all we need to find an objective way to measure the similarity. This can be accomplished by decoding all the object in the training set as a numerical real valued vectors $\boldsymbol{x} \in \mathbb{R}^n$ where n is the number of features of each object. Then we can use any distance function defined in the n-dimensional space of reals like for example the euclidean distance function, in order to give an objective measure that states how similar two objects are. The object C in the training set having the smallest distance to O will be the nearest to O and we will give to O its class. Another strategy could be to take the set S of the first k objects nearest to O. Then take the class of which most the objects in S belong breaking ties arbitrarily.

3.2 Decision Tree

Let $U=\{A_1,\dots,A_n\}$ be a set of attributes or features of a set Ω of objects. Decision Tree (DT) is a directed acyclic rooted tree. To each node i of the DT is associated a single attribute A_i of U and a subset of objects in Ω. The association to subset of Ω to each node is recursively done as follows. The root node contains all the objects in Ω. Let i be internal node and S_i be the subset of Ω associated to i. For every different value v_i of the attribute A_i there is a child C_j of i and the set of objects associated to C_j are the object of S_i for which the value of attribute A_i is V_j. A node is a leaf if the set of objects associated to it contains objects all of the same class. The classification of an object O is made on the following way. Starting from the root we inspect each node i until we reach a leaf. At that point, to O is given the class of the object associated to the leaf. At a generic internal node i we inspect the value v_j of the attribute A_i of O and then, we continue the traverse of the DT in the child C_j of i.

3.3 Bayesian Networks and Bayesian classifiers

Bayesian Networks (BN) are one of the most effective tool for the classification task (Pearl, 1988). Let $U=\{A_1, \dots , A_n\}$ be a set of discrete random variables. We call the set of all the possible different values the variable A_i can take, the *domain* of A_i. A BN describes a joint probability distribution of the set of random variables over U both qualitatively and quantitatively by using a directed acyclic graph (DAG) and a set of parameters. Formally a BN $B=(G,\Theta)$ where G is a DAG whose vertex set is U and Θ contains the parameters of the network in the form $\Theta=\{\Theta|A \in U\}$ where $\Theta_A = P(A|\pi_A)$ where π_A is the set of parents of A in G and $P(A|\pi_A)$ represent the probability distribution of A given its parents π_A. Based on this, we can decompose the joint probability distribution as

$$P(\boldsymbol{U}) = \prod_{\boldsymbol{A} \in \boldsymbol{U}} P(A|\,\Pi_{\boldsymbol{A}}) \qquad (1)$$

Without loss of generality suppose that A_1 is the random variable specifying the class label of a group of objects. In a naive Bayesian Classifier, a strong assumption is made that every distinct attribute A_i and A_j, $i,j>1$ are conditionally independent given A_1. Therefore the joint probability distribution of U (1) can be expressed as

$$P(\boldsymbol{U}) = \prod_{\boldsymbol{1<i\leq n}} P(A_i|\,\mathrm{A}_1)$$

Which simplify greatly the network and the prediction queries.

3.4 Perceptrons, SVM and Neural Networks

In the brain or in the nervous system of a living organism each neuron is composed by a body, called the *soma*, a set of *dendrites* and an *axon*. Both dendrites and axon are filaments that extrudes from the soma. The dendrites resemble the roots of a tree and act collectively as input to the neuron cell while the axon bring a signal to other neuronal cells by using the axon terminals called *Synapsys*.

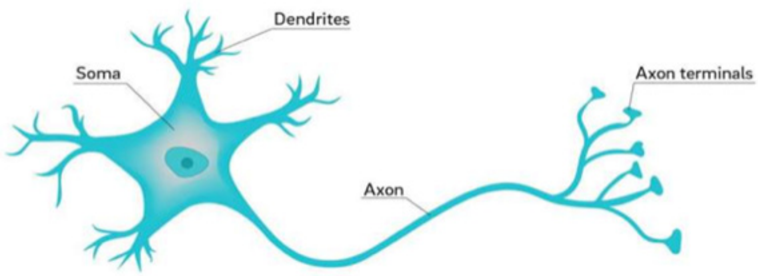

Fig. 2 - A neuron cell.

We assume that if a neuron has n dendrites then there are n possible different signal in input to the neuron and there is only one output signal transported in output by the axon to other neurons. If each of the input signals has strength x_i, $i=1,...,n$ where x_i is a real number, we may assume that the neuron transforms each signal by multiplying it with a weight w_i. Then the sum of the transformed signals can be used by the axon to transmit a signal to other neurons. If we denote by $\boldsymbol{x} \in \mathbb{R}^n$ the input signals and by $\boldsymbol{w} \in \mathbb{R}^n$ the weights associated to each dendrite the signal the axon will transmit can be computed by the following function

$$f(\boldsymbol{x}) = \begin{cases} 1 & \text{if } \sum_{i=1}^{n} x_i w_i + b > 0 \\ -1 & \text{otherwise} \end{cases} \quad (2)$$

where b is a real number called the *bias parameter*. What we obtained here is sometimes called a *perceptron*. Clearly a single perceptron can be used as a binary classifier. In other words, if we think to a single neuron as a binary classifier which can be *activated,* or it can be *deactivated* when it receives some input x then the perceptron mimics the behavior of a neuron.

Therefore, if we represent an object O by a real value vector x of features then we can use a single perceptron as a classifier in order to recognize if the object *O* belong or not to a particular class.

While perceptrons can be used as binary classifiers, there are cases in which we want to classify an object among different classes. For example, the relatively simple nervous system of a bird should be able to classify if an object is a car, is an insect or is a tree. In this case we can use a stack of perceptrons and obtain what we call a Support Vector Machine (SVM) (Hearst, 1998). If we use *D* perceptrons in an SVM we can imagine that all the perceptrons take the same input object but each perceptrons is specialized to be activated only for a certain class and not for the other. The function we obtain is a *D*-dimensional vector $\boldsymbol{y} \in \mathbb{R}^D$

$$\boldsymbol{y} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b} \qquad (3)$$

where W is a $D * n$ matrix of real numbers and b is a *D*-dimensional vector of real numbers. The index of the component of y which take the maximum value will be taken as the number of the class predicted by the SVM. For example, if the possible class are {*Car*, *Insect*, *Tree*} we have that D= 3 and if $y=(0.2, 6.4, -3.7)$ then we may conclude that the class with maximum score is the class 2 that is x is an insect.

The problem with perceptron and in general with the SVM is that they work well if the class of objects are linearly separable, that is if there exists for each class a hyperplane that separates the class from all the other classes. To overcome the problem of classification when the space of the classes is not linearly separable at the end of each perceptron a nonlinear sigmoidal function is applied. Then the output so obtained is sent to another perceptron. The output produced by the last perceptron can be expressed as

$$y = \sum_{i=1}^{n} \alpha_i \sigma(\boldsymbol{w}_i \boldsymbol{x} + b_i) \qquad (4)$$

where w_i is the n-dimensional vector of weights of the i-th perceptron. Such type of classifier is called *Neural Networks*. Cybenko (1989) proved that the above formula can be used to compute any classification function.

A Neural Network is a mathematical object used to roughly mimics the functions of the neurons in a nervous system. Contrary to the classic paradigm of computer programming, in which the programmer needs to have a complete knowledge of the problem to be solved in order to design a correct algorithm, like for example in (Malvestuto, Mezzini, & Moscarini, 2011; Mezzini, 2010, 2011, 2012, 2016, 2018; Mezzini & Moscarini, 2015, 2016), in order to implement a Neural Network the programmer need not to understand the meaning and the mechanism behind the phenomenon to be classified and uses the Neural Network as a black box.

4 Results

Table 3 summarizes the total identified and selected documents by classification techniques. Approximately 67% (49 out of 73 documents) used Decision tree classifiers. Bayesian Classification hold the second highest frequency of use with approximately 49%, then Neural Networks with approximately 40% and Logistic regression with approximately 34%. Support Vector Machines, Miscellanea and K-Nearest Neighbour are used respectively with approximately 23%, 15% and 12%.

Table 3
CLASSIFICATION TECHNIQUES

Techniques	Frequency
Decision Tree [1,3,4,10,11,12,13,15,16,18,19,20,22,24,26,27,28,30,33,38,39,40,43,44,48,49,60,61,62,63,64,65,66,69,70,71,72,73,76,82,84,85,86,88,90,91,93,95,98]	49
Bayesian Classification [3,13,15,17,20,25,27,28,30,34,35,38,39,40,44,46,47,59,60,64,65,67,69,70,71,73,76,78,79,81,86,90,93,94,95,98]	36
Neural Networks [1,2,5,13,16,18,21,26,27,28,29,38,39,41,42,43,45,64,65,66,73,77,83,85,86,93,94,96,98]	29
Logistic regression [3,11,15,16,18,20,26,33,45,48,62,64,64,66,69,70,75,79,82,85,86,94,95,97,98]	25
Support Vector Machines [1,13,18,19,20,21,33,38,39,40,48,71,72,79,85,94,98]	17
Miscellanea [4,15,43,49,60,65,72,75,82,95,98]	11
K-Nearest Neighbour [3,19,20,27,28,64,72,95,98]	9

In addition, we have identified the specific algorithms used in the selected documents, grouped by classification techniques with the result of 53 algorithms: 19 for Decision Tree (Table 4), 11 for Bayesian Classification (Table 5), 6 for Neural Networks (Table 6), 3 for Logistic regression (Table 7), 4 for Support Vector Machines (Table 8), 8 for Miscellanea (Table 9). Instead, we have not identified specific algorithms for K-Nearest Neighbour. Unfortunately, not all the selected documents cited explicitly the algorithms used.

Table 4
DECISION TREE ALGORITHMS

Algorithm	Frequency
C4.5 (j48) [4,13,93,22,27,28,38,24,44,49,60,65,15,71,72,73,76,82,88,91]	20
Random Forest [3,15,26,33,40,43,62,64,70,71,85,95]	12
C5.0 [3,16,18,24,93,98]	6
CART [11,15,24,63,49,38]	6
CHAID [10,61,63,98]	4
ID3 [4,84,93]	3
Random Tree [60,49,90]	3
Gradient Boosting Tree [40,64]	2
ADTree [65,49]	2
AdaBoost [20,64]	2
Decision Forest [94,98]	2
Decision Jungle [94,98]	2
Gradient Boosted Trees [40,64]	2
Boosted Decision Tree [94,98]	2
Decision Table [39,44]	2
EM5.3 [66]	1
Rpart [3]	1
Ctree [3]	1
REPTree [49]	1

Table 5
BAYESIAN CLASSIFICATION ALGORITHMS

Algorithm	Frequency
Naïve Bayes [3,13,20,25,27,28,34,38,39,40,44,60,64,65,67,69,70,71,73,76,79,86,90, 93,95]	25
Bayesian Network [15,30,34,35,65,81,93]	7
TAN [17,35,34]	3
K2 [34,35,67]	3
PC [34,35,67]	3
Bayesian Profile Regression [78,79]	2
Markov chains [46,47]	2
Bayes Point Machine [94,98]	2
Bayesian binary quantile regression [59]	1
Gaussian Naive Bayes algorithm [70]	1
AutoClass [67]	1

Table 6
NEURAL NETWORK ALGORITHMS

Algorithm	Frequency
Multilayer perceptron [5,16,18,29,38,39,45,73,83,77,85]	11
Radial Basis Function [21,65]	2
Fuzz-ARTMAP neural network [41,42]	2
Self-organizing map (SOM) [96]	1
Adaptive Network based Fuzzy Inference System (ANFIS) [2]	1
Probabilistic neural network [45]	1

Table 7
SUPPORT VECTOR MACHINE ALGORITHMS

Algorithm	Frequency
Averaged perceptron [94]	2
Polinomial kernel [39]	1
RBF kernel 39]	1
Least-Square Support Vector Classification [21]	1

Table 8
LOGISTIC REGRESSION ALGORITHMS

Algorithm	Frequency
Iterative Logistic Regression [95]	1
Logit [15]	1
Generalized Linear Model [64]	1

Table 9
MISCELLANEA ALGORITHMS

Algorithm	Frequency
ONE R [15,49,60,65]	4
K-means [4,75,82]	3
JRip [15,49]	2
Random guess [95]	1
Gradient boosting machine [43]	1
Ridor [49]	1
Quest [98]	1
EUSBoost [72]	1

In order to answer to our third research question ("Which data mining tools were used?") we identified each tool used in selected documents. *Data mining* *tool* refers to software used to extract, process and analyze the data. Only 46 out of 73 selected searches present the tools used, therefore we have identified 14 tools summarized in Table 10.The results highlight that the most widely used tools were WEKA, SPSS and R.

Table 10
DATA MINING TOOLS

Tool	Frequency
WEKA [4,13,15,30,49,38,44,60,82,73,86,88,90,91]	14
SPSS [1,5,10,16,19,45,61,77,98]	9
R [3,24,25,43,59,78,79,85]	8
Rapid Miner [1,12,22,60,76]	5
Elvira [34,35,67]	3
H2O [43,64]	2
SAS [66,97]	2
Watson Analytics [69,70]	2
Azure Machine Learning [94,98]	2
Matlab [2]	1
Orange3 [60]	1
Statistica [83]	1
NeuralWorks Professional II/PLUS [45]	1

Conclusion and future developments

This paper presents a systematic literature review on educational data mining techniques used to predict university dropout in traditional courses. We identified 241 studies related to this topic from which we selected 73 papers accordingly to above mentioned inclusion and exclusion criteria. We identified six classification techniques: Decision Tree, K-Nearest Neighbour, Support Vector Machines, Bayesian Classification, Neural Networks, Logistic regression (plus one category for minor techniques called “Miscellanea”).

The educational data mining technique which presented a higher frequency of use is Decision tree (67%), followed by Bayesian Classification (49%), Neural Networks (40%) and Logistic regression (34%).

Moreover, we identified 14 data mining tools used in the studies, highlighting that the most used ones are WEKA, SPSS and R.

It is of high evidence that university dropout prediction is of elevated interest for academic researchers' community and that highly precision techniques are being developed to address this crucial issue. However, we did not find any study about dropout and Convolutional Neural Network (CNN), a very efficient algorithm more frequently used in image recognition researches.

As further developments we intend to analyse the selected documents more in detail, trying to answer to the following questions:

- Which predictive model evaluation metrics were presented in the research?
- What are the levels of reliability reached by the techniques presented in the research?

In conclusion, this systematic review on predicting dropout rates has motivated us to carry out further research to be applied in higher educational data mining field in order to monitoring students' performance in a systematic and even more automated way.

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APPENDIX 1

Queries used in Scopus and WoS.

Scopus

(TITLE-ABS-KEY (dropout OR drop-out OR "drop out" OR "dropping out" OR "attrition") AND TITLE-ABS-KEY ("higher education" OR "university" OR "college") AND TITLE-ABS-KEY ("data mining" OR "neural network" OR "bayesian" OR "artificial intelligence" OR "AI")) AND (EXCLUDE (DOCTYPE, "er")) AND (LIMIT-TO (LANGUAGE, "English")) AND (EXCLUDE (EXACTKEYWORD, "E-learning") OR EXCLUDE (EXACTKEYWORD, "MOOCs") OR EXCLUDE (EXACTKEYWORD, "On-line Education") OR EXCLUDE (EXACTKEYWORD, "On-line Analytical Processing") OR EXCLUDE (EXACTKEYWORD, "Online") OR EXCLUDE (EXACTKEYWORD, "Virtual Learning Environment") OR EXCLUDE (EXACTKEYWORD, "Image Classification") OR EXCLUDE (EXACTKEYWORD, "Image Processing") OR EXCLUDE (EXACTKEYWORD, "Images Classification") OR EXCLUDE (EXACTKEYWORD, "Gene Cluster") OR EXCLUDE (EXACTKEYWORD, "Gene Deletion") OR EXCLUDE (EXACTKEYWORD, "Gene Ontology") OR EXCLUDE (EXACTKEYWORD, "Genetic Selection") OR EXCLUDE (EXACTKEYWORD, "Genetic Variation") OR EXCLUDE (EXACTKEYWORD, "Genetics") OR EXCLUDE (EXACTKEYWORD, "MOOC") OR EXCLUDE (EXACTKEYWORD, "Distance Education") OR EXCLUDE (EXACTKEYWORD, "Distance Higher Education") OR EXCLUDE (EXACTKEYWORD, "Distance Learning") OR EXCLUDE (EXACTKEYWORD, "Distance Learning Course") OR EXCLUDE (EXACTKEYWORD, "Open And Distance Learning") OR EXCLUDE (EXACTKEYWORD, "Massive Open Online Course") OR EXCLUDE (EXACTKEYWORD, "Massive Open Online Course (MOOC)") OR EXCLUDE (EXACTKEYWORD, "Multi-MOOC") OR EXCLUDE (EXACTKEYWORD, "Multivariate Time Series") OR EXCLUDE (EXACTKEYWORD, "Segmented Images") OR EXCLUDE (EXACTKEYWORD, "Entrepreneurial Success") OR EXCLUDE (EXACTKEYWORD, "Breast Cancer") OR EXCLUDE (EXACTKEYWORD, "Immersive Technology") OR EXCLUDE (EXACTKEYWORD, "Web Services") OR EXCLUDE (EXACTKEYWORD, "Web-based Learning") OR EXCLUDE (EXACTKEYWORD, "Traffic Signs") OR EXCLUDE (EXACTKEYWORD, "Brain Tumor Segmentation") OR EXCLUDE (EXACTKEYWORD, "Vis-NIRS") OR EXCLUDE (EXACTKEYWORD, "Tinnitus Dropout") OR EXCLUDE (EXACTKEYWORD, "Amelogenesis Imperfecta"))

WoS

(TS=(dropout OR drop-out OR "drop out" OR "dropping out" OR "attrition") AND TS=("hiher education" OR "university" OR "college") AND TS= ("data mining" OR "neural network" OR "bayesian" OR "artificial intelligence" OR "AI") OR TI=(dropout OR drop-out OR "drop out" OR "dropping out" OR "attrition") AND TI=("higher education" OR "university" OR "college") AND TI= ("data mining" OR "neural network" OR "bayesian" OR "artificial intelligence" OR "AI")) AND LANGUAGE: (English)

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REFLECTING A... "BIT". WHAT RELATIONSHIP BETWEEN METACOGNITION AND ICT?

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Keywords: Metacognition, E-learning, ICT, Learning Outcomes

Using Information and Communication Technologies (ICT) in educational environments has become widespread in latest years. Since research underlined the important role played by metacognition and self-regulation abilities in fostering learning outcomes, the relationship between these aspects appears to be particularly worthy of investigation. In this review, we present 14 studies that have deepened the relationship between ICT, metacognitive skills and learning outcomes by identifying two main categories. Some articles investigated the effects of ICT environments combined with metacognitive aspects of learning outcomes, while others investigated the reciprocal relationship between ICT and metacognition. In general, from our review, the interaction between ICT and metacognition in producing better learning outcomes appears well established and the results highlight a bi-directional relationship between metacognition and ICT, but also allow to draw attention to gaps requiring further research.

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1 Introduction

1.1 What is metacognition?

The latest research on educational psychology has highlighted the importance of knowing how to think and how to learn rather than just 'knowing' and underlined the advantage of focusing on the characteristics of the learning process, rather than on its content elements (Bjork & Yan, 2014). This has stimulated a reflection on the thinking process, on the construction of knowledge and on the systems with which people know and regulate their own learning. The attention of those who design learning environments has thus progressively shifted towards the awareness of one's learning processes and needs. This allowed to identify available opportunities to overcome obstacles in learning, by developing and promoting a strategic and positive emotional-motivational attitude towards the acquisition of learning strategies and methods (Battistelli *et al.*, 2009). All these skills fall into metacognition as a superordinate category concerning cognitive processes. Metacognition can be defined as the individual's knowledge regarding cognitive functioning (Flavell, 1979) - i.e. what one knows about how his/her and other people's minds function. It also refers to the different forms of control that can be implemented before, during and after the execution of a task (Brown, 1987) - i.e. the activities that guide and monitor one's cognitive processes. The main components of the regulation of cognition are planning, monitoring, and evaluating (Manning, Glasner, & Smith, 1996). Planning involves the selection of appropriate strategies and the allocation of personal resources. It includes goal setting, activating relevant background knowledge, and budgeting time. Monitoring refers to self-testing skills necessary to control learning. Evaluation refers to appraising the products and regulatory processes of one's learning. Metacognition generates interest because it enables individuals to monitor their own knowledge and skill levels, to allocate a limited amount of learning resources efficiently, and to evaluate their learning outcomes, ultimately favouring learning (Lee & Stankov, 2013).

Fiore and Vogel-Walcutt (2010) state that students with metacognitive skills can foresee problems that may arise during the learning experience and are able to better allocate their cognitive resources for learning and determine the information they understand or they need. Students with better self-regulation skills typically learn more, with less effort, and report higher levels of academic satisfaction (Barak, 2010).

1.2 Characteristics of the ICT learning environments

If the literature analysing the factors involved in scholastic success has widely shown the key role played by metacognition in supporting effective study, less is known on the role of transversal skills in smart learning environments. However, these environments are particularly interesting because there they are increasingly pervasive in students' lives. New Information and Communication Technologies (ICT) provide new approaches to design learning environments, where many factors can influence learning: materials, activities, motivation, students' learning styles and self-regulation (Ligorio *et al.*, 2010). Importantly, although educational environments are characterized by an increasing presence of ICT (Al-Samarraie, Teo, & Abbas, 2013), this did not (yet) translate into a critical theory on technological education (Whitworth, 2007). The growth of ICT does not always correspond to the ability of researchers to better define and structure their use in different environments. This can cause negative consequences at the level of learning processes (Thomas *et al.*, 2016).

Technological tools can play a crucial role and determine a significant impact on metacognition and self-regulation. For instance, Zimmerman (2008) argues that high-tech learning environments can assist students in using self-regulated learning strategies. Azevedo, Cromley, and Seibert (2004) suggest that learning in a high-tech environment requires self-regulatory skills to organise, navigate, and combine information into feasible mental models. This review aims to answer this and other questions from an empirical perspective: is ICT more (or solely) effective when it includes metacognitive components; is there a relation between metacognition and ICT, and if yes in which direction?

2 Analysing the relationship between metacognition and ICT

We consulted PsychINFO, using the query strings: "ICT" AND ("metacognition" OR "metacognitive"); "e-learning" AND ("metacognitive" OR "metacognition"); "blended" AND ("metacognition" OR "metacognitive"). The search produced 108 results (54 after removing duplicates), that we searched with respect to the relationship between metacognition and ICT. We screened 34 records and excluded 6 by reading the abstract because they were not pertinent to the topic. We then excluded 14 more articles because they did not fit our investigation topic. The articles that met these our criteria and were, therefore, eligible for the review are 14.

The analysis allowed to distinguish two broad categories. Some articles (N = 5) investigated the effects of ICT environments combined with metacognitive aspects on learning outcomes. Other studies tested the relationship between ICT and metacognition, with the majority of studies hypothesizing a direction from ICT to metacognition (N = 8) rather than from metacognition to ICT (N = 1).

Table 1
STUDIES TESTING THE JOINT ROLE OF ICT AND METACOGNITION ON LEARNING (N = 5 studies)

Authors (year)	Type of ICT	Sample	Outcomes investigated	Metacognition measures	Main results
Cacciamani, S., Cesareni, D., Martini, F., Ferrini, T., & Fujita, N. (2012)	Blended learning	67 undergraduate students from Italy	Epistemic agency	Ad-hoc scale	Metacognitive reflection during the online course fostered student's Advanced Epistemic Agency.
Hsu, Y.S., & Lin, S.S. (2017)	Visualisation tool in e-learning	74 11th-graders from Taipei city	Decision-making skills	Ad-hoc scale	Decision-making skills were improved by metacognitive guidance in an e-learning environment.
Kramarski, B., & Gutman, M. (2006)	E-learning	65 9th-graders from Israel	Mathematical problem-solving and self-regulated learning	Improve method (Mevarech & Kramarski 1997; Kramarski & Mevarech 2003)	Students exposed to a metacognitive questioning in E-learning (EL+) outperformed EL students in problem-solving and mathematical explanations.
Sáiz Manzanares, M.C., Marticorena Sánchez, R., García Osorio, C.I., & Díez-Pastor, J.F. (2017)	E-learning (MOODLE)	129 undergraduate students from blended courses	Learning outcomes	Scale of learning strategies (Román & Poggioli, 2013)	A correlation between learning outcomes and metacognitive responses was found in Supplemental blend, but not in Replacement blend courses.
Zhang, W.X., Hsu, Y.S., Wang, C.Y., & Ho, Y.T. (2015)	E-learning (Inquiry-based Online Learning Module)	51 9th-graders from southern Taiwan	Students' inquiry practices	Ad-hoc Questionnaire of Metacognition	Cognitive and metacognitive prompting in e-learning enhanced the students' inquiry practices.

2.1 Metacognition and ICT jointly influencing outcomes in learning

We found 5 studies examining whether taking into account metacognition in ICT educational environments relates to learning outcomes (Table 1).

The experimental study carried out by Kramarski and Gutman (2006) compared a "basic" e-learning environment with one associated with a self-metacognition training and revealed how structuring e-learning activities combined with activities on metacognition led to better mathematical problem-solving in Israelian high-school students, especially with respect to the use of self-monitoring strategies during problem-solving.

Similarly, a recent study with 11th graders (Hsu & Lin, 2017) tested decision-making (DM) skills of students of socio-scientific subjects. Students were divided into two groups: the first group was only provided with a visualisation tool in e-learning (control group), while the second also learned with a DM module that included metacognitive guidance to support understanding, planning, and monitoring (experimental group). A comparison between the two groups indicated that the two versions of the DM learning modules had similar effects on the improvement of students' DM skills, but the experimental group overcome the control group in overall skills in DM and in monitoring (in terms of self-evaluation of DM skills). Results in the same direction were found with respect to the relationship between scientific inquiry and metacognition in high-school students (Zhang *et al.*, 2015). Specifically, an inquiry-based e-learning environment together with cognitive and metacognitive prompts was associated with greater tendencies towards inquiry practices among students, concerning especially their planning and analyzing abilities.

A study on epistemic agency (when students negotiate their ideas with one another, instead of relying on teachers) with undergraduate students (Cacciamani *et al.*, 2012) suggested that opportunities for metacognitive reflection on the students' own participation strategies during an online course were amongst the best practices for fostering epistemic agency, therefore evidencing the important role that metacognition can have in allowing positive effects of ICT.

Sáiz Manzanares *et al.* (2017) further showed the benefits of combining e-learning with metacognition. The authors focused on the special benefits that metacognition can have when framed in a e-learning context, investigating the relation of metacognitive strategies with the type of learning pattern in Learning Management Systems (LMS). In a sample of 129 university students, the authors found a positive correlation between metacognitive responses and learning outcomes when using a supplemental blend (that is combined with face-to-face feedback), but not when using a replacement blend (that is when the feedback is given only on the platform).

2.2 Metacognition and "ICT": Unidirectional or bi-directional relationship?

We identified only one study that tested the relationship from metacognition to ICT (Table 2).

Table 2
STUDIES TESTING THE RELATIONSHIP BETWEEN ICT AND METACOGNITION (N = 9 studies)

Authors (year)	Type of ICT	Sample	Outcomes investigated	Metacognition measures	Main results
Al-Samarraie, H., Theo, T., Abbas, M. (2013)	E-learning	245 undergraduate students from southern Malaysia	Understanding a research article	Sub-scale of Thinking skills (Bernard, Brauer, Abrami, and Surkes, 2004)	Structured information (i.e. title, introduction,...) influenced learners' metacognitive activity and their understanding of research articles.
Hsu L.L., & Hsieh S.I. (2011)	Blended learning	99 undergraduate nursing students from Taiwan	Learning outcomes	Metacognition scale (Hsu, 2010)	Blended learning improved learning outcomes by facilitating metacognition and self-regulation.
Hsu L.L., & Hsieh S.I. (2011)	Blended learning	223 undergraduate nursing students from China	Learning outcomes	Metacognition scale (Hsu, 2010)	No differences were found on a Metacognition Scale between students in traditional and blended classes.
Klein, H.J., Noe, R.A., & Wang, C. (2006)	Blended learning	600 undergraduate students enrolled in either classroom or blended learning courses	Motivation to learn and course outcomes	Metacognition scale (Ford et al., 1998)	Motivation to learn was related to course satisfaction, metacognition, and course grades. It also mediated the relationships between delivery mode and metacognition.
Lee Y.H., & Wu J.Y. (2013)	Online reading activities	87.735 high-school students across 15 regions (PISA 2009)	Reading literacy	Ad-hoc scale	The positive effect of online activities on reading was mediated by metacognitive strategies.

Ramirez Arellano, A., Bory-Reyes, J., & Hernandez-Simon, L.M. (2019)	E-learning (MOODLE)	137 undergraduate biology students from a blended course	Learning outcomes (overall grade)	Motivated Strategies for Learning Questionnaire (Pintrich & De Groot, 1990)	Metacognitive self-regulation and organization predicted students' performance in blended learning.
van Vliet, E. A., Winnips, J.C., & Brouwer N. (2015)	Flipped classroom	170 undergraduate psychobiology students from Amsterdam	Motivated Strategies for Learning Questionnaire (Pintrich & De Groot, 1990)	Motivated Strategies for Learning Questionnaire (Pintrich & De Groot, 1990)	The flipped-classroom enhanced critical thinking, task value, and peer learning. However, the effects did not persist in a retention-test five months later.
Yang, Y.F. (2012)	Blended learning	108 undergraduate technology students with English reading difficulties from Taiwan.	Reading skills	Web-based functionalities, (dialogue box, forum, chat room, and annotation tool)	Students in blended learning outperformed the control group in reading by fostering the use of metacognition.
Zhao, H., & Chen, L. (2016)	E-learning	289 university distance learners from Mainland China and Hong Kong.	Self-regulated learning (SRL)	Ad-hoc scale	Self-regulation in e-learning environments was influenced by information quality, communication quality, and user satisfaction.

Ramirez-Arellano, Bory-Reyes, and Hernandez-Simon (2019) conducted a study with 137 Mexican university students, testing the predictiveness of 19 variables (with respect to emotions, motivation, cognitive and metacognitive strategies, and behaviour) on the overall students' performance. Six of these predictors, explaining the 67% of the variance were found to be significant. Among these predictors, metacognition and self-regulation abilities explained the 5% of variance. The authors therefore showed that metacognition and self-regulation play an important role in defining students' performance, and they are an actual predictor of positive learning outcomes in blended learning.

Instead, scholars have largely hypothesized the opposite direction, from ICT to metacognition (8 studies; Table 2). Among these, the study carried out by Al-Samarraie, Theo, and Abbas (2013) revealed that the degree of attention, motivation and interaction in an e-learning educational environment was associated with higher levels of metacognition which, in turn, predicted better learning performances in university students. This study therefore highlights the benefit of online learning, if this is characterized by motivational components. Similarly, the study by Hsu and Hsieh (2011a) on a sample of 99 senior undergraduate nursing students revealed that blended learning courses contributed to learners' learning outcomes by facilitating their metacognitive development and self-regulatory skills. In a study by Klein, Noe, and Wang (2006), students enrolled in blended learning condition, showed a higher motivation to learn compared with their peers involved in the traditional classroom. Also in this case, motivation to learn was, in turn, related to students' metacognition. Furthermore, motivation to learn partially mediated the relationship between delivery mode and metacognition.

In the study by Zhao and Chen (2016), a sample of distance learners showed how user satisfaction, information and communication quality influence self-regulation in the e-learning environment. Predicably, self-regulation learning dimension was also influenced by the time (in years) spent using the e-learning mode. Learners who attended distance learning for less than 1 year and between 1-3 years were found to be better than those who attended distance learning for 4-6 years in the self-regulated dimension.

In a study by van Vliet, Winnips, and Brouwer (2015), significant differences were found between students of flipped classes and traditional lecture learners. Participants showed differences in their levels of metacognition and learning outcomes in relation to the teaching method employed. The flipped-classroom pedagogy had positive effects on critical thinking, task value, and peer learning of students. However, the effects of flipped classes were not sustained in a 5-months follow-up.

Lee and Wu (2013) compared two different activities of online reading (social entertainment and information-seeking), conducted by students aged 15 from 15 different regions of the PISA (Program for International Student Assessment) 2009 dataset. The results showed that only information-seeking activities were associated with better understanding of metacognitive strategies which, in turn, were associated to better reading literacy. Therefore, benefits on metacognition are dependent upon ICT environments that stimulate individuals to be active actors in the online activity.

A study also took into account the benefits that ICT could produce with respect to special populations. Yang (2012) considered university learners with English reading difficulties as participants, in order to understand how such special sample could benefit to a greater extent of the learning environment. The online interface system employed in the blended learning supported the use of metacognition, monitoring and regulation of one's own learning through four functions: dialogue box, discussion forum, chat room, and annotation tool. This led to better results in learning outcomes in students who used the blended modality compared to those assigned to the control group (with on-site instruction only).

Taken together, the results hereby presented suggest a positive relation between the use of ICT and learning outcomes. Note however that some study did not find evidence for a relation between ICT and metacognition (Hsu & Hsieh, 2011b), highlighting the need of further research that helps clarify the relation between the two constructs.

3 Discussion

Our results showed that e-learning environments can have beneficial effects on learning outcomes, and this effect is greatly favoured when they are structured in a way to take advantage of metacognition. Second, they show that ICT can also foster metacognition and better learning outcomes *per se*, without metacognitive prompts. To understand why this may happen, we can rely on the further results of our analysis.

The studies presented highlight that ICT and metacognition are likely in a bi-directional relationship. Indeed, we found studies showing that ICT can foster metacognition, and that therefore help explain why online activities may have an effect on learning outcomes (i.e. they stimulate metacognition). There are several explanations as to why this may happen. For instance, they can foster greater motivation to learn, which in turn relates to the importance of adopting metacognitive strategies (Klein *et al.*, 2006). Consider that, in some cases, ICT allows to record the actions performed by the individual and offer him/her feedback regarding the operations he/she has performed. This feedback is extremely important so that the person becomes aware of his/her own mental mechanisms and learns how to control his/her own learning strategies. Often, ICT explicitly requires students to reflect on the choices to be made and therefore invite them to ask themselves about the mental processes that are activated in order to identify the most suitable paths. Other times, ICT "force" learners to scan their thoughts in stages or sequences, thereby facilitating the awareness of the mental operations that are put in place in carrying out a task. These represent an optimal use of ICT, that can act on mental processes and therefore may even have wider beneficial effects on unrelated field (although this is yet to be tested, we argue that is an interesting avenue for future research). Also, metacognitive reflection develops thanks to social interaction and these tools can actually encourage and support cooperation, favouring "shared" metacognition, to the extent that the e-learning environment is interactive (Cacciamani *et al.*, 2012). The possibility of online collaboration via ICT has led to the transformation of the communication processes themselves. This re-modulation presents an interesting potential in terms of transformation in a metacognitive sense of distance learning processes (De Beni, Meneghetti, & Pezzullo, 2010).

On the one hand, although ICT can promote a more metacognitive individual, our analysis also revealed evidence for the reverse pattern, that is basic self-regulatory skills are needed to take advantage of web-based training (Ramirez-Arellano *et al.*, 2019). Also, metacognition appears to moderate the relationship between ICT and learning outcomes, that is ICT produces better learning outcomes only for those students with better metacognition or provided with metacognitive training (e.g., Lee & Wu, 2013). The implication of this conclusion is that individuals should be equipped with metacognitive skills, otherwise they would not be able to benefit of the ICT revolution. Given that many individuals may lack sufficient metacognitive skills, we recommend to measure metacognitive skills even in the context of web-based learning to obtain information about the tasks to be implemented. For instance, it is possible to structure web-based activities to foster the acquisition of those skills that can be improved, develop new strategies by which to promote the process of assimilation of concepts during the learning processes, increase the learner's confidence, planning the study in a more efficient manner in order to achieve specific learning objectives (Sanchez-Alonso & Vovides, 2007).

These results allows several conclusions. First, the scarce number of studies investigating the relation between ICT and metacognition calls for the need of research. Second, we prefer avoiding trivial conclusions on the fact that, simply, ICT has beneficial effects on metacognition and learning. In fact, since the relation between the two constructs may be more complex than previously thought, it is important to understand the condition that favour the different outcomes. In other words, it would be irrealistic and too simplistic to merely argue that ICT favours learning. Instead, ICT requires a set of (meta)cognitive abilities that should be taken into account when designing web-based course. Unfortunately, the advantages offered by web-based learning and ICT are often accompanied by a lack of critical theory on technological education (Whitworth, 2007) and do not always correspond to the ability of researchers to better define and structure the use of ICT in different environments. This discrepancy can possibly cause negative repercussions both at the level of learning and at the level of individual psychological processes (Thomas *et al.*, 2016). The structuring of web-based environments must include not only the technological characteristics and the individuals' characteristics, but also take into consideration learning processes, metacognition (Kramarski & Gutman 2006) as well as cognitive (Klein *et al.*, 2006) and motivational aspects (Ramirez-Arellano *et al.*, 2018).

Conclusion

Our analysis reveals that the relationship between metacognition and ICT is (at least) three-folded. On the one hand, working in technology-mediated contexts supports the development of metacognitive skills which, in turn, lead to better learning outcomes. On the other hand, metacognitive skills are necessary to take advantage of web-based training. In general, the relationship between these two variables appears to be tight and partly circular: while better metacognition allows learners to efficiently access the use of ICT, technological tools and web-based learning can foster monitoring and self-regulation processes. But there is a "third" hand, supporting the combined use of e-learning and metacognition to produce the best learning outcomes. Specifically, it appears important that ICT are accessed by learners in a metacognitive way, that is that they are not passive receivers of information, but they are facilitated by the characteristics of these tools (e.g., (a)synchronic communication, monitoring features) and metacognitive prompts.

The use of ICT can contribute to the creation of powerful learning environments (Smeets, 2015), but their use requires a critical reflection that must take into account different aspects related to students, to teachers and their approach to ICT, and to how to structure learning mediated by ICT in a way that metacognitive and self-regulation abilities are empowered and together contribute to facilitate learning.

According to Siemens and Baker at the International Conference on Learning Analysis and Knowledge in 2012, Learning Analytics consists in measuring, collecting, analyzing and reporting data concerning learners and the contexts where they learn, with the aim of optimizing learning. Our findings allow to advance this definition, to the extent that the context of learners is not only physical, but determined by their set of knowledge, skills and individual differences, that may be expressed differently based on the object of learning and to the specific settings where this occurs. In particular, by highlighting the deep interplay between metacognition and ICT, our analysis points to the need of taking into account motivational and metacognitive factors in interpreting learning outcomes, therefore qualifying these factors as key to benefit from ICT. Although they are partly determined at the level of individual, they are also highly contextual, since individuals' skills and motivation can be contextually activated and determine the whole set of psychological processes allowing learners to analyze data and productively use them to take maximal benefits of new technologies. A future challenge for ICT consists in our opinion in understanding how psychological processes can be contextually activated and influence the different learning stages.

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AN AGNOSTIC MONITORING SYSTEM FOR ITALIAN AS SECOND LANGUAGE ONLINE LEARNING

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Keywords: Italian SLA; Agnostic Monitoring System; Digital Learning Unit; Experience API; Learning Record Store.

This contribution follows the trend in educational research to collect data and create an information-based system to improve learning effectiveness. However, the value of quantitative data collected through online platforms is a subject of debate: when starting from data (inductively) meaningful interpretations are hard to discover; on the other hand, when starting from *a priori schema* (deductively), there is a risk of lack of flexibility and responsiveness to the changes. Hence, the need to hypothesize a different approach.
For this purpose, a monitoring system whose architecture we defined as agnostic has been built and tested. That system was connected to an online learning environment with free educational resources, whose operating learning fulcrum is the Digital Learning Unit (DLU), an original theoretical-practical device which allows interpretative assumptions to be made on the data obtainable from the system.

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Although minimal, the results achieved through the piloting are sufficient to enable the monitoring system as an information provider about learning experiences, resources, and the environment itself. The interpretative hypotheses made possible by the DLU legitimize the assumption of an abductive approach which, without incurring in the aporias mentioned above, allows us to transform mere quantitative data into useful information to support the learning process.

1 Introduction

In the last about ten years, since International Conference on Learning Analytics & Knowledge (LAK) (Siemens & Long, 2011), collection, analysis and visual representation of data concerning learners and learning contexts have become crucial in academic research, especially as far as e-learning is concerned.

However, researchers are aware of the issues arisen from the computational analysis of a high amount of data (Siemens, 2013). In order to interpret the collected data, either machine learning and data mining techniques (inductive approach) or filters based on *a priori* preset criteria (deductive approach) could be applied. Still, they both have limitations. The first approach might result in blurred phenomena mechanisms, producing only forecasts and effects rather than causes. With the second one, the referenced framework might become too rigid, and therefore not flexible and not responsive to the changes. This work should be considered under this theoretical issue and the more general debate on learning analytics (Ferguson, 2012; Chatti *et al.*, 2012; De Waal, 2017).

This paper is aimed to analyse and share the results of a piloting experience that has been conducted throughout the 2nd level Master in "E-Learning per L'Insegnamento dell'Italiano A Stranieri" (ELIIAS, "E-Learning for Teaching Italian to Foreigners"), by the University for Foreigners of Siena. The learning activities therein have been tracked by the agnostic monitoring system in the description of which the main part of this work consists of (§§ 4, 5 & 6).

The piloting was made possible by setting up a learning environment and a more specific place, the Digital Learning Unit (DLU), where the learning experiences and the monitoring system were tested[1]. In the next section features and functionalities of the learning environment will be described. The following is instead dedicated to the DLU, the aforementioned device capable of interpreting the data stored into the monitoring system[2].

[1] In addition to the monitoring system, the learning environment and the Digital Learning Unit (DLU) are also elements of original conception. The DLU is described here for the first time. Its original Italian name is *Unità Didattica Digitale* (UDD). We plan to issue a complete work about it soon.

[2] Given the complexity of the experience described in this paper, and the different fields that were explored, we cannot provide a complete list of approaches and theoretical frameworks that were used to make the experience itself possible. However, we have tried to pinpoint some of the authors and contributions that are useful for the reader to understand the broader scenario of this research.

2 The Learning Environment

Throughout the design process of the learning environment in which the piloting here presented was carried out, some guiding principles were borrowed from a decade of experience with MOOCs (Cormier & Siemens, 2010; Yuan & Powell, 2013).

The learning environment has the following characteristics:

1. It is open and not reserved for the formal and institutional dimension of the learning processes;
2. It is participatory, not teacher-centred but primarily focused on social community interactions;
3. It is distributed, meaning it is not centralized: learners need to work without space and time constraints; they are free to work in their chosen places, and according to their times;
4. It is always connected, i.e., it supports a network approach to lifelong learning since the system remains open and connected indefinitely.

Moreover, from MOOCs' massive dimension derives the impracticality of any class group. Now, given that the audience is here indefinite and non-massive – it can be either massive or small – the lack of a teacher or a tutor implies the following distinctive feature:

5. It is here assumed a self-learning approach and, strictly connected, self-evaluation, possibly integrated by forms of peer assessment.

Finally, as has been argued, acquiring a second language is not about the transmission of declarative knowledge; rather, it implies developing procedural competences (Diadori, Palermo & Troncarelli, 2015). Hence, it is necessary to have the following:

- A considerable variety of learning activities, i.e., interactive contents (not just multiple choices, filling exercises, reordering, etc.);
- A flexible learning environment that could be integrated and modified according to the needs;
- A standard for monitoring learners' work and progress.

In order to meet these conditions, the learning environment has been provided with an adequate number of interactive contents (many of which were enriched media: interactive videos, augmented images, etc.)[3]; then, instead of a Learning Management System (LMS), a Content Management System (CMS) was chosen, suitably integrated with a number of plugins[4]; eventually,

[3] A major challenge for our work with enriched media is represented by the concept of media aggregator (Rossi, 2017).

[4] The inadequate use of LMSs had been criticized (Bonaiuti, 2006). A theoretical framework about using a CMS is contained

the whole system was used as an activity provider, i.e., to send xAPI statements to a Learning Record Store (LRS) (see § 5.2).

As of April 2018, learning resources have been created and tested. Around the middle of July, a two-week piloting was carried out within the Master ELIIAS.

Further characteristics of the learning environment were the following:

- It could be freely navigated, was networked and destructured (see § 4);
- Interactive contents were self-consistent and limited in duration. Learners could freely assemble them through the labels associated with each unit (CEFR[5] level, linguistic-communicative ability, semantic area);
- The monitoring system was designed to detect data from the learning environment, the resources, and the learners' behaviour. The agnostic architecture was set up for tracking interactions.

This experiment followed an ongoing trend to consider the learning experience as a whole, collecting information even from informal or non-formal learning activities.

3 Digital Learning Units

In this section, the Digital Learning Unit (DLU) will be described. DLU is indeed the learning experience's specific place where the monitoring system was to be tested. Above all, its digital structure makes it a suitable device for interacting with the monitoring system. As a matter of fact, the construct of DLU is an integral part of this study since it is necessary and consistent with the logical steps that lead to the final result, the development of an agnostic monitoring system capable of interpreting data through an abductive approach (Peirce, 1984; Bonfantini, 1987; Magnani, 2000).

Contributions about learning objects and OER (Wiley, 2000; Fini & Vanni, 2004; Giacomantonio, 2007; Fini 2012; Wiley, Bliss & McEwen 2014) and studies on Italian second language acquisition (SLA) (Freddi, 1994; Balboni, 2002; Vedovelli, 2002) converge into the DLU conception. Therefore, a definition of DLU is only possible combining the structural element with the educational purpose, i.e., the digital object with the theoretical and methodological framework.

Apart from being considered an operating model for Italian SLA, DLU is first and foremost a digital structure that allows formulating interpretative

in Collins & Ollendyke (2015). The post-LMS scenario is represented by the "Next Generation Digital Learning Environment" (NGDLE) (Brown, Dehoney & Millichap, 2015). Other ideas of "multiple integrated systems" can be found in xAPI.com website (https://xapi.com/do-i-still-need-lms/) and Fiumana, Cacciamani & Bertazzo (2016).

5 Common European Framework of Reference for Languages: Learning, teaching, assessment (CEFR) (Council of Europe, 2001 & 2018).

hypotheses about the data stored along with the tracking of learning experiences. Such digital structure provides both a mark-up system for linguistic, communicative and semantic data, as well as an architecture built to generate information (xAPI statements) to be sent to the monitoring external software (LRS).

The DLU has the following features:

1. It is a study session with a predetermined duration, although in a time frame of generally 15 to 60 minutes;
2. It includes an educational objective, a textual input, some learning activities, a theoretical purpose (declarative knowledge) and a final communicative activity (procedural competence);
3. It generates xAPI statements to be sent to an LRS for the monitoring process;
4. It contains linguistic, communicative and semantic descriptors expressed by categories and/or tags to formulate hypotheses about the stored data and to connect each DLU to others to build learning micro-paths.

The DLU structure can be described as follows: it generally starts with a brief presentation of the topic and the learning objective; it also includes the duration of the work session, the level of linguistic competence according to the CEFR, and the descriptors mentioned above. Typically, it goes on with the following steps:

1. Engagement or warm-up activities, i.e., activities carried out before the presentation of the core text. The Italian SLA literature refers to them with terms such as *motivazione* (motivation) (Freddi, 1994; Balboni, 2002) or *contestualizzazione* (contextualization) (Vedovelli, 2002);
2. Presentation of the core text (verbal, audio, visual) with testing activities to verify its comprehension. Italian SLA literature calls this *globalità* (globality) (Freddi, 1994; Balboni, 2002) or *input testuale* (textual input) (Vedovelli, 2002);
3. Focus on linguistic, communicative, lexical, or cultural aspects. This step involves what Italian SLA studies refer to as with *analisi, sintesi, riflessione* (analysis, synthesis, and reflection) (Freddi, 1994; Balboni, 2002), and consists on a single instance of work on one of the structural aspects before mentioned. From a different theoretical perspective, Vedovelli (2002) refers to this phase with *attività di comunicazione da/sul testo* (communicative activities from/upon the text), which involves metalinguistic activities on the core text[6];
4. Final communicative activities. The action-oriented approach

[6] It might be worth to point out that the DLU's structure is placed at a higher level of abstraction than the two aforementioned Italian SLA perspectives, with respect to which it is therefore theoretically neutral.

recommended by the CEFR is assumed here. Specifically, this phase is defined as *output comunicativo* (communicative output) as conceived in Vedovelli (2002).

The DLU structure might be interpreted otherwise, according to the teacher or the educational designer sensibility or theoretical perspective. It might be focused, for example, on engagement activities followed by the core text presentation, or again on a warm-up session on a known text to prepare learners to a different learning focus. In any case, every alternative interpretation of the structure should always end with a final step based on communicative activities.

4 Objectives

4.1 Approach

Our main objective was to design an open and flexible monitoring system shaped on the open and flexible learning environment. To build the learning environment, a new approach, flexible, informal, networked, and open, has been chosen – instead of a traditional, rigid, formal, linear, and closed setting. These are the main characteristics of a destructured environment mentioned in § 2. To such an environment nothing could be done other than adopting a monitoring system equally open and bottom-up.

Moreover, tools not solely designed for learning purposes, but also able to detect low-level activities data, were taken into account (e.g., which pages learners use the most, which paths they prefer to follow, the feedback they give on the learning activities, etc.).

The information collected from the website is useful to evaluate the system's usability while providing useful suggestions to improve the ease of use and facilitation of students all along the language acquisition process.

4.2 Architecture

The monitoring system was intended to collect and cross-reference data on learners' interactions. Then, it had to be capable of letting meaningful correlations surface from the crossing data. All these would have helped to understand if such a destructured system worked better than a more traditional and structured one.

The specific purpose of the work was building a so-called "agnostic architecture" for the data analysis, capable of interacting with destructured environments and of suggesting possible queries rather than answers to predetermined questions.

Therefore, this work is not based on a traditional approach to the evaluation, nor on sets of questions to be answered. Instead, a more experimental approach was preferred: the most considerable quantity of data on learners' behaviours (interaction with the environment, navigation data from the website, the resources, and the communication tools) was collected. Later on, the collected data were cross-referenced in order to look for meaningful correlations and better understand learners' approach towards their learning experience and the real effectiveness of such an open learning environment.

The next paragraph focuses on how the agnostic monitoring system was designed, which tools have been selected, and if it works, i.e., if it provides relevant information.

5 Tools and Methods

5.1 Issues

An open learning system has to deal with diversity. Different technologies and systems need to interoperate in a secure and standardised way. In other words, both machines and humans should be able to read the data.

In this case, it was not just a matter of finding a tool capable of managing a variety of systems. Another problem, at the monitoring level, came from the educational concept, or rather from the disintegration of the traditional course in a network of self-consistent micro-paths. Learners' interaction with the DLUs had to be thoroughly recorded to get as much information as possible about the overall learning experience.

Data collection required the following: to monitor in-depth the interactions between learners and learning resources; to track the navigation within the environment to identify the paths that learners set up; to receive feedback concerning either resources or the learning environment.

5.2 Standard Choice

First of all, it was necessary to find a standard specification to communicate with the selected software (mainly the CMS and the authoring tool)[7]; it had to be able to read multiple activity streams and express them with a standardised language.

Experience API (xAPI) was chosen. xAPI is a protocol specification developed for learning technologies to collect data from a wide range of online and offline experiences[8]. The APIs capture in a consistent format the data that

[7] In this case, as a CMS WordPress was chosen (https://wordpress.org/), even though other tools, like Drupal, Joomla, etc., could have been used. H5P (https://h5p.org/) was the authoring tool of choice. About the use of WordPress in Italian SLA see Giglio (2014).

[8] The xAPI specification was developed on behalf of Advanced Distributed Learning (ADL, https://www.adlnet.gov/). Its first version was called Tin Can API (2013), then renamed Experience API (https://xapi.com/).

are coming from different software technologies. In so doing, different systems can securely communicate, collect, and share the activity streams using the protocol's internal vocabulary.

xAPI is based on an inclusive logic approach: any learning experience, as long as connected to digital technology, can provide tracking data in a standardised language. Therefore, with xAPI[9] it is possible to bring out the tracking data about the learner's real experience, including where and when it takes place. A bottom-up logic approach perfectly suitable to the concept which considers the learning process a cross-experience, beyond the formal course dimension, ahead of the LMSs.

This protocol allows to record the learners' activities in detail, and this is very relevant from an SLA point of view because it provides valuable elements to assess whether and how a given linguistic input has turned into an intake (Krashen, 1985).

Once it was determined to collect the data with xAPI, it was necessary to decide where to store them. Therefore, the learning environment has been connected to an LRS. There, the learners' activity streams were stored.

As LRS, Learning Locker was chosen, an open source software that offers a free version suitable to our purposes[10]. Learning Locker stores the tracking data received with the xAPI protocol and aggregates them according to the criteria set by the user. The selected data can be later downloaded in.csv format and can then be elaborated in a different environment.

6 Piloting and Results

6.1 Context and Limitations

Setting up the learning environment and the assessment system, as well as the piloting, are activities that fall within the framework of the Master ELIIAS.

Such a project included a two-week piloting with about 50 learners. The limited number of participants and the reduced timeframe did not give enough data to evaluate the learners' learning and the environment itself.

Said so, the collected data allow to answer a simple and basic question, namely, if our agnostic monitoring system can say something about the learners' behaviour. In other words: if it works.

[9] xAPI's syntax consists of RDF triples based statements: actor + verb + object. The statements can also include contextual data: context, result, timestamp, etc. More references are available on Github ADL section (https://github.com/adlnet/xAPI-Spec).

[10] URL: https://www.ht2labs.com/learning-locker/.

6.2 Reading the Data

Thanks to the data collected by xAPI it is possible to analyse the behaviour of a single or a group of learners. Besides, data coming from different systems can be cross-referenced to find meaningful trends[11].

We carried on the analysis both for individual and groups but, due to the limitations mentioned above, only the results regarding homogeneous groups will be discussed[12].

The first group of results has been obtained through the application of filters and quantity features to the columns Result and Verb. It was possible to notice that:

- Learners' activity produced 7,614 statements (6,883 referred to interactions with 0 points, 482 related to passed activities, and 249 to not passed activities);
- The statements related to the field answered (there is a true/false for every item which requires an answer) are 886 (433 with a positive result, 241 with a negative one, 218 without any answer);
- The statements related to the field *completed* (related to the completion of an entire activity) are 184 (49 with a positive result, 8 with a negative one, 127 without any result).

It is essential to mention that a large part of learners involved in the piloting seemed to have quickly explored the resources without carrying out the testing activities. Therefore, the number referred to the passed activities is pretty low.

6.3 Correlations

The second group of results has been obtained by correlating activity level and success percentage with homogenous groups of learners by age group and by linguistic competence.

Fig. 1 shows the relations between the data about age, the average level of interactions, and success percentage.

The most active are the eldest learners, between 50 and 60 years, but the relationship between the activities and the success percentage shows a different trend: the best result comes from the age group between 30 and 40 years.

[11] Gathered data have been filtered and grouped with OpenRefine (http://openrefine.org/), to simplify and quickly read the original JSON code, and to order data according to a quantity criterion.

[12] It was also possible to analyse the interactions between a student and a DLU: the time taken, the scores obtained in a single activity, the level of competence acquired at the end. In this way, a detailed record of all interactions could be extracted for each DLU.

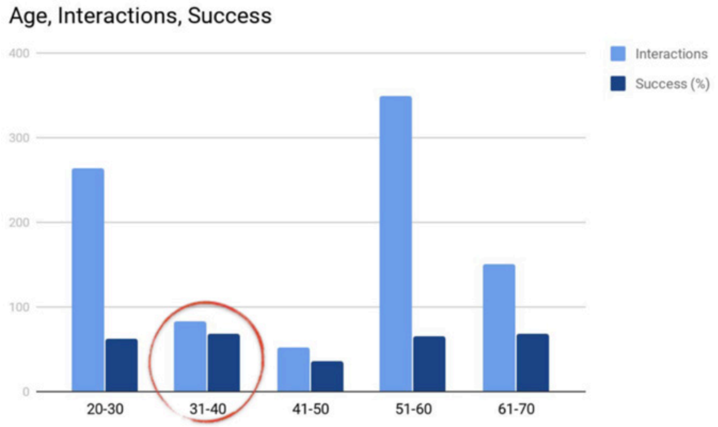

Fig. 1 - Interactions and success percentage compared to age.

Then, in fig. 2 the linguistic levels of competence have been compared to success percentage. In this case, learners with a B2 level of competence are the most active, with a double average number of interactions if compared to the others.

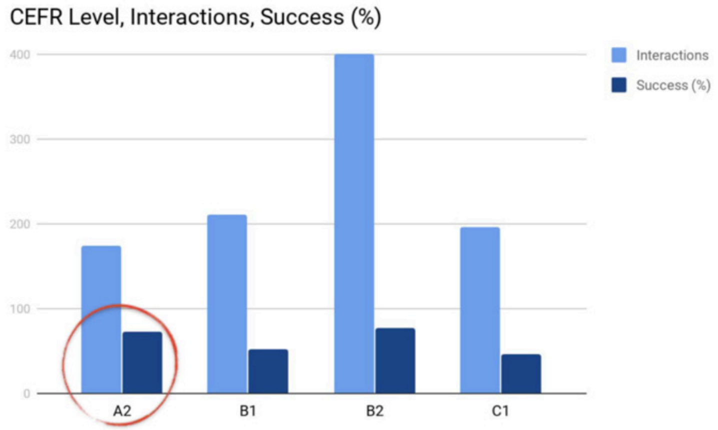

Fig. 2 - Interactions and success percentage compared to linguistic level (CEFR).

The correlation between the linguistic level and success percentage confirms that those with a B2 level of competence of Italian had better performances than the others.

Nevertheless, considering the correlation between the average number of interactions and the success percentage, the "best" are the A2, since they were able to take advantage of both interactions and resources.

Conclusions

Beyond the limitations mentioned above, the piloting produced some answers: the agnostic monitoring system appears to work. It suggests possible queries and shows valuable and meaningful trends to evaluate the learning experiences, the resources, and the environment itself.

The first result comes from the data analysis, that seems to confirm the learners' trend to significantly and extensively interact with the DLUs, even though not paying too much attention to proficiently completing the interactions. In other words, they showed a more inclined attitude towards exploring resources rather than completing them.

Hence the questions: Are the resources not attractive or usable enough to retain learners? Does the open and destructured environment lead to an overly serendipitous approach? Is it not functional enough to motivate learners to complete the activities?

The collected data are not sufficient to answer these questions: as said before, the experimental timeframe was too short, and the number of involved learners was too limited. An even crucial element could then be the learners' motivation since their purpose was not only learning Italian but also testing the resources.

This outcome encouraged us to deepen this experience creating additional resources, to obtain a whole set of new DLUs, starting from all CEFR levels of competence, and test both the monitoring system and the DLU reliability with a more significant number of learners. Indeed, this research has thrown up many questions in need of additional investigation. It is therefore required a further and broad study to establish the tendency of the learners to either quickly explore the resources or to make full use of them. In any case, it will be possible to reflect upon the resources themselves, the destructured environment, or the motivation. Still, a similar piloting could be conducted in similar context, e.g., with other foreign languages.

A second result concerns the approach to make sense of the data suggested at the beginning: an approach neither inductive, based on data mining or machine learning techniques, nor deductive, i.e., filtered by preset criteria, but abductive was chosen. This approach uses the data collected from the DLUs to guide the hypothesis-making process, and later verify them on the data collected from all the objects capable of issuing xAPI statements.

In so doing, it is possible to generate new hypotheses and test them, without forcing the adhesion to a single framework but maintaining a rebuildable relationship between raw data (xAPI events) and high-level strategies.

As a more general perspective, this research should focus on generating and sharing reports produced by this system with all the parties involved in the learning environment: authors, tutors, learners and, of course, researchers. This solution might translate in creating an endpoint capable of converting the data into a standard format like JSON, available for external parties. The authors of the learning contents might evaluate and maybe re-elaborate the DLUs. The tutors would notice in real-time the unexpected behaviours of the learners or groups of them. The interactions' data with the proposed contents might also help learners to notice their strategies and become more aware of their ability to learn – a crucial competence for SLA, as also CEFR clearly stated. And this is the contribution and the role of the researcher: conceive, implement and keep improving a monitoring system which, even with mere quantity data, might be able to support the learning process.

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DATA-DRIVEN MODELING OF ENGAGEMENT ANALYTICS FOR QUALITY BLENDED LEARNING

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Engagement analytics is a branch of learning analytics (LA) that focuses on student engagement, with most studies conducted by computer scientists. Thus, rather than focusing on learning, research in this field usually treats education as a scenario for algorithms optimization and it rarely concludes with implications for practice. While LA as a research field is reaching ten years, its contribution to our understanding of teaching and learning and its impact on learning enhancement are still underdeveloped. This paper argues that data-driven modeling of engagement analytics is helpful to assess student engagement and to promote reflections on the quality of teaching and learning. In this article, the authors a) introduce four key constructs (student engagement, learning analytics, engagement analytics, modeling and data-driven modeling); b) explain why data-driven modeling is chosen for engagement analytics and the limitations of using a predefined framework; c) discuss how to use engagement analytics to promote pedagogical reflection

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using a pilot study as a demonstration. As a final remark, the authors see the need of interdisciplinary collaboration on engagement analytics between computer science and educational science. In fact, this collaboration should enhance the use of machine learning and data mining methods to explore big data in education to provide effective insights for quality educational practice.

1 Introduction

The pervasive integration of digital technologies into teaching and learning in Higher Education (HE) generates a large volume of data that can be mined in search for patterns. Learning analytics (LA) emerged in this context with the aim to understand and optimize learning and the environments in which it occurs (Ferguson, 2012). Most studies in LA focus on student engagement as trace data are about students' behavior in the Virtual Learning Environment (VLE) (Vytasek *et al.*, 2020). Compared to traditional studies on student engagement, engagement analytics has differential characteristics. First, it uses trace data that are automatically archived in the VLEs, while traditional studies use data collected manually and purposely. Second, trace data are large volume, multi-faceted and fine-grained which require complex computational methods such as Decision Tree (Wolff *et al.*, 2013) and Neural Network (Okudo *et al.*, 2017) for analysis, while traditional studies usually adopt qualitative methods (such as thematic analysis) and simple statistics such as descriptive statistics (Fisher & Marshall, 2009) and T-test (De Winter, 2013) for data analysis.

Engagement analytics has the potential to advance the ways of reflecting on student engagement because trace data, as a new type of data, require more advanced methods to analyze. However, engagement analytics' research currently focuses mainly on techniques for handling data rather than reflecting on how these techniques can contribute to optimize pedagogical practices – the learning analytics' goal. One possible problem relates to the use of MOOCs rather than blended learning as the context of most empirical studies on LA. Given that MOOCs are still supplementary elements rather than a replacement for university teaching (Li & Yang, 2018), results of engagement analytics on MOOCs fail to provide implications for most common blended learning practice in HE.

This paper explores data-driven modeling of engagement analytics as a helpful approach in promoting teachers and students' reflections that improve the quality of teaching and learning practice in the most common context of blended learning in HE.

Though trace data are currently generated from online activities, in blended learning the findings of engagement analytics should affect the practice of teaching and learning both online and face-to-face. Furthermore, with more and more "smart classrooms" available (Kim *et al.*, 2018), we can expect multimodal (such as audio, video, image, text, etc.) trace data in the future (Blikstein *et al.*, 2016).

2 Background

In this section, four main constructs are introduced with the aim of providing a conceptual basis for our claims: student engagement, learning analytics, engagement analytics, modeling and data-driven modeling.

2.1 Student Engagement

Student engagement is defined as the time and effort students devote to educationally purposeful activities (Kahu, 2013). One of the pioneer researchers to emphasize the importance of student engagement is Richard Snow (1980). Although engagement is not the only factor that influences learning outcomes, research shows that it might trigger deeper learning (Dunleavy & Milton, 2008). More recently, Kuh (2004) created instruments to measure student engagement, demonstrating positive correlations of student engagement with retention and academic success (Richards, 2011).

Blumenstein *et al.* (2018) present three elements of engagement: affective/emotional engagement (e.g. enjoyment, boredom, anxiety, etc.) regarding students' social and psychological responses toward their education; cognitive engagement, concerned with how students think about their learning and academic ability, experiences, and environment; behavioral engagement related to actions such as attendance in class, level of participation and time spent on assessment activities. These three elements seem to play a role in defining the quality of educational experience. Furthermore, Chickering and Gamson (1987) indicate seven principles to improve college and universities quality experience which can be deemed as connected with engagement: 1. encourage contact between students and faculty; 2. develop reciprocity and cooperation among students; 3. use active learning techniques; 4. give prompt feedback; 5. emphasize time on task; 6. communicate high expectations; 7. respect diverse talents and ways of learning. Gibbs (2010) states that the more students are engaged in the seven principle activities, the more they learn. Beside this, Gibbs underlines that the crucial variable for educational quality is student engagement, which is facilitated by the level of academic challenge, the extent of active and collaborative learning and the extent and quality of student-faculty interaction.

An initiative that gave momentum to the interest towards student engagement is the National Survey of Student Engagement (NSSE), first launched in 1999 by Indiana University. It focused on the extent to which students participate in the educational processes that contribute to the outcomes (NSSE, 2018). However, while NSSE focuses on macro level (such as institutions, regions, countries, etc.), current engagement analytics mainly focuses on micro level (such as learning activities, courses, etc.).

2.2 Learning Analytics

Learning analytics (LA) is defined as the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs (Ferguson, 2012). Sharples *et al.* (2013) argue that "LA enables visualization and recommendations to influence student behavior while a course is in process".

Log data about learners and their activities (log to the courses' sites, assignments delivery, participation in forums, drop-out, etc.) can be dealt with through big data techniques (Daniel, 2015). However, the real challenge is generating the right pedagogical questions to interrogate big data in a way that teaching and learning quality can be effectively supported, also considering ethical concerns (Prinsloo & Slade, 2017). It has been claimed that LA can help the teachers to find early indicators of student problems, learning material inadequacy, unclear interfaces, etc. This could also support teachers' more focused intervention, improving educational quality (Viberg *et al.*, 2018). LA can also help students' self-regulation along the learning process as an essential soft skill for workers of the future society.

2.3 Engagement Analytics

Engagement analytics refers to studies in the field of learning analytics that focus on student engagement (Vytasek *et al.*, 2020). Student engagement, deemed highly relevant in quality teaching and learning, is still hard to define in operational terms, a fact that has crucial impact on data mining techniques "*It is important to recall that engagement is a theoretical concept and it cannot be measured directly. When online learners interact in an electronic environment, they leave a data trail of when and where they have been, what documents they have accessed, who they talked to, and how well they are doing on web quizzes. LA is a growing field that analyzes this transactional data either looking for specific information for a single learner, or for more general patterns of interaction from which one might measure progress, infer engagement and possibly predict outcomes*" (Richards, 2011).

Engagement (and its effects) have been measured in several forms. Hung *et al.* (2012) found that students with higher engagement (as measured by the frequency of login, modules accessed, clicks, and discussion board posts) tend to have higher final grades. In a model that accounted for student demographics and the number of teacher comments throughout the course, Liu and Cavanaugh (2012) showed that the total number of minutes a student spent logged in to an online biology course, was the strongest predictor of final scores.

The Social Networks Adapting Pedagogical Practice (SNAPP) tool for extracting student online network data and visualizing them as social graph structure (Dawson *et al.,* 2010), was claimed to support teacher interpretations about the quality of learning activities. However, though the graph illuminates the most active participants as well as the messages and connections among students and teachers, it does not provide information about the quality of the engagement.

2.4 Modeling and Data-Driven Modeling

A mathematical model embodies a set of statistical assumptions concerning the generation of some sample data and similar data from a larger population. To create the model, relevant data is selected; hence the model is repeatedly tested, with the available data (Kennedy & Bancroft, 1971).

Data-driven modeling is an approach to build models that is based on the data analysis about a system (input, internal and output variables) without explicit knowledge (Solomatine *et al.*, 2008). One example to explain data-driven modeling and non-data-driven modeling can be demonstrated with reference to two approaches to qualitative data analysis: grounded theory and thematic analysis. Grounded theory has three stages in coding: initial coding, focused coding and theoretical coding (Charmaz, 2014) while thematic analysis has only one step, which is to analyze the corpus with a predefined list of themes (Mohammed *et al.*, 2016). Non-data-driven modeling is similar to thematic analysis, and both are a process of deductive reasoning. Data-driven modeling is similar to grounded theory, and both are mainly a process of inductive reasoning, that brackets the previous knowledge for avoiding potential influences in the analysis.

3 Connecting Engagement Analytics to the Practice of Blended Learning

This section will argue that data-driven modeling of engagement analytics is helpful to assess student engagement and to improve the quality of teaching and learning. The first part explains why data-driven modeling is chosen for engagement analytics (instead of predefined framework, normally used before the era of big data). The second and third part explain how engagement analytics can improve the teaching and learning practice using our pilot study as a demonstration. Our assumption is that engagement analytics can show learners' patterns and they are potentially useful to enact better teaching and learning.

3.1 Data-driven modeling of engagement analytics

There are two approaches for engagement analytics: top-down and bottom-up. In the former, we have a predefined framework to model student engagement while, in the latter –also called data-driven modeling of engagement analytics–, we do not have any predefined framework. We are familiar with the top-down approach as it is the dominant approach to study student engagement in traditional studies, where we collect data from surveys, interviews, observations, quasi-experiments and so on. In these cases, we usually have a predefined framework because we need a specific perspective to look at the data. For example, we design the questions in the survey or the protocol for the classroom observation. An exception is grounded theory, which we mentioned before as an example to explain the data-driven modeling.

Such predefined framework has several limits. First, since engagement analytics use big data, it is easy to find things statistically significant but unfortunately many of them are pedagogically meaningless (Shaffer, 2017). Second, most trace data used currently in engagement analytics present only behavioral engagement, even though student engagement is a complex concept composed of behavioral, emotional and cognitive aspect (Fredricks *et al.*, 2004). Third, trace data are only recordings of quantitative students' behavior in the VLEs, and fails to account for the content of student engagement and its quality. For instance, how can we explain the data which suggests that students with low engagement (e.g. in forum posts and writing) obtain the best final grade, without analyzing the content of their posts?

It is vital to remember that data-driven modeling of engagement analytics is more difficult to conduct given that it requires several interventions from the analysts that facilitate the emerging of patterns from data. Thus, the work of analysts will directly affect the quality of research. Specifically, trace data are the raw data in the engagement analytics. It is the analyst who selects the data that are relevant to engagement based on the dataset to be explored. The analyst's background knowledge on student engagement and education in general will influence in a decisive way which data will have to be selected, which has a fundamental impact on the engagement analytics' analysis itself.

Machine learning and data mining methods such as Decision Tree (DT) and Neural Network (NN) can be used as data-driven modeling methods for engagement analytics. Specifically, DT can use students' forum views in the first 15 days, second 15 days, third 15 days (several input variables) to create a model that predicts if they will pass or fail the final exam (the value of a target variable). NN can use students' forum views and their academic performance (as inputs and outputs of the NN) in the previous academic year to train the model for predicting students' academic performance this academic year (outputs of the NN) by using their forum views (inputs of the NN). Both DT and NN require analysts to adjust the model's parameters, thus, the quality of the model will depend on the quality of the parameter adjustment. Once we design the model on student engagement, analysts are responsible to explain the model, which also requires extensive knowledge on student engagement and education in general. As explained earlier in this paper, educational researchers usually use available educational theories (a predefined framework) to model data on student engagement (Yang *et al.*, 2018) while computer scientists usually use machine learning and data mining methods (data-driven approach) to do it. The former loses the opportunities to conduct engagement analytics due to the lack of knowledge in machine learning and data mining while the latter, who can conduct engagement analytics, may concludes things that add little value to the field of educational sciences (Wen *at al.*, 2014; Al-Shabandar *et al.*, 2018) due to the lack of relevant knowledge. Educational researchers and computer scientists complement each other in terms of their knowledge on engagement analytics.

3.2 Engagement analytics promotes reflections and quality of teaching/learning practice

Effective engagement analytics should be timely and specific, in order to promote reflection and innovative practice (Shute, 2008). We argue that visualization on student engagement over time is an efficient way to present patterns emerging from the data. It promotes reflection for both the teacher and the student. For teachers, it can present the average of student engagement for the whole class and individual engagement levels. This information provides an easier way to detect disengaged students, not only to provide timely feedback to students but also to assist teachers on contrasting cheating and plagiarism. For students, it can present their activities in the online environment throughout the duration of the course, which encourages them to reflect on their learning styles, meta-cognitive skills, time management, etc. In this respect an important reminder is to use the peer comparison and class averages carefully with regard to the visualization offered to students because it could discourage students who are struggling and result in maladaptive learning (Urdan & Midgley, 2001).

Likewise, effective engagement analytics also promotes the improvement of quality teaching. For example, visualization of student analytics might bring implications on the learning design for quality teaching (Ghislandi, 2015;

Ghislandi & Raffaghelli, 2015), such as when to post a question in the forum (check the most active time for students' participation online) and what kind of learning activities are attractive for students (check the number of views and contributions by students).

Most current studies on engagement analytics focus on embracing the data mining and machine learning method to explore student engagement but fail to make informed decisions about how to improve engagement in learning.

With no doubt, we should embrace the cutting-edge methods for engagement analytics to facilitate the positive change in practice. Since the dominant method is still to model engagement for predicting academic performance (Vytasek *et al.*, 2020), the feasibility of including cognitive and emotional engagement for the data-driven modeling should be explored. However, the lack of interdisciplinary thinking, mixing the search of optimal algorithms in computer science with the pedagogical reflection, is a clear issue. This leads us to recommend interdisciplinary research in learning analytics.

3.3 An example of data-driven modeling for engagement analytics' visualization: Group-Based Trajectory Modeling

Based upon the prior debate we built two visualizations on engagement analytics in an undergraduate course at a university in the North of Italy. Both use the course's log data from online forums. The first visualization was created in Tableau (Fig. 1a, Fig. 1b), it respectively presents two students' forum views during the course from late February to the middle of May. The horizontal axis shows the date while the vertical axis shows "number of records" that present the number of forum views per day. Fig.1 shows a significant difference between two students' trajectory of forum views, which is hardly discovered by traditional forum analysis such as the mean of forum views per students in the course. Student A in Fig. 1a is a student that got the maximum grade in the final exam while student B in Fig. 1b is a student who was absent for the final exam. Though Tableau is only a tool for visualization rather than modeling data, this type of data-driven approach of real-time visualizing in the teaching and learning process will not only assist the teacher to understand individual students' engagement in the learning activities but also make students aware of their efforts and time to study in a course, which impacts student learning and assessment (Viberg *et al.*, 2018).

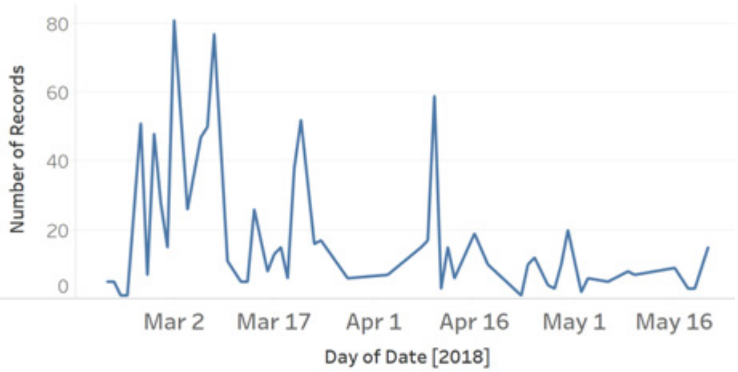

Fig. 1 (a) - Summary on student engagement in the online forum (Student A)

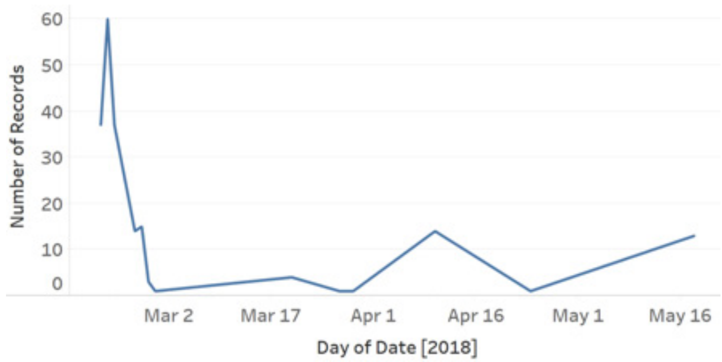

Fig. 1 (b) - Summary on student engagement in the online forum (Student B)

In the large class setting, for instance, with 300 students, it will be difficult for the teacher to first check individual student engagement in the teaching and learning process. Thus, it is necessary to have a data-driven modeling method to categorize students into several groups, so the teacher can understand who belongs to the low-engagement group and provide helps for their learning. Group-Based Trajectory Modeling (GBTM) is used as an example to show how to group students without a predefined framework. GBTM is a statistical method that aims to identify the distinct trajectories or patterns of change that exist within a population (Nagin, 2005). In the context of student engagement, it will identify groups of students in terms of their trajectory of engagement in the online forum. GBTM is conducted in R 3.6.1 with the package crimCV.

Fig. 2 shows the result of applying GBTM on students' learning trajectory. The number of groups shown in Fig.2 is set as three based on the result of model fits methods – Akaike Information Criterion, Bayesian Information Criterion and Cross Validation (Burnham & Anderson, 2004; Arlot & Celisse, 2010).

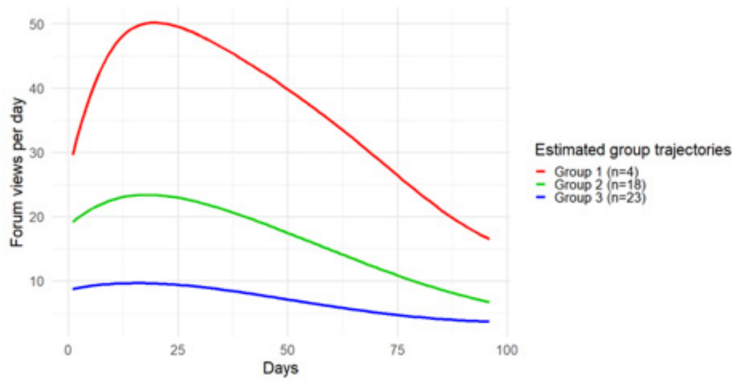

Fig. 2 - Data-driven modeling method to categorize student engagement

Colored lines in Fig.2 shows the mean value of three groups about student engagement in the online forums of the course. Group 1 was composed of 4 students, who participated actively in the online forums. The peak of engagement for Group 1 was 50 forum views per day. Group 2 was composed of 18 students, and it had a similar shape of trajectory compared to Group 1. In fact, both Group 1 and Group 2 experienced an increase in engagement at the beginning of the course and a decline after the peak value. This increase was due to the design of the course that requires students to access the online forums more frequently. The peak of engagement for Group 2 was less than 25 forum views per day. Group 3 was composed of 23 students that did not participate in the online forum actively. There is not a remarkable peak value in the trajectory of Group 3 and the maximum of forum views per day is less than 10. With this kind of visualization, the teacher can easily identify, in the early phase of the course, which student belongs to which group of engagement level (Vuorikari *et al.*, 2016). In case, most students belong to the "low-engagement" group, the teacher can adjust the activities in time to improve student engagement in the teaching and learning process. Furthermore, the teacher can have a general understanding on different patterns of student engagement emerging from the data. This is hardly to discover with the traditional methods on student engagement as it can't identify subgroups of trajectory without a predefined framework.

Conclusion

This paper argues that data-driven modeling of engagement analytics is helpful to analyze student engagement and to promote reflections that improve the quality of teaching and learning practice.

We considered two approaches to engagement analytics: one is to use a predefined framework and the other is data-driven modeling. There exist at least three major limitations of the first approach, which we have discussed extensively in this paper, First, while working over big data, it is easy to find statistically significant patterns, however many of them are educationally meaningless (Shaffer, 2017). Second, student engagement is a complex concept, composed of several elements discussed in the paper, which are difficult to include in a predefined framework given that most trace data focus solely on behavioral engagement. Third, trace data record students' quantitative behavior in the VLEs and rarely addresses the qualitative side of behavioral engagement.

As discussed here, current studies have shown shortcomings in addressing pedagogical reflection and classroom practice. For these reasons data-driven modeling could reveal more robust evidence in pedagogical practices as it avoids an improper predefined framework which can lead to misleading interpretations. Moreover, data-driven modeling of engagement analytics has the potential to promote reflections supporting teaching and learning quality.

Our pilot study attempted to support the rationale above by providing two visualizations. Fig. 1 shows the possibility of detecting at-risk students in the early phase of the course when the teacher adopts a data-driven approach of visualization on individual student. However, it is difficult for the teacher to check individual students in the large class setting. Thus, we introduced a data-driven modeling method (GBTM), a statistical method that can identify the distinct trajectories or patterns of change that exist within a population. Therefore, the teacher can understand several patterns of student engagement and who belongs to which patterns in the course. It will trigger a continuous improvement of tailored student support and design for learning activities.

Another contribution of this paper is highlighted in the adoption of the Group-Based Trajectory Modeling to analyze student engagement, as we are one of the first users to implement this method most commonly used in the clinical and medicinal fields in educational studies.

As for the study limitations, it is possible that there are ongoing studies being carried out which address different claims and perspectives related to the importance of data-driven modelling for student engagement that we fail to explore. Moreover, the study focuses on testing a theoretical idea about what approach is suitable for engagement analytics and proposes two ways to explore student engagement rather than an empirical study that could be directly generalized for others to adopt.

In terms of future research, interdisciplinary teams of educational researchers and computer scientists should collaborate on engagement analytics. The algorithms dealing with Big Data are conceptual and need to be carefully discussed and refined through the lens of these two disciplines (education and computer science), to make sure that big data insights promote the improvement of educational practice.

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USER RATING AS A PREDICTOR OF LINGUISTIC FEEDBACK QUALITY IN QUESTION AND ANSWER PORTALS

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Keywords: Question and Answer, informal language learning, corrective feedback, Italian

Question and Answer portals allow users to post and answer questions on different issues, among which foreign languages. The present paper focuses on feedback requests, i.e. questions in which users of the site ask for linguistic feedback on short sentences or phrases. In particular, it reports on a research on the degree of reliability of the evaluation of answers provided by the portal's users to identify correct and good linguistic feedback. An observational approach was adopted for about 600 answers in the Italian version of Yahoo! Answers. Each feedback was evaluated by two expert teachers and their rating was then compared with the evaluation provided by the site's users. Results show that, while the correlation between the votes of the community and the rating of the experts is rather weak, answers with a positive evaluation generally contain a correct feedback. We conclude, therefore, that caution must be exercised when utilising users' evaluation as guidance on feedback choice.

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1 Introduction

The present observational research aims at investigating whether user assessment of answers in a Question and Answer portal (hence, Q&A) is a reliable marker of the quality of linguistic feedback provided therein.

Everyday many learners autonomously resort to online services, which constitute one among the many options nowadays available for language learning. Although such venues generally operate outside the domain of formal education, it is nonetheless important for language educators and advisors to know their potential to help learners make the most of them. In particular, since the format of Q&A implies that a question receive different answers, it is important for the learners to develop strategies to identify the most suitable one(s).

1.1 Q&A and informal language learning

Since the Internet has been available to the public, experts have been prompt to recognize its potential for language learning. Interaction has been pivotal in language learning theories for about the last forty years and it comes as no surprise that the possibility to interact online, especially with native speakers, has ever since been seen as a great benefit for learners (see e.g. Chapelle, 2006; Ziegler, 2016). This trend has gained momentum with the rise of the so-called web 2.0 and social media, in which the role of users further expanded to that of users and producers of content (Harrison & Thomas, 2009). Research on social media and language learning has consequently flourished in the last years with many works investigating the potential of such tools (see e.g. Lomicka & Lord, 2016; Zheng, Yim & Warschauer, 2018). The present research focuses on Social Networking Services (hence, SNS), in particular the use of SNS for self-directed, informal learning, i.e. the purposeful usage of SNS to learn or to improve a language (Reinhardt, 2019).

Although quite neglected by second language research, Q&A (e.g. Yahoo! Answers or Quora) have much to offer to learners. The mechanism behind Q&A is rather simple: a user posts a question and other users provide an answer and/or, in some cases, evaluate answers by other users (see Adamic *et al.*, 2008 and Jin *et al.*, 2015 for an overview of Q&A). Both activities, namely providing and assessing content, constitute the backbone of social media. Since a feature of Q&A is that questions receive different answers, users' evaluations of answers have a central role in the economy of these services. Indeed, as is common in online venues (for instance, in online commercial sites), users may rely on such evaluations for help on what to choose, in this case the most suited answer to their question.

1.2 Corrective feedback in Q&A

Starting from general-purpose taxonomies of questions in Q&A Torsani and Dettori (2018) argue that this format yields to different language-related usages. However, while they recognise that each of such usages may influence language learning, it is to what they call "language support" questions that they look to as a remarkable option for language learning. Language support questions focus on such issues as grammar rules, vocabulary or feedback requests and their answers generally provide linguistic material learners can process and hence improve their linguistic skills. Asking such questions, in either a formal or informal environment or fashion, is a common experience for language learners and Q&A simply amplifies the number of potential experts. Among language support questions, feedback requests constitute a promising subset because learners can ask experts or native speakers for a fast and informal linguistic feedback on their utterances. Not a secondary asset for them.

While feedback has been traditionally researched from the perspective of classroom teaching and learning (see e.g. Brown, 2016 and Lyster & Saito, 2010), the spread of network technologies has meant a broadening of interests towards peer feedback delivered in online interaction (see e.g. Bower & Kawaguchi, 2011 and Vinagre & Muñoz, 2011). However, in the case of SNS learners have raised concerns about the quality of the feedback provided by peers (Stevenson & Liu, 2013). Dispelling any such concern, therefore, is of primary importance for learners and advisors alike, in order to assess whether these services deserve a position among the tools for language learning.

1.3 Investigating feedback in Q&A through Learning Analytics

In Q&A a request request receives multiple answers and the questioner must choose the one that best fits their needs. This leads to an important issue: how can a learner be helped choose the best answer? As stated before, the evaluation of an answer provided by other users should ideally constitute a reliable tool for learners. A premise of social media is indeed what is known as the "wisdom of the crowds" (Surowiecki, 2005), best exemplified by Galton's experiment in which the mean of all the estimates of the weight of an ox was close to the real weight of the animal (Galton, 1907). This fascinating perspective, in high regard in the heyday of social media and Web 2.0, has however been progressively questioned, as social media have in some cases become a channel for unscientific information (see e.g. Vosoughi, Roy & Aral, 2018). The issue of users' evaluation validity, therefore, arises also from an educational perspective and its role, in this case, in helping a questioner choose the best feedback must consequently be submitted to scrutiny. Learning Analytics (hence, LA) appear to be a convenient tool to achieve an understanding of this issue. In particular, given the social nature of Q&A, it is to Social Learning Analytics (hence, SLA, Shum & Ferguson, 2012) we turn to for this task (see below).

1.4 Research question

In line with the premises of social media, we expect users' evaluations to be a reliable indicator of the quality of an answer. We also expect users' evaluations to be indicators of good and bad feedback alike (i.e. negative user assessment indicates a bad feedback and positive user assessment indicates a good feedback). Finally, based on the notion of wisdom of the crowds, we expect such reliability to increase with the number of votes assigned to an answer. Therefore, the present research aims to answer the following question:

1. Are users' evaluations of answers a valid means to help a questioner choose good linguistic feedback? In particular:
    - Is there a correlation between the overall users' evaluation of an answer and its quality?
    - Are user ratings more reliable when detecting good or bad feedback?
    - Does reliability increase with the number of ratings?

2 Materials and methods

2.1. Methodological Approach

Because of the social nature of Q&A we have adopted a SLA approach (see above), proposed by Shum & Ferguson (2012), who set off from the features (both technical and ecological) of social media for learning to define a peculiar ambit for LA. Such approach focuses on the participatory nature of online social learning rather than on the features of formal education. As they argue, «the focus of social learning analytics is on processes in which learners are not solitary, […] but are engaged in social activity, either interacting directly with others (for example, messaging, friending or following), or using platforms in which their activity traces will be experienced by others (for example, publishing, searching, tagging or rating)» (p.5). Users' ratings constitute one of the types of data SLA takes into account. In particular, the analysis of any kind of content produced by participants falls within the "content analytic" category of their proposed taxonomy (Ferguson & Shum, 2012), which consists in the application of LA principles to user-generated content. Because the purpose of LA and SLA alike is to provide information to improve teaching and learning, such approach is important in that it can guide potential learners towards using answer evaluations as a reference point. Because of the explorative nature of the present research, we adopt here a somewhat simple statistical approach to investigate whether users' evaluations of answers containing linguistic feedback are a reliable predictor of such quality.

2.2. Data set

A hundred feedback requests and the corresponding 614 answers were collected from the Italian version of the Yahoo! Answers portal. To be included in the data set, questions needed to:

- be posted by a learner of Italian;
- request feedback on a phrase or sentence;
- contain at least one overt error;
- have at least one answer;

Questions and answers were collected in a spreadsheet, in which every row contained a single answer together with the corresponding question and users' evaluation; for instance (all texts from the data set are reported as they are with no correction):

> [question id] 20130127122439AALCNCL; [question title+body]: *quale frase e' giusta?? (in italiano)? si dice1. mi piacciono tutti i lavoro che riguardano l'italiano 2.mi piacciono tutti i lavoro che riguardano all'italiano???? grazie in anticipo sono straniera...;* [answer]: *Mi piacciono tutti i lavori che riguardano l'italiano. Così e giusta*: [positive evalutations] *1*; [negative evaluations] *0*;

2.3 Research design

Two mother tongue teachers of Italian (hence, the Experts) independently rated each answer with a holistic score ranging from -5 to 5 on a version of the above-mentioned spreadsheet from which users' evaluations were removed. Questions in the data set were not chosen based on factors such as difficulty or frequency of errors and are, consequently, quite heterogeneous in this respect. Therefore, the Experts received no assessment grid or specific instruction as to how rate answers: they were only asked to rate the quality of the linguistic feedback based on the request.

We then calculated the mean of the two scores as a reference score (hence, Expert Assessment, EA) for each answer against which we compared the assessment of the portal's users, i.e. the difference between the sum of positive and negative assessments (hence, UA). In the example quoted above the answer has positive evaluations =1; negative evaluations =0; and, consequently, UA =1. We excluded zero values from the number of UA either because the answer received no assessment or because they had an equal number of positive and negative evaluations. UA and EA are different measures. UA corresponds to the sum of all individual (negative and positive) votes. A user can only say whether she/he approves or not an answer, without specifying how much. EA, on the contrary, corresponds to the mean of two scores given on a scale; in other words, experts can specify if they find an answer particularly good or bad.

To answer the research question(s), different tests were run to measure the agreement between experts and users.

First, the correlation between EA and UA was calculated to determine whether UA can be considered a good marker for answer quality, i.e. the larger the overall UA the higher EA. We expect that the better the answer (receiving a high score from the Experts) the higher number of positive votes it receives by the users.

To observe whether users are more capable of detecting good or bad feedback, we ran a chi-square test considering the number of positive/negative UA and their agreement with positive/negative EA. In this case, we adopted a binary perspective; votes were considered in agreement if they shared the same overall positive or negative orientation.

Finally, to observe whether the ability to detect good/bad feedback increases with the number of evaluations, we ran a chi-squared test on the number of agreements and non-agreements on answers receiving one, two/three and four or more evaluation. Here, we assume that the higher number of votes an answer receives, the higher the agreement with the experts.

3 Results and discussion

The Experts provided 500 (81.43%) overall positive and 114 (18.57%) negative ratings (*N*=614). As both explained, they independently adopted a rule of thumb according to which a simple, but correct, feedback would receive a small positive score (1 or 2); a good feedback (e.g. one comprising a useful linguistic focus on the error) would receive a higher value; a useless one (e.g. an off-topic answer) would receive 0 or -1; finally, a misleading one (i.e. a feedback which does not correct errors) would receive a score below 0. The figures reveal that many instances of feedback were acceptable to them and a large share also good to excellent. According to the Experts, therefore, about 4/5 of the answers provide a (more or less) useful feedback, which is what one may reasonably expect since answers consist in feedback on the respondents' mother tongue.

The members of the community provided 928 individual votes (1.51 votes per answer): 478 positive and 450 negative ones. In our data set 214 (35%) answers have an overall positive and 166 (27%) a negative UA score. 193

(31%) answers received no evaluation, while 41 (7%) answers received an equal number of positive and negative evaluations (hence referred to as neutral), thus resulting in UA=0.

(RQ 1.a) A correlation test between UA and EA returned a significant, but quite weak, positive result. For this test, only answers with at least one user vote were considered. A Pearson correlation of $r(N=422)=0.31$, $p<0.01$ was found between UA and EA. UA scores explain R2=9% of the variance of EA. UA is an indicator, albeit weak, of the quality of an answer.

Next, we focused on the agreement of the overall positive or negative sign between EA and UA.

Table 1
UA AS A PREDICTOR OF EA

	Correctly identified by UA	Not or incorrectly identified by UA	total
Positive EA	197 (39.40%)	303 (60.60%)	500
Negative EA	48 (42.10%)	66 (57.90)	114

Table 1 reports all the cases in which UA correctly identifies or not feedback, i.e. UA and EA have the same (positive or negative) sign. Only 39% of correct/good instances of feedback received a positive UA, while 61% received a negative, neutral or no evaluation. A similar ratio (42% vs. 58%) applies to negative EA.

Table 2
AGREEMENT BETWEEN UA AND EA

	Agree with EA	Not agree with EA	total
Positive UA	197	17	214
Negative UA	48	118	166
total	245	135	380

(RQ 1.b) While most answers are not correctly identified through UA (which confirms the scarce correlation between UA and EA), a clearer picture emerges if positive and negative UA are considered separately. Table 2 reports the number of instances of overall positive and negative UA and the cases in which these agree or not with EA. A chi-square test on agreement returned a strong result, with $\chi 2\ (1, N=380) = 162.71$, $p<0.001$: positive UA were in line with EA, while negative evaluations generally were not. Therefore, while not all positive EA are identified through UA, a positive UA generally entails a positive EA. This scenario, however, does not apply to negative UA. In other words, an overall positive UA is a good predictor of the correctness of the feedback contained in the answer, while an overall negative one is not a good predictor of a bad answer.

(RQ 1.c) A chi square test was run to determine whether the ratio between agreement/non agreement changes as the number of evaluations increases, but the result was not significant and it is therefore not possible to reject the null hypothesis that agreement does not change based on the number of assessments (see Table 3).

Table 3
AGREEMENT BETWEEN EA AND UA BASED ON THE NUMBER OF VOTES

Number of votes	Agree with EA	Not agree with EA
1	121	64
2/3	88	52
4 or more	36	20
Total	245	136

The answer to our research question was not as straightforward as expected and our findings suggest that, while user assessment can provide some support for learners in choosing a good feedback, caution must nonetheless be exercised.

First, a significant correlation does exist between UA and EA, but it is rather weak and is of little help in assessing the overall quality of feedback. This was a major expectation, since we assumed that the better an answer, the higher the number of positive evaluations. However, this is not always the case and factors other than linguistic correctness of a feedback must intervene in the evaluation of an answer on the part of the members of the community. Politeness, for instance, seems to be rather important for some users, who sometimes assign negative ratings to an answer when it contains offensive or apparently impolite language regardless of the correctness of the feedback. For instance, q.id 20100827102957AA28mFP asks which of two forms is correct: (…) *amore mio senza di te muorirei... il mio dilemma è : muorirei oppure morirei?* (my dear, I would die without you… what I do not know is morirei or muorirei?), a user correctly answers morirei, but somehow awkwardly adds “Italian (here meaning grammar) is not an optional”. While the Experts based their assessment on the correctness of the feedback and gave this answer positive evaluations, users gave it six negative votes (and no positive one), thus resulting in a strongly negative UA.

The answers to our second and third sub question are perhaps more encouraging. Although most instances of feedback (about 60%) are not correctly identified by UA, a positive UA generally entails a correct/good feedback. Ideally, a learner should aim at the best answer; however, since their objective is receiving linguistic feedback, even a simply correct answer constitutes a useful support. Furthermore, a connection between number of votes and ability to detect good/bad feedback could not be demonstrated and it is not possible to reject the null hypothesis that the two are unrelated. If this were confirmed it would mean that, counter to the mythology of social media, even a single positive vote is a good marker of correct feedback.

A somewhat positive balance can finally be drawn from these findings. Indeed, since feedback quality in SNS is a concern for learners (Stevenson and Liu, 2013), our findings demonstrate that, in the case of our data-set, user votes constitute a valid support in identifying good feedback.

Conclusions

The present research has focused on feedback delivered through Q&A portals and, in particular, on the reliability of users' evaluations of answers. The findings show that, while there is a certain discrepancy between experts and users, user ratings constitute a reliable tool for detecting correct/good feedback.

From the vantage point of language education, the integration of feedback through Q&A has different implications, of which we will focus here on the impact of the findings of the present research from a LA perspective. Since the main objective of LA is to provide information to improve learning, in this case informal, our findings suggest that, with due caution, feedback in Q&A can be a valid option for learners, who can rely on users' vote when they need to choose an answer. In a survey of SNS for language learning, Lin, Warschauer and Blake (2016) found that receiving feedback from peers was much valued by their participants. However, while participation in the services considered in that study suffered from a somewhat sharp drop in the long run, Q&A constitute a fast and lightweight alternative, which can be more easily integrated into everyday language-related formal and informal activities.

While it furthers our knowledge of informal language learning in SNS, the present research has, however, some limitations, which should be kept in mind when considering its findings. The first limitation of this research is that it focuses on the correct/incorrect dichotomy and does not account for the factors affecting users votes: for instance, in the discussion we hinted at the possible influence of affective factors in determining users' votes. The scant number of user votes constitutes the second limitation. When considering user evaluations in other Internet services (e.g. feedback on products in e-commerce sites) figures are considerably higher, therefore our findings should be confirmed by research on more sizeable data-sets. A third limitation is that the research was conducted on the Italian language and it is not clear whether its findings are generalizable to other languages. While, for instance, in our data set it was arguably native speakers that provided feedback and votes, in the case of more diffused languages, like English, also non-native (and non-proficient) speakers might participate and alter the overall quality/assessment balance.

Besides these limitations, however, we must acknowledge that even a narrow ambit like feedback in Q&A appears to be a rather complex phenomenon and different aspects must be taken into account when trying to provide an accurate picture of it. For instance, we did not focus on fundamental issues, such as the ability of the learners to recognize (and choose) the best answer and the contribution of users' votes to this choice. As the case of affective factors seems to suggest, feedback evaluation in Q&A stretches beyond the correctness of the answer. Both the quantitative and qualitative perspectives of SLA illustrated in Ferguson & Shum (2012), therefore, offer important insights in this matter and their findings should be integrated to achieve a clearer understanding of this tool.

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A SOCIAL NETWORK ANALYSIS APPROACH TO A DIGITAL INTERACTIVE STORYTELLING IN MATHEMATICS

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In this paper we present a social analysis of the interactions among the students involved in a trial of the Italian PRIN project "Digital Interactive Storytelling in Mathematics: a Competence-based Social Approach". The instructional design is based on collaborative scripts within a digital storytelling framework where the story follows the interactions among the characters played by the students and an expert (teacher or researcher). We report the results of a trial that involved teachers and students from the upper secondary school, analysing from a Social Network Analysis point of view the interventions of the expert, the involvement/participation of the students and the interactions among peers and with the expert. We also briefly discuss potentialities and limitations of the currently available tools to perform this kind of analysis, in view of the broader perspective offered by the Learning Analytics approach.

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1 Introduction

This work reports a social analysis of the interactions among the students in a classroom trial of the PRIN project "Digital Interactive Storytelling in Mathematics: A Competence-based Social Approach", which is focused on competence-oriented online mathematics learning (Albano & Dello Iacono, 2018a). The project aims to provide a methodology for designing digital interactive storytelling in mathematics (DIST-M) frameworks based on a Vygotskian approach, where learning is first socialized and then interiorized (Vygotsky, 1980). From the mathematics education point of view, this also fits the discursive approach to mathematics learning (Sfard, 2001). Moreover, the story(telling) allows a more contextualized competence-based learning and fosters the confluence of narrative and logical-scientific thinking (Bruner, 1986).

The instructional design is based on collaborative scripts within a digital storytelling framework. Starting from a didactically interesting mathematical problem, we devise personalized learning paths where students (divided into groups) and the expert (teacher or researcher) play well-defined roles. The story evolves according to the interactions among the characters and the stimuli coming from the expert, all mediated by the communication tools available on the online learning platform (Moodle).

We report the results of a trial that involved teachers and students from an upper secondary school. In order to better understand the potential of learning platforms as a contextual factor in mathematics learning, we perform a Social Network Analysis of the interactions among the peers and with the expert, and of the involvement/participation of the students (Albano, Pierri & Polo, 2019a). In this way the expert can also analyse (and possibly address in an appropriate way) peer discussions and measure students' engagement.

2 Theoretical framework

This work integrates findings from different research fields and therefore it cannot be cast within a single theoretical framework. However, we briefly recall the main inspiring theoretical aspects. Our activity design is mainly focused on collaborative learning; in particular, on computer-based collaborative learning (Weinberger et al., 2009), where pre-structuring and regulating social and cognitive processes are clearly prescribed. To this aim we use the concept of *script*, which refers to a sequence of actions directed to define a well-known situation (Schank & Abelson, 1977). In didactics, scripts are typically externally imposed and support students within a collaborative/cooperative learning context by means of roles to play and actions to carry out to succeed in the story and in learning (King, 2007).

We also follow a collaborative and Vygotskian approach, based on social and individual construction of knowledge, which favours the natural development of argumentative and communicative skills. Students, engaged in the activities planned by the scripts, analyse and explain their reasonings and, by thinking, arguing and interacting with their classmates, can validate their own arguments and take into account those of the others.

All this leads to a deeper and more conscious knowledge. In order to improve the collaborative learning experience, we adapt the scripts to individual and group characteristics by means of adaptive collaboration scripts (Baker, 2003), which are more effective in promoting a better self-regulation of learning (Demetriadis & Karakostas, 2008), especially in online environments (Azevedo *et al.*, 2005).

We also consider the Joint Action Theory in Didactics (JATD) (Sensevy, 2012) to conceptualise the educational process and specify the joint action between teacher and pupils, concerning whether or not to provide the answers. Indeed, if the teacher wants to engage students in the didactic process, he should make them responsible for their learning process. If the didactic process is milieu-driven, the teacher must manage the didactic relationship to make the students explore the milieu and its feedbacks.

3 The design of the digital interactive storytelling

All teaching activities take place within a narrative framework, in a situation that can be engaging and familiar to the student. The setting of the story is science fiction where a group of four friends find themselves communicating with aliens, from whom they receive mysterious messages made up of numbers and mathematical operations (as shown in Figure 1).

Fig. 1 - The user interface and the mathematical problem.

Students are faced with the following problem (Mellone & Tortora, 2015) placed in narrative form (Zan, 2012): given four consecutive natural numbers, show that the difference between the product of the second and third and the product of the first and fourth is always 2. The problem is interesting because admits many solving strategies and generalizations and promotes reflections on some fundamental mathematical concepts.

The story evolves over time and each student plays a different role within each scene of the plot (Albano, Pierri & Polo, 2019a), as does the expert who moderates the interactions within the group.

The whole educational path is implemented with Moodle, which provides the tools for all educational activities (Choices, Books, Lessons) and social interactions (Chats and Forums) foreseen by the instructional design (Albano, Dello Iacono, & Fiorentino, 2016). We have chosen and carefully configured the most effective tool for each educational and communicative need. We use chats for all informal communications within the group, excluding the expert, who takes part in the forums to facilitate the transition towards more advanced mathematical communicative registers (Ferrari, 2004).

The appearance of the learning environment has been completely adapted to make it look like a comic book, as shown in Figure 1. A few lines of custom CSS and the use of Labels to access "ghost activities" allowed us to present in this way all the involved activities and resources. Moreover, the extensive use of access conditions allowed us to design several parallel and personalized educational paths according to the roles and groups of all students within the story. Some plugins allowed the dynamic creation of groups and the setup of some synchronous passages (instant polls) well integrated within the narration. Finally, some GeoGebra activities (Albano & Dello Iacono, 2018b) were also integrated within Moodle to support students in the production of conjectures, arguments and proofs (Albano & Dello Iacono, 2019b).

Playing a specific role, each student is actively involved in three consecutive actions: *Inquiry, Conjecture* and *Proof*.

The *Inquiry* foresees that each student comes to the formulation of a personal conjecture about the proposed math problem and shares it with his classmates using a Chat.

The *Conjecture* aims at the social refinement of what has been individually produced, both in terms of content and formal expression. Starting from what everyone has found and shared, students are engaged into a discussion among peers to formulate a shared conjecture to communicate to the expert. While conjecture comparison takes place in the Chat, the communication with the expert foresees a Forum, which encourages and fosters the production of text expressed in more evolved registers.

Finally, the *Proof*, by means of discussion with the expert, leads to the organization of the shared conjecture arose from the teamwork into a formal mathematical proof.

4 Tools and Data analysis

The standard reports normally available on learning platforms provide a lot of information on students' use of content and activities. However, they do not carry enough information to understand the (kind of) interactions among students, an essential component of collaborative learning. In this work we try to investigate the level of student engagement and the reactions provoked by the expert's interventions analysing their interactions with the help of some automated data collection and visualization tools. For this purpose, the educational design conveys all communicative activities in Chats and Forums, making them effective markers of the interactions among the students. Unfortunately, the most immediate tool, the Chat, for its communicative peculiarities (inherently one-to-many, without identifiable recipients), is not suitable for the type of automatic analysis we have planned. Moreover, the immediate and colloquial register of Chat discussions also imposes an accurate review of the corpus with the elimination of large portions of irrelevant messages before attempting any serious analysis. So, unless some sophisticated natural language preprocessing is used, Chat discussions are difficult to use with automatized tools. Consequently, in this first analysis we only used Forum posts, for which there are some tools for the automated analysis of social interactions.

We used Moodle's Forum Graph (Chan, 2013) plugin to perform a qualitative and quantitative analysis. It scans all interactions within a Forum and creates a directed graph (see Figure 2 for an example) where:

- each node represents a single active user and its size grows according to the number of user messages; this is useful to grasp at a first glance the most active users and the almost silent ones;
- users with different roles are displayed using different colours, so students and teacher/expert can be easily recognized;
- each edge represents the interaction between two active users (i.e. a user responding to a post from another user) and their thickness indicates the number of (mutual) replies.

In this way it is simple to spot influencers and followers within the groups. Additionally, to allow more detailed analysis, the plugin also displays:

- the overall number of started discussions and replies, and the users who made the largest number of posts;
- shows or hides the names of all active users, by labelling the nodes with

their names or numeric IDs;

- the numbers of started threads and given answers for each active user as the pointer hovers the corresponding node.

By clicking on one of the nodes, the plugin also shows a popup window with the log of all threads started/replied by the corresponding user. By clicking on one of these threads, it is displayed within the Forum.

5 Classroom experimentations

In this paper, we report our first attempt to apply some Social Network Analysis tools to a preliminary trial which involved 30 secondary school students and their teacher.

Two classroom experimentation has been run: the first one during the 2017/18 school year with a 9^{th} grade class, the second during following year with a 9^{th} and a 10^{th} grade classes. The school grade has been determined to better integrate the topic of the model problem within the classroom mathematics curriculum. The first experimentation provided precious feedback to fine tune the whole design.

In the following our attention will be focused on the final and most important phase: the Proof. We report excerpts taken from the Forum and analyse the influence of the domain expert (the teacher) on the students, according to the JATD theory.

Our hypothesis is that the storytelling environment, and the social interaction, through forums and chats, can favour the development of argumentative practices among students. So, we used Forum Graph to investigate the interactions within the Forum used during the classroom trial. We performed two types of analysis:

- a quantitative one involving the whole graph, also seen as a complex network;
- a qualitative and semantic one, focusing on the type of intervention and, therefore, on the instructional implications.

The plugin returned graphs as the one shown in Figure 2 where the black node in the middle represent the teacher/expert.

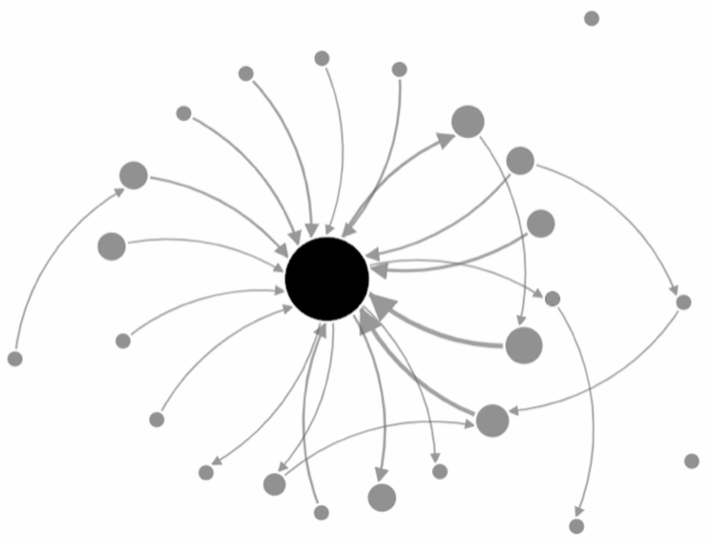

Fig. 2 - The interaction graph produced by Forum Graph.

As expected, being the mediator within the Forum, this is the largest node in the graph. The other nodes represent the students involved in the discussion. Some interesting considerations can be easily derived by carefully inspecting the graph. For instance, we can easily recognize 5 different node sizes corresponding to 5 levels of interaction (in the following denoted as L_1, …, L_5), where $L_\#$ indicates that the corresponding user made # posts (either starting ones or replies). L_1 nodes therefore denote students who:

- started one discussion if no edge connects the node to any of the others (as those in the upper right or lower right corner of Figure 2);
- answered to a single post of another student or of the expert, if only one arrow comes out of the node;
- in the latter case the arrow indicates the user whose post has been answered.

From Figure 2 it is possible to identify 14 L_1 nodes, 2 of which without outgoing arrows. Each of these students started a new discussion that no one, not even the expert, followed up. Figure 2 also shows 1 L_2 node, 5 L_3 nodes, 2 L_4 nodes and 1 L_5 node. In these cases, the thickness of the edge is proportional to the number of interactions between the two connected users, regardless of who answered to whom.

Forum Graph also allows to identify some interesting interactions, such as the one highlighted in Figure 3.

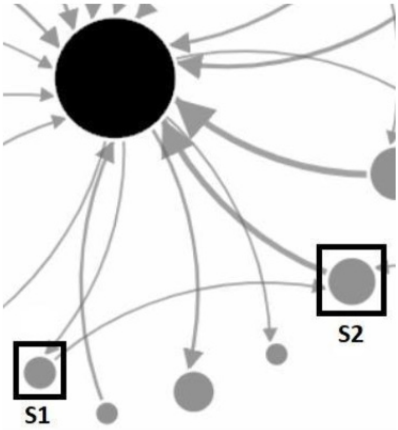

Fig. 3 - Focus on students S1 and S2.

Figure 3 highlights the interactions between the expert (the black node) and students S1 and S2. By clicking on any of their nodes, the plugin shows the underlying conversation so we can immediately observe their mutual influence:

> **S1**: *...because, in my opinion, writing the quadruplet in literary form, replacing the smallest number of the quadruplet with b and obtaining the following others by adding the appropriate number, we get a small literary expression that results in the number 2. In fact, from b; (b+1); (b+2); (b+3) where b belongs to the set of natural numbers it follows that [(b+1)*(b+2]-[b*(b+3)] = b^2+2b+1b+2-b^2+3b =2. We can consider this expression as the formula for calculating the various expressions derived from the quadruplets given to us by the aliens. And to explain that it works with any natural number, large or small…*
> **Expert**: *…Is the same if we replace a letter to the largest number of the quadruplet? Why are you so convinced that the value you attribute to A is not important? ...*
> **S2**: *...First of all I thought of taking a letter, say C, as the first number so, for the others, we have: C+1, C+2, C+3. In the quadruplets to get as a result 2 you have to make the subtraction between the product of the second and third number and also the product between the first and fourth number, so, taking into account C, we can calculate (C+1) (C+2) - C(C+3) and if we simplify this small expression we will see that 2 will come out of it because: (C+1) (C+2) - C (C+3) = C^2+ 2C +1C + 2 - C^2+3C=2. This expression, as we have seen, could be the right formula to calculate the quadruplets given by aliens. Moreover, we have seen that whatever value we give to C, either a small or a large number, the result, as we have seen, will always be 2…*

We underline that the discussion in the forum was anticipated by moments of sharing in chat where the informal conversations have anticipated and facilitated the more formal discussion with the expert in the Forum. Indeed S1 states: *[...we cannot communicate with aliens with our language because it is not certain that they understand it so we must use a quadruplet ...]*, as well as S2: *[...In my opinion we must create a quadruplet through a formula, which we will also use for demonstration...]*.

According to JATD theory, we can observe how the expert makes inference on student's statements, inducing her to think about their *motu proprio* interaction with the milieu.

By carefully analysing the graph and its peculiarities it is possible to find many interesting hints about how students interact and how the expert can improve and gently drive the overall discussion. In such a way, he leads the teamwork to an initial formal mathematical demonstration, as quoted by the students in the forum with the expression "*Moreover, we have seen that whatever value we give to C, either a small or a large number, the result, as we have seen, will always be 2…"*. However, we also underline that the reach of such tools is not limited to the ex post analyses of the interactions; in fact, they can (and should) be used for the early detection of what is going wrong (a discussion that does not start as desired, isolated members or entire groups struggling to establish a fruitful collaborative work) and timely undertake appropriate corrective actions. In this sense, they build a bridge between the simplicity of activity report analysis and the complex insight promised by the forthcoming Learning Analytics tools.

6 Discussion and conclusions

In this work we used a software tools to analyse the complexity of the interactions taking place online within a collaborative learning framework.

We started from the hypothesis that the storytelling environment, and the social interaction, through forums and chats, can favour the development of argumentative practices among students.

Our choice, Forum Graph, allowed a qualitative and quantitative analysis of Forum interactions, giving the teacher a better insight of the global flow of information, identifying influencers and followers. We also used the tool to spot and observe some significant discussions, analysing the argumentative skills of the students, from a qualitative point of view.

We realized that Forum Graph is (also) a valid didactic tool that, by displaying the discussions among students in real time, helps teachers to create an "augmented reality" that allows a better understanding of the social dynamics of the groups, increasing their capacity of analysis and intervention.

Such opportunities are difficult to imagine without the support of eLearning platforms and automated tools. On the other hand, the limitations and needs not met by these tools provide interesting indications for their further development. For instance, the fact that Forum Graph only shows one edge for each pair of users makes it rather difficult to understand the level of mutual influence (since the direction of the arrow, as experimentation revealed, is of little significance). Another currently missing feature, essential in cooperative online frameworks, is the ability to analyse Chats, where the most immediate communication takes place, and therefore is the best place to look for students' convictions and misconceptions. We are aware that this kind of analysis will require the integration of many high level tools such as Natural Language Processing, Big Data techniques and a deep field knowledge, to analyse, "understand" and present data in a form suitable for teaching purposes.

To sum up, tools like Forum Graph build a bridge between what can be easily set-up and used now and the forthcoming generation of tools arising from the Learning Analytics research, whose integration in the learning platforms has just begun.

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LEARNING ANALYTICS -SCIENTIFIC DESCRIPTION AND HEURISTIC VALIDATION OF LANGUAGES NLG

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The educator is a "Translator" ie manufacturer of algorithms for a teaching in the infosphere. The teacher who turns into a robotic mind perhaps of the type R2D2 a research droid, will be the emblem of our future. The work aims to validate the moments of transformation through which, over the centuries, the mathematical sciences, with the help of philosophy, have elevated the languages Natural Language Generation (NLG) to formal models. The starting hypothesis is to corroborate an epistemological statute, which entrusts mental processes with logical-mathematical reasoning following four models: Chomsky (1956), which, with descriptive grammar, marks a new model for the rewriting of languages; Gross (1975), which, with the relationship between linguistics, informatics and mathematics, generates a relation concerning a strongly transdisciplinary domain, in which linguistics

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realizes models and procedures of the informatics type; Silberzstein's Nooj system (2015) for the elaboration, description and analysis of fixed INLG sentences. The focal part of the research is the comparison work that the team has carried out to validate the processing of languages according to the Transformational Analysis of Direct Transitive by M. Silberzstein and the lexicon-grammar; the probabilistic calculation, according to the Probabilistic latent semantic Analysis (Hoffmann, 1999) and the empirical method.

1 Introduction

This research focuses on mathematical models for the description of languages and on some new generation software for the construction of natural languages The research hypothesis conducted in 2013 at the chair of written Italian by Bucciarelli and the team of Balboni with the project by Ateneo Ca' Foscari in which researchers go to analyze the scientific aspects of specialized languages to emphasize the interest that the theme of the specificity of these languages arouses from the sociolinguistic and socio-semiotic. Therefore, the team relies on epistemological models of reference because they are determined by the will to provide certainties to lay basic empirical foundations to the research with :- Popper's theories that with the principle of falsifiability or possibility of confutation and defines an interpretation of science based on error and leads to elaborate new theories that prove to be fallacious, because so much more can be circumscribed the horizon of truth. In our opinion, if the calculation of the possibility leads us to a possible solution of the truth, we need to rely on a second model that gives certainties such as: -Learning analytics, the integrated techniques of analytical learning mediated by didactic research and applied to data mining in Cabena *et al.* (1998). that is, the set of techniques and methodologies that have as their object the extraction of useful information from large amounts of data through automatic methods using the filtering methodologies "FC. This means the transfer of the possibility to the heuristic certainty of the collection given there seems to be a right solution for the analysis and description of the lexicon. The authors then rely on hypotheses to be validated to models the irrefutable and therefore confront themselves with those who previously explored the same areas of research such as:

Chomsky's model (1964), which, with descriptive grammar, marks a new model for the rewriting of languages. He proposes algorithmic forms to explain linguistic facts and shifts from the lemma to the minimum sentence the centrality of the role of representation of the semantic unit of signification; Gross's model (1975), which, with the relationship between linguistics, informatics and mathematics, generates a relation concerning a strongly transdisciplinary domain, in which linguistics realizes computer models and procedures to refine, formalize its own data and its own methods and then proceed to a taxonomic classification of the possible sentences in Italian through the lexicon-grammar L.G.L.I.; Silberzstein's Nooj system (2015) for the elaboration, description and analysis of fixed sentences, which introduces the concept of text constructor supported by large "neutral" linguistic resources (dictionaries, morphology, sentence structure and transformation grammars), which can be used both to analyze and to automatically generate INLG (2017). The focal part of the research is the production according to the Transformational Analysis of Direct Transitive by M. Silberzstein according to the lexicon-grammar of the transformation of N0 V N1 into finished automata with the calculation of the Probabilistic latent Semantic Analysis (Hofmann, 1999). Our research question is: is the linguistic text subject to mathematical laws? We will try to give an answer keeping in mind that a sentence can be manipulated through spontaneous or pre-established algorithms and an algorithm can be considered a finite logical sequence of operations that is subject to mathematical laws. Our idea is that language is as innate as number and man manipulates it according to an algorithmic sequence of mathematical laws. We will try to show how natural language is subject to mathematical but random laws, while fixed language is subject to pre-established mathematical laws and therefore predictable.

2 Reference model: Noam Chomsky transformational grammar (TGT)

The transformation of elaborated codes and methods is carried out in the theory of the generative transformative grammar by Chomsky, in Lightfoot (2002), to which some essential elements are already present in the work "Syntactic Structures", characterized by the search for innate structures of natural language, an distinctive element of man as an animal species, overcoming the conception of traditional linguistics centered on the study of the peculiarities of spoken languages. He states that to understand the functioning of a language is not enough to discover its structure, since it is not enough to describe the components and relationships between them, nor to analyze and classify them. The formal grammar, that is to say, the generative grammar is a set of rules that "specify" or "generate" recursively (that is, through a rewriting system) the well-formed formulas of a language. This definition includes a large number of different approaches to grammar. The term "generative grammar" is also widely used to refer to the school of linguistics in which this type of formal grammar plays a crucial role. In fact, it is in the formal languages that the Chomsky hierarchy finds in the theory of proof, the validation and elevation of languages to mathematical techniques. In fact, it is the branch of mathematical logic that considers demonstrations in turn as mathematical objects, facilitating their analysis with mathematical techniques, one of which is… *an algorithm that is a procedure that solves a given problem through a finite number of* *elementary steps, clear and unambiguous, in a reasonable time.* Chomsky (1957) points out that the "creativity" governed by the rules for which the new sentences are "generated" constantly and, therefore, the linguistic capacity that each speaker possesses not only consists of a set of words, expressions and sentences, but which is also a set of defined rules and principles. In fact, mental grammar is a competence of the speaker, which allows him to compose and transform an infinite number of sentences, based on innate knowledge and the universal principles that regulate the creation of language. The deep structure represents the core of the semantic relationships of a sentence and is reflected through transformations in the structure of the surface (which closely follows the phonological form of the sentences) and, therefore, it is only the competence of the speaker to transform the sentence.

3 Language environments the lexicon grammar an elementary calculation

During a decade of experimental work carried out in the Department of Communication Sciences of the University of Salerno in collaboration with other research centers and, in particular, with the "Laboratoire d'Autornatique et Linguistique (CNRS - Paris 7)", new methods for linguistic investigation have been developed. Research has been carried out based essentially on the construction of syntactic lexicons that, taking advantage of the opportunities offered by computerized data processing, point to a description, as exhaustive and formal as possible, of a specific language. The research is part of the project "Lexicon grammar of the Italian language (LGLI)". The theoretical reference model is represented by the "Operator-argument Grammar " (Harris, 1964).A rigorously analytical approach has been derived in which, despite the centrality of the syntax and the scientific nature of the rules of transformation, the grammar of a language should no longer be interpreted as an abstract model, but be investigated based on concrete statements. The activity focused on the deepening of methods for linguistic research and was directed, for the interested parties, to identify the modalities of curricular applications for a modern glottodidactics (Ibrahim *et al.*, 2003). If we would like to proceed with a taxonomic classification of the possible sentences in spoken Italian, it would be appropriate to clarify the importance of the verb in the sentence through the method of research and experimentation of L.G.L.I. (Elia *et al.*, 1981) On the basis of these premises, to describe a language from a lexical-grammatical point of view, we will have to do so. Research on sentence structures involves a lexicon-grammatical classification of verbs and controls the real possibilities of aggregations with nominal forms. According to the theories of Harris and Chomsky, when studying the combinatorial possibilities of sentences, they are considered "free" sentences that have a wide possibility of changing lexical entries within the N position (productivity of class N.) A second characteristic of simple sentences is characterized by the co-occurrence of a class of compatible operators and verbs. The third, of idiomatic sentences that are also called fixed sentences. Therefore, by operating a syntactic classification of Italian verbs we will have the following results of identification of the sentence, as well as the following syntactic mechanisms:

- Handling of conversion and replancements
- A taxonomic classification
- DB categorization

The basic structure "SB" is represented by sentences that present one or more arguments, with a greater presence of direct and inferior complements of prepositions.

- Catullus wants Lesbia = N_0V N_1
- Catullus hates Lesbia = N_0 V N_1

The classification operation is not simple because there are more lexical-grammatical entries than a single word, since the lexical system is rich and "irregular" in the creation of constellations due to the meanings that can be multiple: Max hates Maria:- Max is hateful with-Maria;- Max has hatred with Mary;- Max has in hatred with Mary. For a new grammar and a new positional calculation, and a new code like: Completive sentences have been defined as simple ones, because verbs have a semantic content that is not clearly defined and the sentence is completed when the first verb is completed with the other effect:

- N_0V Ch S (43)
- N_0 V The fact Ch S(43)

It is a simple calculation for the production of these complete and direct sentences introduced by the phrase the fact Ch:

- N_0 V Che F cong = Enea checks that everything is in order
- N_0 V F o se F = Enea checks whether Max has told the truth

In the lexical-grammatical classification of the Italian Elia *et al.* (1984), the class No V Ch F has a remarkable presence of emotional verbs. These verbs are 440, of which 298 are inserted in the class (43) Elia (1984). Verbs that are included in the class (43) have a homogeneous behaviour: they present a human subject (active), except for someone who is not active [-human] (Elia, 1984, p.16). In the following tables the occurrences and the computational probabilistic calculation of the verbs of will are explained, as we would define them, properties of the class (43) and among these it is opportune to include the extension of N0 V Ch F(43) (love, hate) :

N_0 =: Nhum	N_1 = $V^0\Omega$
N_0 =: Nnr	N_1 = di $V^0\Omega$
N_0 =: il fatto Ch F	N_1 = $N_{1\text{-inf}}\Omega$
N_0 =: $V^1\Omega$	N_1 = se Fo se F ciò
N_1 di V_1 Ω	Ppv = lo
N_0 V	N_1 = Nhum
N_0VN_1 contro N_2	N_1 = N-hum
N_0V (presso con) Nhum	N_1 = il fatto ChF
	N_1 di Nhum
N_1 =: Che F	N_1 da N_2
N_1 =: $V^0\Omega$	N_1 dal fatto ChF
N_1 =: Aux $V^0\Omega$	ChF a N_2hum
N_1 di $V^0\Omega$ N_1 =: di Aux $V^0\Omega$	Passivo
Neg/interrog = Fcong	N_1 =: N_1Agg[1]
Imp = Fcong	N_1 =: Agg[1]ChF
N_1 =: Che Fcong	N_0V (essere cong)
N_1 =: Fcong	N_1 hum per Aux $V^1\Omega$

Fig. 1 - A Descriptive table and inclusion in classroom (Elia, 1984)

4 Linguistic environments NooJ: Probabilistic latent semantic analysis"

Starting from the description of the linguistic environment Nooj we propose the transformation of Silberzstein's sentence into a probabilistic calculation. [… *it is true that the probabilistic calculation must be elaborated in the laboratory, but man unconsciously produces involuntary calculations in the manipulative reproduction of some textual techniques, or for advertising and market needs. As indicated in this analysis (Silberztein 2016)]* NooJ allows linguists to formalize various types of linguistic description: orthography and spelling, lexicons for simple words, multiword units and frozen expressions, inflectional and derivational morphology, local, structural and transformational syntax. One important characteristic of NooJ is that all the linguistic descriptions are reversible, i.e. they can be used both by a parser (to recognize sentences) as well as a generator (to produce sentences). (Silberztein 2011, 2016) show how, by combining a parser and a generator and applying them to a syntactic grammar, we can build a system that:

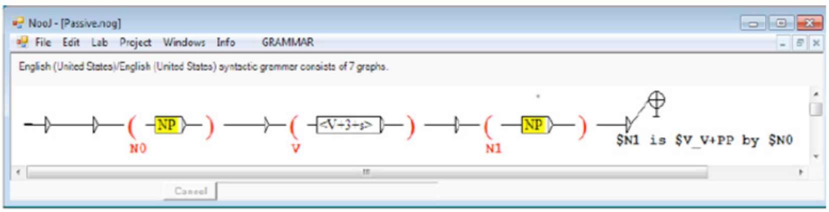

Fig. 2 - A descriptive table in formal logic (Silberzstein, 2011)

In the sentence *Joe loves Lea* = N_0 V N_1 the three variables, in which the acronyms were used, were used:-*variable = $NO = Joe's acronym;* -variable = $V = acronym of loves; variable = $N1 = acronym of Lea. Outgoing acronyms, second ALU: Plays the string: *$N1 is $V_(V_V+PP) of $NO* which equals Lea is loved by Joe:- *$NO cat. the word Lea; $V op. supp. (is); $V op.optional choice (love, lover etc.) $N1 cat. the word Joe;* The author shows how in Silberztein (2016), any serious attempt to describe a significant part of a language will involve the creation of a large number of elementary transformations. "Probabilistic latent semantic analysis" (PLSA), also known as probabilistic "Latent semantic indexing" (PLSI, especially in information retrieval circles) is a statistical technique for the analysis of two-mode and co-occurrence data. The purpose of the "EM algorithm" (Hoffmann, 1999) is to increase, and possibly maximize, the probability of the parameters of a probabilistic model M with respect to a set of data, results of a stochastic process that involves an unknown process, thus indicating with the current Θ^0 parameters of the model. The objective is, therefore, to obtain a new set of parameters Θ such that: The standard procedure for maximum likelihood estimation in latent variable models is the Expectation Maximization (EM) algorithm. EM alternates two coupled steps: (i) an expectation (E) step where posterior probabilities are computed for the latent variables, (ii) an maximization (M) step, where parameters are updated. Standard calculations yield the E-step equation: parameters Θ such that:

$$\log P(s|\theta, M - \log P(s\,\theta^0, M) > \_0$$

By introducing the hidden variables, we will have:]

$$P(s|\theta, M) = \frac{P(s,\pi|\theta, M)}{P(\pi|s,\theta, M)}$$

So, moving on to logarithms:

$$\log P(s|\,\theta, M) = \log P(s,\pi|\theta, M) - \log P\,(\,\pi|s,\theta, M)$$

Multiplying the current parameters by the probability distribution of the hidden variable M, $P(\pi|s,\theta^0,M)$ and adding up all the values that the hidden variable can take is obtained:

$$\log P(s\,\theta, M) = \Sigma_\Sigma \mathrm{P}(\pi|\mathrm{s},\theta^0, M).(\log P(s,\pi|\theta, M) - \log P(\pi|s,\theta, M)$$

An auxiliary function is defined Q(Θ | Θ^0) as the expectation value of the logarithm of the joint probability of s and p on the possible values of the hidden variable:

$$Q(\theta|\theta^0) = \Sigma_\pi P(\,\pi|s,\theta^0\,, M).\log P(s,\pi|\theta, M)$$

The expression to be made maximum becomes:

$$\log P(s|\theta, M) - \log P(s|\theta^0 \ , M) =$$
$$= Q(\theta|\theta^0) - Q(\theta^0 \ |\theta^0 \ ) - \ \Sigma_\pi P(\pi|s, \theta^0 \ , M). log = \frac{P(\ \pi|s, \theta, M)}{P(\pi|s, \theta^0, M)}$$

The third term of the second member of this equality is the relative entropy of the distributions $P(\pi||s, \theta, M)P(\ \pi|s, \theta, M)$ which, as seen in the previous section, is always positive. It follows that

$$\log P \ (s|\theta, M) - logP(s|\theta^0, M) > -Q(\theta|\theta^0 \ |\theta^0)$$

This inequality is the core of the EM algorithm. In fact, if we can calculate a set of parameters Θ^0 that makes the difference of the auxiliary functions positive; this will increase the probability of the model with respect to the data. In particular, the objective is to find the values that Θ^{MAX} maximize this difference, that

$$\theta^{MAX} \ = argmax_{\ \theta} \ Q(\ \theta|\theta^0)$$

The EM algorithm is therefore composed of two steps

- Calculation of the expectation value Q(Θ | Θ^0) starting from the parameters of the current model
- Maximization of Q(Θ | Θ^0) in the variables Θ in the variables

From an initial hypothesis about the parameters of the model, these two steps are applied iteratively until convergence is reached when the updating of the parameters no longer increases the probability. The algorithm does not guarantee the achievement of the maximum global probability, but only its increase with each subsequent application and the convergence to a local maximum. In addition, sometimes it is not possible for this to carry out the maximization stage exactly, or at least not in an efficient and computationally economic way From grammar to the description of an automaton: Once you have obtained a context-free grammar, it is easy From grammar to the relative non- deterministic automaton as S: =aS|aB; B::b|B = we will have finished robot

5 Finite grammar and infinite languages

Viewed from this perspective, we take the view that we might draw an analogy between Universal Grammar Model and Second Language Learning. Universal Grammar might be able to enable students to map or link the structure of a foreign language that will last forever, even if students do not study this second language any more. Later, if we wanted to reach the mastery of any second language, we would have to go over it by practicing its language skills. That is to say, learning a second language might be considered as a gradual change from declarative to procedural knowledge. In order to achieve this, students may use some strategies, which begin as declarative knowledge that can become proceduralized with practice (procedural knowledge).Then, how could this be explained in a more detailed way?Anderson 1983, 1985 (cit. in O'Malley & Chamot, 1990) defines declarative knowledge "as the knowledge about the facts and things we know and stored in terms of units of meaning that can be represented by propositional networks requiring a schema."The principal value of schemata is that they facilitate making inferences about concepts; consequently, in learning, the new information is linked to prior knowledge stored in memory in the form of knowledge frameworks or schemata. Here, in our view, the principles and parameters model of Universal Grammar plays an important role by building up a mental dictionary in the students' mind. For example, according to the Oxford Advanced American Dictionary: *Entrust / In 'trust / verb / [VN] Entrust A (to B) / Entrust B with A* to make someone responsible for doing something or taking care of someone. As procedural knowledge is concerned, as well, Anderson (1983, 1985) defines it "as the things that we know how to do and includes mental activities such as language production skills (writing, speaking), and language comprehension skills (reading, listening). In line with the previous example, this is the result:Entrust A to B**.** *He entrusted the task to his nephew.* Entrust B with A. *He entrusted his nephew with the task.*Here, we believe that the principles and parameters of Universal Grammar also plays an important role by enabling students to know not only the dictionary meaning of words or pronunciation, but also how they are used and behave in sentences as well as the creation of the ability to interact with other people.In other words, Chomsky (1964) distinguishes between syntactic and lexical components, on the one hand, and between deep structure and superficial structure of the syntax, on the other. Based on these assumptions, then, as Noawak *et al.* (2002: 612) indicate, a grammar is a finite list of rules specifying a language: Subsequently, as Noawak *et al.* (2002: 612) specify "there is a correspondence between languages, grammars and machines. 'Regular' languages are generated by finite-state grammars, which are equivalent to finite-state automata. Finite-state automata have a start, a finite number of intermediate states and a finish." Progressing in the exposed sense, Chambers *et al.* (2004) also bring to light certain aspects relating this topic when they state that experts and researchers in the field of Information and Communications Technologies (ICT) and language learning are increasingly emphasizing that, once a new form of technology has become available, the starting point of research projects should not be the innovation itself but rather its role in the language learning process. Nevertheless, as stated by, Popper's epistemology and its demarcation criterion of science that makes the scientific nature of theories coincide closely with their falsifiability, is the N. Chomsky model, which with the descriptive grammar marks the transition of a heuristic model of formal grammar to the language rewriting. It proposes algorithmic forms to explain linguistic facts and shifts the centrality of the representation role of the semantic unity of signification from the headword to the minimal sentence, to describe and analyze. It follows the reference model Nooj M. Silbersztein for the description, analysis, production of fixed sentences, paraphrasing of sentences, and is specified on the facts of automatic data processing. Like this manner, this paper aims to integrate research and practice in this emerging field for further research and development in these areas.

Conclusion

In this validation process the team has tried to make sense of this research,elaborating a working hypothesis, built on scientific bases, proposing choices of models, technologies in use, empirically valid theories. The validation technique presented is: -dissertation on natural languages; analysis and description of the language according to the lexicon-grammar; transformation into online languages and data collection and description of a fixed sentence. The hypothesis ends with a heuristic certainty on the calculation of quantum emotions. The answers we give are the suguenti: The human mind will govern the robotic mind with infallible tools, but will it be able to transmit real emotions? The research continues.

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LEARNING ANALYTICS FROM A MOOC ON 'LANGUAGE AWARENESS' PROMOTED BY THE EUROPEAN COMMISSION

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Keywords: Learning Analytics; Language Awareness; MOOC; CPD; online social interaction

The contribution is aimed at reporting and commenting on some significant Learning Analytics collected from a MOOC on language awareness, addressed to teachers, trainers and educators from all over the world, promoted by the European Commission through the School Education Gateway platform and moderated by the authors. The role of MOOCs for teachers' continuous quality professional development will represent the starting point of the discussion, according to the following research question: "What impact can a MOOC on language awareness have on teachers' professional development?" After a brief overview of the inspirational background and of the MOOC syllabus, data will be highlighted and commented on with reference to the attendees' participation, motivation and online social interaction, according to the following categories identified in the literature: pedagogical issues, learner issues, technical issues. Among the different learning environments and media channels used during the course, Learning Analytics from the Facebook Group, the forum and the Twitter chat will be described and commented on as crucial dimensions of the learning experience.

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1 Introduction

In the last few years, there has been a growing interest in the automatic analysis of educational data to enhance the learning experience, a research area referred to recently as learning analytics (Chatti *et al.*, 2012). Learning analytics (LA) is defined on the LAK11 website[1] as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs". Siemens (2010) views LA as "the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning". The 2011 Horizon Report identified learning analytics as a possible key future trend in learning and teaching (Johnson *et al.*, 2011). According to Johnson *et al.* (2011), LA "refers to the interpretation of a wide range of data produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues. Data are collected from explicit student actions, such as completing assignments and taking exams, and from tacit actions, including online social interactions, extracurricular activities, posts on discussion forums, and other activities that are not directly assessed as part of the student's educational progress. The goal of Learning Analytics is to enable teachers and schools to tailor educational opportunities to each student's level of need and ability. Learning Analytics promises to harness the power of advances in data mining, interpretation, and modelling to improve understandings of teaching and learning, and to tailor education to individual students more effectively". Although different in some details, these definitions share an emphasis on converting educational data into useful actions to foster learning.

In the following paragraphs Learning Analytics on online social interaction in different learning environments within a MOOC addressed to teachers' professional development will be discussed, in order to find answer to the following question: "What impact can a MOOC on language awareness have on teachers' professional development?"

2 MOOCs for teachers' professional development

MOOCs (Massive Open Online Courses) represent an innovative way to enhance continuous professional development for teachers and to build up effective online communities of practice (Wenger, 1999; Downes, 2012). According to Laurillard (2016), MOOCs fit well with the combination of instruction and peer community learning, interweaving formal and informal learning pathways and highlighting the social dimension of the learning

[1] https://tekri.athabascau.ca/analytics

process. She also states that "there is genuine potential for this technology to engage adults in the emerging economies in a form of professional development that would be commensurate with the immense challenge of capacity building on this scale for the teaching profession across the range of skills they need" (Laurillard, 2016, p. 15).

Teachers are supposed to develop a wide range of skills (subject skills, transversal or soft skills, the so called "21st century skills") and they have to keep up with recent innovations and trends in the knowledge society. MOOCs can help to attain these goals as they can be a cost and resource effective means to deliver quality education in order to further professional teacher development (Evans, 2002). As Marquis (2013) states: "teachers are expected to nearly continuously take classes or attend trainings that will enhance their ability to do their job, yet we never acknowledge the effort or take any solid measures to support it – little to no financial support and no releases time to do the work. But there is a real need for teachers to keep up with the rapid pace of educational innovations and technologies for learning, as well as changes in primary content areas. […] MOOCs could provide one possible solution to this problem".

Bali (2013) mentions five reasons for teachers to use MOOCs for their professional development, in particular:

- observe how others teach online
- join community conversations about topics of interest
- "e-live" the student experience, a sort of simulation of the students' activities online
- learn something new following certain directions
- find suitable resources on a given theme.

It is self-evident that MOOCs are on the rise and can be utilized for teachers' continuous quality professional development.

The literature reviews (Littlejohn *et al.*, 2016; Koukis & Jimoyiannis, 2017) mention a wide range of issues related to MOOCs, which can be grouped under three categories:

- pedagogical issues: pedagogical design; content and resources; learning material and syllabus
- learner issues: learner motivation; values and expectations; learner dropout rates; learners' participation
- technological issues: learning objectives; instructional design; technologies used; Learning Analytics.

The discussion in the following paragraphs will try to analyse some Learning Analytics from the above-mentioned categories, as an attempt to dig into the field of learning sciences which can help "understand learning contributing both to theory and practice" (Baker & Siemens, 2014: 253).

3 Pedagogical issues: The inspirational background

The MOOC, which is the subject of this contribution, was promoted by the European Commission, delivered on School Education Gateway Teacher Academy, moderated by the authors and coordinated by Nair Carrera, from EUN (European Schoolnet). The title of the MOOC was "Embracing language diversity in your classroom"[2] and was aimed to enhance teachers' awareness of the language competences of their students and how to benefit from them, as well as to provide them with different tools and resources to support them in delivering curricular subjects in different languages.

The MOOC was addressed to primary and secondary school teachers and teacher trainers from Europe and beyond, working in bilingual and CLIL (Content and Language Integrated Learning) (Coyle *et al.*, 2010; Cinganotto, 2018; Cinganotto & Cuccurullo, 2019) contexts regardless of the subject taught.

The course raised awareness about how having students from diverse nationalities and speaking different languages in the same classroom can actually be used as an asset providing a benefit and added value in a framework of 21st-century skills.

The content was strictly related to the latest Council Recommendation on a comprehensive approach to the teaching and learning of languages (2019), focusing on the importance of "language awareness" as a transversal dimension to the curriculum.

Eric Hawkins, called 'the father of language awareness', had been advocating for explicit reflection on both native and foreign languages as an integral part of the school curriculum since the 1960s. He proposed a 'trivium' of language studies, which consisted of mother tongue study, foreign language study and language awareness work (Hawkins, 1984).

Being language aware means that a teacher can understand the possible challenges that language presents to learning, regardless of the subject taught and can help better students, especially those who are learning a subject through an additional, foreign or second language, considering the multiethnic and multicultural dimension of our schools (Narcy-Combes *et al.*, 2019; Nikula *et al.*, 2016).

Learning more than one language can have a hugely positive impact

[2] http://academy.schooleducationgateway.eu/web//embracing-language-diversity-in-your-classroom/foro/-/message_boards/message/1191820

on working memory, selective attention, processing information, and mental flexibility. The ability to use more than one language means we can communicate with people from diverse linguistic and cultural backgrounds. We live in an increasingly global world and language skills make travel easier, provide opportunities to study abroad and improve career prospects.

The latest Council Recommendation on Key Competences for Lifelong Learning (2018), reshaped the concepts related to the key competences needed (from reading and writing, horizontal skills to digital competences), using the terms "literacy" and "languages competences", which allow us to talk about communication from a broader perspective, considering L1, L2, L3, LS, Lingua Franca etc. and all the different language varieties which represent an integral part of the individual linguistic repertoire.

4 Learner issues: The participants

Starting from the above-mentioned inspirational background, the MOOC attracted 1135 participants from all over the world, as shown in the map below (Fig. 1).

Fig. 1 – The map of the MOOC[3]

The majority of the participants (1135 pins) were from Europe, but there were also participants from the USA, from Africa and from Asia.

1264 participants filled in the initial survey; 88.2% of them were female.

38.36% between 46 and 55 years old and 33.73% between 36 and 45; 12.58% over 55. It is a very interesting statistic, showing the teachers' will to study and innovate their teaching practices even though not so young.

A visual rendering of the participants was realized through a webapp,

[3] https://www.zeemaps.com/map?group=3153298&location=Europe

"Mosaically", allowing all the participants to upload their picture to be collated and shown in a very dynamic and interactive poster, as shown below (Fig. 2).

Fig. 2 – Course mosaic[4]

As far as the participants' professional profile, the majority of them (64.5%) were secondary school teachers and 27.7% primary school teachers, as shown in the table below (Fig. 3).

This means that the topic of integrating language diversity in the school curriculum may be critical at secondary level: secondary school teachers may feel the need to be equipped with new skills and tools to cope with bilingualism and multilingualism in their classes. At lower levels these issues may be probably easier for a teacher.

7.9% of participants were teacher trainers: unfortunately, this is a very small percentage for such an important role.

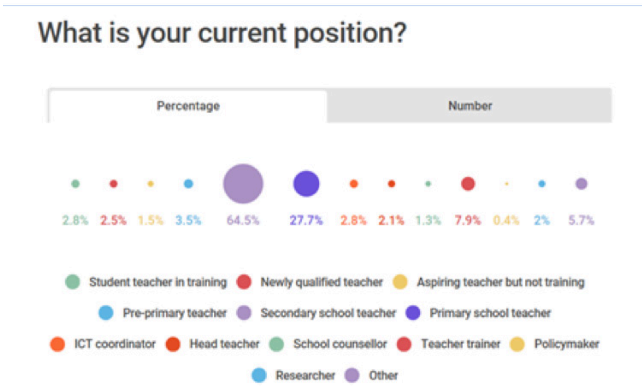

Fig. 3 – Professional profile of the participants

35.6% of the participants had more than 20 years of experience in education

[4] https://mosaically.com/photomosaic/b2da5e3f-c45a-4c84-9957-83f747408126#

(Fig. 4) and this confirms the idea that teachers are a very special category of professionals, eager to learn and to innovate, even though not so young, yet experienced.

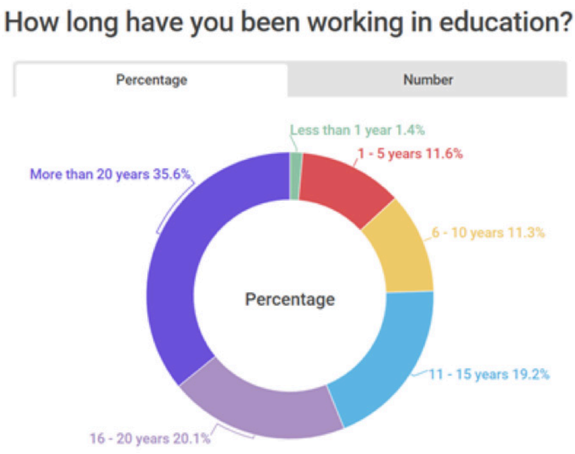

Fig. 4 – The participants' experience in education

The question in the initial survey: "Do you feel well prepared to provide your students with different tools and resources in order to support them to deliver curricular subjects in different languages?" got 42.8% of the answers in position 3 of a Likert scale: this means they feel quite confident with new technologies for language learning (Fig. 5).

Fig. 5 – The participants' confidence with new technologies

81.4% of the participants stated they had enrolled on the course to innovate their classroom practice and 60.9% to find useful resources (Fig. 6). MOOCs are considered useful learning opportunities to innovate and to get content, links and materials to be used in class, as mentioned in paragraph 1. Textbooks may not be so helpful in this field; therefore, this kind of professional development may be a precious opportunity for teachers to improve their teaching style and techniques.

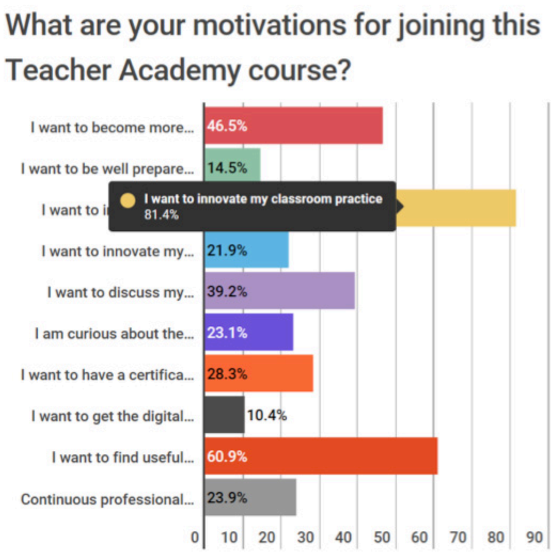

Fig. 6 – The participants' motivation to join the course

5 Technical issues: learning environments

The main learning environment used for delivering the MOOC was the School Education Gateway platform where all the resources and the "Learning Scenarios" produced by the participants were delivered and where a specific Forum was moderated throughout the course.

The media channels used for communicating and interacting during the course were the Facebook Group and the Twitter hashtag *#languagesmooc.*

Some Learning Analytics collected from those environments will be highlighted and commented on, with the aim to find answer to the following research question: "What impact can a MOOC on language awareness have on teachers' professional development?"

6 Methods

In order to analyze data collected from different social and learning environments used for the MOOC, the Learning Analytics Process proposed by Chatti *et al.* (2012) was adopted. It is an iterative cycle generally carried out in three major steps: (1) data collection and pre-processing, (2) analytics and action, and (3) post-processing.

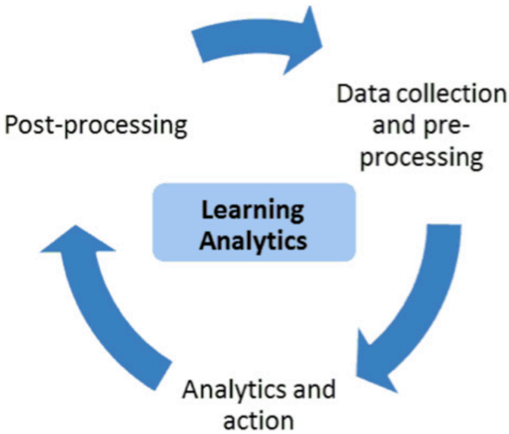

Fig 10 - Learning The Analytics process

As Chatti highlights, "the first step in any LA effort is to collect data from various educational environments. This step is critical to the successful discovery of useful patterns from the data". The collected data may be too large and/or involve many irrelevant attributes, which call for data pre-processing. Data pre-processing also allows transforming the data into a suitable format that can be used as input for a particular LA method. Several data pre-processing tasks, borrowed from the data mining field, can be used in this step. These include data cleaning, data integration, data transformation, data reduction, data modeling, user and session identification, and path completion (Han and Kamber, 2006, Liu, 2006; Romero, Ventura, 2007).

The data we collected from the different learning and social environments refer to the participants' number of logins, showing their interest in the different content of the pathway; data also refer to their interaction and contribution in the forum, in the Facebook Group and in Twitter. We also use a qualitative approach, collecting some data using NVivo software, which is commonly used for qualitative analysis.

The next step of the process, post-processing, crucial for the continuous improvement of the analytics exercise, can involve compiling new data from additional data sources, refining the data set, determining new attributes required for the new iteration, identifying new indicators/metrics, modifying the variables of analysis, or choosing a new analytics method. This is our field on research at the moment and we are still working at this stage.

What makes learning analytics a 21st century model is that dynamic data mining helps both learners and educators improve their behaviors and techniques in real-time.

7 Results and discussion

7.1 The participation in the modules

2581 registered for the course and 1421 participants actually started and attended it.

In order to get the module badge and the final certificate, the participants had to download the material from each module and complete their own "Learning Scenario", conceived as an individual outcome of the course, in the shape of a lesson plan on the topic of the MOOC and their own "Learning Diary", thought of as the digital portfolio of each participant, collecting memories, pictures, resources, considered relevant for their own personal and professional growth.

Here is the overview of the syllabus, developed over 4 modules:

- Module 1: The importance of language awareness
- Module 2: Turning language diversity into an asset for your teaching
- Module 3: Content and Language Integrated Learning
- Module 4: Multilingual classroom projects.

The MOOC started on 24th September 2018 and it is still open from the Open Educational Resources perspective in order to make the material available for further consultation.

The brainstorming module, aimed at getting familiar with the platform and the learning environment but with no badge, was not attended as expected. This gives an idea of how important badges and formal recognition are for teachers' professional development: "gamification" can be effectively adopted in MOOCs to enhance attendees' motivation and increase completion rates (Khalil et al., 2018). Another reason for this low rate of attendance may be the fact that, as emerged from the initial survey, the majority of the teachers were quite confident with technologies and may have felt ready to start the learning activities directly, skipping the brainstorming module.

In terms of log-ins to the course, the first module was the most popular one, probably due to the participants' enthusiasm starting a new initiative.

Here is the number of participants starting and finishing each module (Table 1).

Table 1
NUMBER OF PARTICIPANTS STARTING AND FINISHING EACH MODULE

	How many started	How many finished
Module 1: The importance of language awareness	1385	1127
Module 2: Turning language diversity into an asset for your teaching	864	769
Module 3: Content and language integrated learning	770	682
Module 4: Multilingual classroom projects	712	458

The first module was started by 1385 participants and completed by 1127, while the other modules were probably considered less attractive and interesting. Dropping out throughout a MOOC can be a natural phenomenon, especially considering such a high number of participants.

In this case the first module on the importance of language awareness was the core of the course, strictly linked to the main message of the Council Recommendation on languages. So, we may say that placing this module as the first one was probably a good choice.

The highest number of log-ins to the course was registered at the beginning, during the first module (Fig. 7), confirming the great initial interest in the topic of the course.

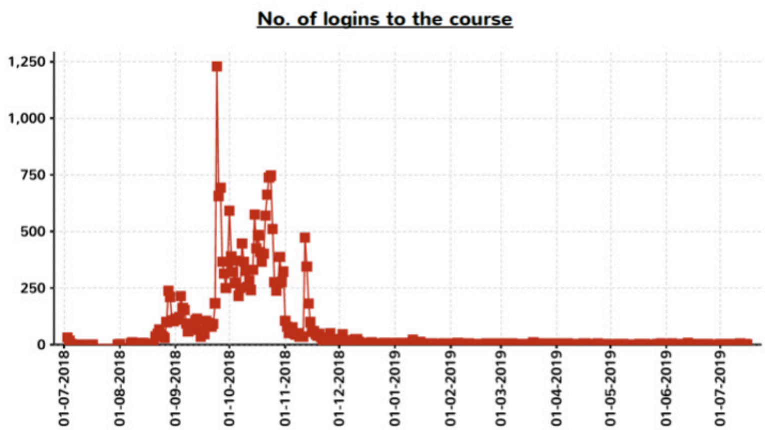

Fig. 7 – Number of log-ins to the course

These are the starting dates for each module, in detail:

- the first module started on 24 September 2018
- the second module started on 1st October
- the third module started on 8 October
- the fourth module started on 15 October.

All the moderated activities ended on 31st October 2018, although the materials and resources were left available for consultation and still are.

It is worth highlighting that there was some activity in the course till July 2019. This means some teachers were particularly interested and wanted to go back to the platform later, probably during their activities in class, in order to get ideas, materials, resources. This is a very positive outcome, showing the efficacy of the learning pathway provided by the MOOC.

On 26 September a live synchronous meeting with Sarah Breslin, Director of the ECML (*European Centre for Modern Languages*) of the Council of Europe took place and this was a very important event for the course, also because it coincided with the European Day of Languages and the European Commission thought it was a good idea to celebrate it in this way. That is why there was a very high number of log-ins to the platform that day.

The details of the log-ins to each module show once again the boom which occurred in the first module, reaching 2500 log-ins. The colours in the graph below, associated with each module (Fig. 8) also show that Module 1 (in red) keeps attracting the participants' attention, being visited, even if at a very low percentage, until now. The Module 3 on CLIL (in purple) received about 1000 log-ins, some more than Module 2 (in yellow); last position is taken by Module 4 (in light blue), with less than 1000 log-ins. It is interesting to note that we can see some bits of yellow (Module 2 on language diversity) and light blue (Module 4 on multilingual projects) in diachronic perspective up to now, while there is no trace of purple (Module 3 on CLIL) after the end of the course.

It is actually an interesting but surprising outcome at the same time, the fact that CLIL may not have been so popular nor attractive for the participants. It may be interpreted in different ways: some teachers may already be familiar with this methodology, especially at upper secondary school level and may already be implementing it in their classes, therefore they may be eager to learn something new, as the ideas proposed in the other modules, especially in Module 1 on language awareness, which has been perceived as somehow innovative, even if it actually relaunched and revisited themes well known in the literature. Another hypothesis may be linked to the natural process of dropping out, as CLIL is presented as the third content of the course, so towards the final part of it.

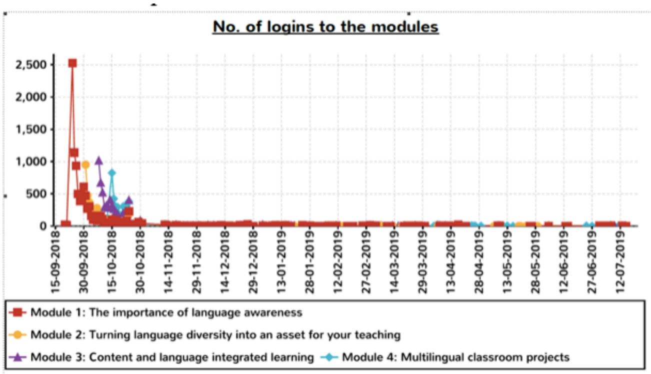

Fig. 8 – Number of log-ins to the modules

7.2 The key words of the training

Using Nvivo software, an attempt to gather the most common words used by the participants during the course, in relation to the content of the course was made.

As far as Facebook is concerned, all the posts added to the Facebook Group, counting 917 members since the beginning of the course, were collected and a specific query about word frequency was launched. This was the result (Table 2).

Table 2
FACEBOOK GROUP WORD FREQUENCY QUERY

Word	Length	Count
2018	4	600
tag	3	590
learning	8	309
course	6	175
scenario	8	162
visualizza	10	154
review	6	151
thank	5	147
thanks	6	140
link	4	128
language	8	105
please	6	104
work	4	98

Word	Length	Count
com	3	86
designer	8	79

The first position is the year of the training course, 2018, followed by the word “tag”, occurring 590 times: participants usually tagged other participants or the files they uploaded. “Learning” and “course” are quite popular, as naturally linked to the initiative. It is worth underlining the frequency of the words “scenario” and “review”, two important tasks of the course: the design of a “Learning Scenario”, mentioned earlier, assigned as a tangible output of the course and the “Peer Review”, the review of an activity uploaded by a colleague, according to certain criteria, from a peer learning perspective. The participants had many lively discussions on Facebook: they were proud of their “Learning Scenarios” and were eager to share them with their colleagues, collecting their feedback in a very constructive way.

“Thanks” and “thank” are often used by the participants who were grateful to administrator and moderators for all the work done.

The same analysis using Nvivo was made collecting the forum posts, selecting all the threads related to each module[5].

The outcome of the word frequency query mostly generated the word which was mainly associated with the topic of the module, as the four tag clouds below show:

Module 1 Module 2 Module 3 Module 4

Fig. 9 – Word frequency tag cloud for each module

In module 1 one of the most frequent words (apart from “language”, “module” and “https”, related to the different links suggested in the forum) is ECML, mentioned during the module, with particular reference to the webinar run by Sarah Breslin, the Director of the institute.

One of the most popular words in the Module 2 forum is “webinar”: in fact, on 5th October another webinar, run by Nell Foster, from University of Ghent,

[5] The tables for each module word frequency query are included in the Appendix.

Belgium took place and it was very successful: the participants discussed it a great deal later on in the forum. Two webinars were probably not enough for a four-module MOOC, as they were much appreciated by the participants: an important lesson learnt for future similar initiatives.

In module 3 "CLIL" and "methodology" are the protagonists of the cloud, being the main topic of the module. It is quite significant how the word "student" is central and popular only in the Module 4 forum and in the Module 2 forum, even if with lower numbers: students should be the real protagonists of all the learning and teaching process.

In module 4 forum we also find the word "project", strictly linked to the content of the module, but also to the interesting discussions coming from the participants willing to keep in touch even after the course, by cooperating at eTwinning or Erasmus projects with their own schools: a very useful follow up of the MOOC, which can be considered one of the main results and benefits for the participants.

7.3 The discussion forum

In order to analyze the contributions posted in the discussion forum, we filled in a 'weekly notable contribution grid' (Fig. 11), generally adopted in EUN MOOCs.

URL/location or just copy text here	What? (E.g. Learning Diary, interesting link, tweet, lesson resource, controversial or interesting comment, etc.)	Name of participant	Date (ideally of when contribution was made)	Your name
Week …				

Fig. 11 - Weekly Notable contributions grid

The purpose of the table was to collect participant contributions that we could highlight in weekly course emails and give as examples in discussions to enhance participation and foster learning.

Analyzing a forum is a rather complex process. It is within the forum that a process of continuous creation and evolution takes place, it is there that communicative exchanges are fostered and encouraged, it is there that knowledge is built in a collaborative manner, through the mutual support among participants who share strategies, models, paths.

This is how the forum becomes a learning space, a scenario where the moderator is the manager and facilitator of the discussions. The correct management of the communication process involves the ability to be able to read the requests of the participants, be able to respond adequately and be able to manage the communicative dynamics, maintaining an interpersonal relationship that is complex for its being mediated. Given the almost total absence of meta-communicative elements, communicating online means mainly using a text-based method: linguistic (lexicon, style) and non-verbal (punctuation, abbreviations, capital letters, emoticons) modes come into play. To analyze the complexity of the interactions, various approaches (Cacciamani, 2003) can be adopted; however, the most widespread models for the analysis of the interactions in asynchronous discussion groups supported on a forum, take into consideration both quantitative and structural parameters. In most cases, the starting point is the quantitative data as an indicator of a qualitative phenomenon.

The analysis is generally carried out:

at a first level on:

- the number of discussions
- the number of replies to the opening messages of the discussions
- the number of visits per discussion

at a second level on:

- the total number of messages entered (used to evaluate the level of participation in general)
- the number of messages sent by students in relation to the number of messages sent by tutors (to assess the level of active participation of students)
- the number of messages produced per student (to verify the presence of more or less active students in the virtual classroom)
- the number of messages produced in a given period of time (to understand the level of student participation)
- the length of messages (to understand the qualitative progress of the discussion)

from these data we can learn about:

- the depth of a discussion (number of messages in reply)
- the depth of the forum (given by the average of the depths of the discussions)
- the forum density (given by the ratio between the total number of messages entered as a reply and the total number of discussions)
- the lurking index (given by the relationship between visits and replies).

As illustrated in Fig. 12, 11 categories of threads were created by the moderators with a total number of 558 messages by 176 participants. The category dedicated to the 'learning activities' had the highest number of threads and posts, being the core of the course, followed by the category opened for the sharing and the feedback on the 'learning diaries', a cross curricular task for the participants, excluding the category of technical issues, irrelevant from a learning point of view.

Due to the nature of the content course, in Module 2 and Module 3 we added only two categories, which explains the significant lower number of threads and posts, compared to Module 1 and Module 4; the analysis of this trend was the focus of the second step in the learning analytic process: 'analytics and action'. Basing on the pre-processed data and following the objective of the analytics exercise, we moved to explore the results in order to discover hidden patterns that could help to provide a more effective learning experience.

Category	Subcategories	Threads	Posts	
European Day of Languages	0	8	27	Actions
Introduction	0	8	49	Actions
Learning Activities: Peer Reviews (Lost and Found) If you delivered an empty text box in the first step of your activity, or if you forgot to attach the file, please share your work in this category. It won't be recorded in the Learning Activity space, but at least your reviewer (or the colleague whose work you reviewed) will be able to find your file on the forum.	0	65	86	Actions
Learning Diaries You can use this forum category to post your Learning Diaries and ask other participants for feedback.	0	44	80	Actions
Module 1: Building bridges between formal and informal learning	0	12	52	Actions
Module 2: Empowering students through personalized learning	0	2	9	Actions
Module 3: Content and language integrated learning	0	2	9	Actions
Module 4: Strategies to empower students through collaborative learning	0	21	56	Actions
Notable contributions Please find here our notable contributions every week. If you spot other great contributions from a fellow participant, please don't hesitate to share!	0	4	4	Actions
Recommendations Please post any recommendations of how we can improve the course here.	0	2	2	Actions
Technical Issues & Questions Please first check the FAQ section to see if there is an answer to your question or issue. If you cannot find an answer, please post your question or comment here.	0	37	107	Actions

Fig. 12 - Total number of categories, threads and posts

The quantification of the interactions serves to highlight the trend of the threads, allowing the reader to identify critical and weak points. The progress of the discussion can be represented taking into consideration two factors that Simoff (2000) calls 'weight of the link' and 'weight of the term'; the first involves a direct link between the messages, the second can also link messages that are apparently distant from each other and define a very articulated and complex structure. In any case, the analysis models of the threads cannot be separated from an analysis of the contents of the single messages, to understand if they refer to the didactic path, to other interests or if they represent independent contributions with a social emotional background. Here comes the qualitative analysis, which focuses attention on individual messages, and is relevant for understanding and analyzing the progress of discussions and communication and monitoring learning.

Messages are usually divided into sub-categories:

- messages that refer to personal or emotional experiences
- messages referring to information material or information request
- messages that try to pose new problems to open questions
- discussion summary messages
- messages that propose new topics for discussion

Of course, analyzing messages from a typological and content point of view is very difficult, given the fragmentary nature of network communication and the frequency of cross-references, citations, and commingling in electronic messaging. Fafchamps (1998) distinguishes between:

islands, messages that do not refer to others that preceded them and that in turn do not produce replicas

dialogues, or small sets of two or more messages closely related to the same topic

cobwebs, sets of different messages linked and crossed with one another.

A typical example of ‘islands’ messages was the ‘welcome thread’ in Module 1, were participants only introduced themselves without interacting, while ‘dialogues’ were created in the ‘learning diaries’ discussion where they had been invited to comment on others’ productions. Examples of ‘cobwebs’ messages can be found at the end of the course in the category for finding partners in E-twinning projects (Fig. 13), both for the content of the discussion and the time it had been started, at the end of the course, when the learning community had been set through the online social communication channels.

Find partners for eTwinning projects		Jelena Milenkovic	29	443	Date: 24/10/18 21:04 By: ΟΥΡΑΝΙΑ ΛΑΜΠΟΥ	Actions

Fig. 13 – Example of cobwebs

7.4 The twitter chat

Before the ending of the course, there was a successful experience of running a Twitter chat. As illustrated in Fig. 14, even if it was the first experience of this kind of communicative exchange for most of the participants, there was a huge number of impressions (the times users saw the twits) and engagements (clicks, retweets, replies, follows and likes divided by the total number of impressions). 'Formal and informal learning' and 'Language awareness' were the most twitted questions, which meant for us, as moderators, the evidence that the course had reached its aims.

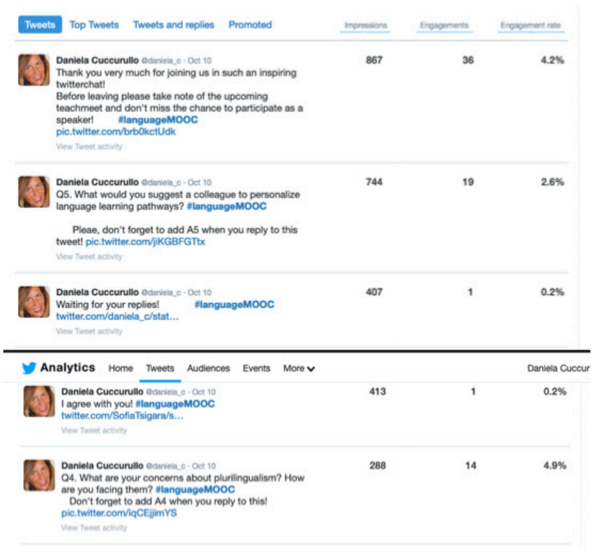

Fig. 14 - Analytics of the Twitter chat

Conclusion

The paper aimed at reporting and commenting on Learning Analytics collected from an international MOOC on language awareness and language diversity at school promoted by the European Commission.

Some main learner issues, pedagogical issues and technical issues considered relevant by the authors were highlighted as lessons learnt for future training initiatives. In fact, data linked to the attendees' professional profile, motivation, participation and online social interaction can help understand better the efficacy of a training pathway in order possibly to modify it in the future and to increase the attendees' opportunity for success.

Teachers like this kind of opportunity for professional development, especially as they interweave formal, informal learning and social exchange, key dimensions for an educator.

Our research question: "what impact can a MOOC on language awareness have on teachers' professional development?" got a wide range of interesting inputs: participants find the MOOC as an alternative and engaging way to inspire and enrich their professional activities. They have the opportunity to select the content and the part of the pathway they find more relevant; they are happy to accomplish certain tasks assigned, as the "Peer review" and the "Learning Scenario"; they can reflect and share their ideas with the other participants in the forum and in the Facebook Group. They also like interacting online in synchronous, considering their active participation in the live webinars with the experts and in the Twitter chat organized by the moderators. These live dimensions of the training are perceived as fundamental for the teachers' professional development and should be probably implemented further in future training initiatives.

Discussing Learning Analytics collected from the different environments of the MOOC helped us get deeper "awareness of the impact of social dimensions of learning and the impact of learning environment design on subsequent learning success" (Baker & Siemens, 2014: 265).

Appendix

MODULE 1 FORUM WORD FREQUENCY QUERY

Word	Length	Count
https	5	22
module	6	22
ecml	4	21
language	8	21
course	6	14
www	3	14
com	3	11
aspx	4	10
awareness	9	10

default	7	10
find	4	10
learning	8	10
please	6	10
tabid	5	10
introduction	12	8

MODULE 2 FORUM WORD FREQUENCY QUERY

Word	Length	Count
webinar	7	4
see	3	3
students	8	3
classroom	9	2
create	6	2
every	5	2
families	8	2
Italian	7	2
multilingualism	15	2
speak	5	2
strategies	10	2
thanks	6	2
2module	7	1
activate	8	1
another	7	1

MODULE 3 FORUM WORD FREQUENCY QUERY

Word	Length	Count
clil	4	11
methodology	11	7
Italian	7	4
language	8	4
module	6	4
teachers	8	4
another	7	3
course	6	3
idea	4	3
think	5	3

find	4	2
good	4	2
ideas	5	2
interesting	11	2
just	4	2

MODULE 4 FORUM WORD FREQUENCY QUERY

Word	Length	Count
students	8	17
project	7	16
like	4	9
school	6	8
English	7	6
learning	8	6
teachers	8	6
aged	4	5
chemistry	9	5
heritage	8	5
share	5	5
something	9	5
teachmeet	9	5
activity	8	4
also	4	4

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IMPROVING LEARNING WITH AUGMENTED REALITY: A DIDACTIC RE-MEDIATION MODEL FROM INF@NZIA DIGITALES 3.6

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Keywords: Augmented reality, Smart City, Childhood Education

The diffusion of information and communication technologies, in the last decades, appears to be a great opportunity in teaching and learning processes, not necessarily due to different learning supports.
Augmented reality (AR), in particular, appears one of the plausible solutions for transforming learning methods, supporting students to have educational experiences able to involve all the senses and increasing motivation and engagement levels.
This paper provides an approach for using augmented reality in human learning in the context of a novel didactic re-mediation model. Moreover, this paper includes also the description of an application (Mobile App) developed as one of the results of Inf@nzia Digitales 3.6 project.
The described learning experiences are designed for children from three to six years. The main topic of the experiences is represented by the discovery of geometric shapes in a smart city, and their understanding as road signs.

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1 Introduction: the context and the target

In recent years, it has been recognized an increasing interest for digital technologies that profoundly transform educational processes as we traditionally know them. In Italy, some of the objectives by the new National Digital School Plan (Ministerial Decree 851/2015) consist in the construction of an active and interactive learning system where spaces, materials and technologies are adapted to the users, in order to create educational settings increased by technology (Miur, 2015).

Technology Enhanced Learning (TEL) researches are focused on emergent technologies creating a meaningful learning for students. In particular, Augmented Reality (AR) seems to have a high potential for pedagogical applications. AR is a new media supported by specific hardware and software technologies which overlays virtual objects (augmented components) into the real world (Azuma et al., 2001). Currently, there are three main types of AR devices: i) Head-mounted displays and Wearables, ii) Mobile handheld devices, and iii) Pinch Gloves. The devices belonging to the second category, i.e., mobile devices, are prevalent and can be easily put into learning settings.

Meta-review and cross-media analysis demonstrate many advantages that AR offers when it is adopted in educational settings, also comparing AR to non-AR systems for learning: in fact, AR systems seems to increase content understanding, students' motivations, physical task performance, spatial abilities and collaboration among learners (Radu, 2014; Akçayır e Akçayır, 2017). In particular, the key elements that guarantee a greater learning experience are multiple and simultaneous content representations, according to the cognitive theory of multimedia learning (Mayer e Moreno, 2003; Mayer, 2005) and the physical involvement in the activities (Vincenzi et al., 2003; Shelton e Hedley, 2004).

Most of the studies on the use of AR in educational context are applied in higher and primary education settings: the state of the current AR application in Early Childhood Education is still in its infancy (Bacca et al., 2014). However, in recent years some pilot studies have proved the potential of using AR in different domains of learning in the age segment from three to six years (Huang, Li e Fong, 2016; Yilmaz, 2016).

Starting from these premises, the Inf@nzia Digitales 3.6 Project[1] tried to integrate the new possibilities offered by ICT with the main pedagogical theories for children from three to six years, in order to enhance the fruition of cultural assets or points of interest in smart cities. Cities, in fact, offer a poten-

[1] Inf@nziaDigiTales3.6 is a research and development project co-funded by the Italian Ministry of University and Research under the PON Research and competitiveness 2007-2013: Smart Cities for Social Inclusion. A quite complete description of the project can be found in Miranda, Marzano & Lytras, 2017.

tially infinite number of real-life situations (e.g., visiting museums) that can be exploited to build situated learning experiences.

2 The didactic re-mediation model from Inf@nzia DigiTales 3.6

2.1 Cultural re-mediation and digital storytelling

Child development, especially in the range from three to six years, is characterized by the progressive appropriation and transformation of the cultural artifacts offered by the environment in which they live (Vygotsky, 1962; Bruner, 1986). In these years, is not a coincidence that children perfect language acquisition and their mental representations, or abstractions of real objects that continue to exist, in their mind, even in the absence of it (Piaget, 1964). Indeed, they create imaginary situations to go beyond the limits of their concrete and real possibilities of action, also using symbolic play (Bretherton, 1984).

Even ICTs provide the ability to generate other representations of the world, implementing a real transformative action on reality. This is the exemplary case of AR that supplements reality with virtual objects superimposed on the real world. Considering the continuum that leads from the real world to the virtual one, AR is the most proximal to what happens in reality, connoting the concrete learning experience and interactivity (Milgram e Kishino, 1994). In fact, while Virtual Reality (VR) tends to replace the real world with a completely different and ad hoc one, AR enriches it because real environment is augmented by means of virtual objects. This increases the user's perception and interaction with the environment by providing visual information that the user could not directly detect by means of her/his senses.

From these assumptions, the didactic re-mediation model from Inf@zia Digitales 3.6 is based on the integration of natural and media languages, and starts from the principles of re-mediation theory (Bolter e Grusin, 1996; Bolter, Grusin & Grusin, 2000). Bolter and Grusin define re-mediation as the representation of a media in another media, and affirm that it is founded on two conflicting and antithetical approaches: immediacy and hypermediacy. In the logic of immediacy, the purpose of the medium is to disappear, removing the mediated nature of experience (e.g. immersive technologies). Instead, in the hypermediacy logic, the mediated nature of experiences is clearly visible (e.g. hypertexts).

Starting from the works of Deuze (2006) and Manovich (2001) can be defined a new remediation mode, named *ad-mediation* (Ciasullo et al., 2016), which is not focused exclusively on the contraposition between old and new media (Immediacy vs Hypermediacy) but considers the knowledge acquisition through continuity or through differences related to prior knowledge (Similarity vs Dissimilarity).

The combined use of AR and mobile devices fosters the natural integration of natural and media languages in the context of a sort of game experience, guided by narrative plots, in which children are able to move on the different axes of knowledge mediated by technology, including those related to Symbolism/Realism (fig.1).

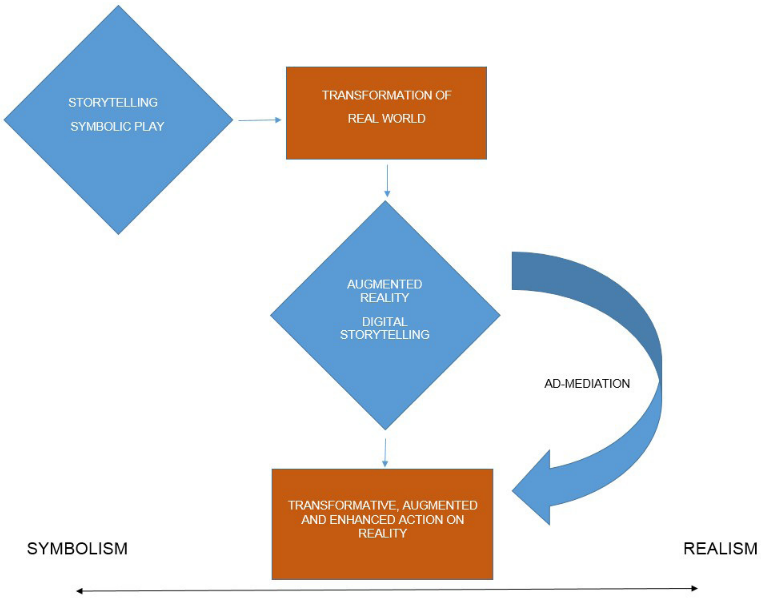

Fig.1 - Cultural ad-mediation in Inf@nzia Digitales 3.6

Therefore, learning mediated by technologies can be one of the main tool for exploring *possible worlds* through the action of a narrative thought (Bruner, 1990) that assembles and gives meaning to children's cognitive experiences. The result is the meaningfulness, already in this age group, of activities that integrate narrative thinking with new technologies, through the use of digital storytelling (Lambert, 2013; Robin, 2008), preferably interactive (Gaeta et al., 2015) to allow them to manipulate cultural objects (Capuano et al., 2016).

An additional enabling technology to support gathering and processing of data in the (smart) city is represented by ontologies (Miranda, Orciuoli e Sampson, 2016). Lastly, it could be also possible to enrich data and content coming from the city by using social media content (Cuzzocrea et al., 2016).

2.2 Meaningful learning and metacognition

Further inspiration for the model comes from Ausubel's contributions to meaningful learning (1968). According with Ausubel, learning in a meaningful way indicates, for students, processing information actively. Learning becomes meaningful only if new content can be integrated with that controlled in previous cognitive schemas. This is possible when prior knowledge is ascertained and recalled during learning processes, causing an extension of students' cognitive structures. This mechanism can be compared to assimilation and accommodation processes described by Piaget (1947) during the intellectual child development, where intelligence is the result of a state of balance between the organism and the environment.

In addition, the *Italian National Indications for the Curriculum* (Miur, 2012) in the description of school learning environment, emphasizes the importance of enhancing the experience and knowledge of students. In fact, a child involved in a learning process already brings with her/him a rich wealth of experience and knowledge acquired outside the school. Such wealth should be appropriately recalled, explored and problematized by teaching processes in order to make sense of what has been learned.

This approach presupposes a continuous reflexivity, intended as a solicitation to the metacognitive processes of learners and focused on developing her/his self-awareness related to the learning experience (Flavell, 1979). Recognizing encounterd difficulties and strategies adopted to overcome them, acknowledging mistakes, but also understanding the reasons of failures and knowing their own strengths are all necessary capabilities to make children aware of their learning styles and able to develop autonomy in the study. Learners should be supported in understanding their tasks and goals, recognizing difficulties and estimating their abilities, learning to reflect on their own results, assessing progress, identifying limits and challenges to be faced, being aware of the results of their actions and drawing considerations.

2.3 Intelligent tutoring

Another aspect of the proposed model is represented by socio-constructivist pedagogical approach, and concerns the relevance of the social dimension of human learning. In this approach, forms of interaction and collaboration can range from mutual aid to cooperative learning to forms of tutoring and cognitive apprenticeship. In kindergarten and primary school, a significant role in supporting learning is assumed by working in pairs, through the helps provided by a more experienced peer or by an adult figure, according to the Vygotsky (1978) principle of proximal development zone (ZPD).

The teacher, or a more experienced peer, plays a scaffolding function (Wood et al., 1976) providing support and guidance that are necessary to resolve problematic situations and/or tasks that the child is not yet able to perform alone. Of course, to be functional, these tasks should not be too much above the cognitive abilities of the student.

While human tutor's behavior is highly adaptive because he estimates the ZPD and the current state (cognitive and affective) of the learner and selects the task to propose, technology-based instruction needs artificial intelligence systems providing individual learners with hints, examples, explanations and problem solutions. To solve these problems researchers designed and developed software that can simulate the actions of a human tutor, monitoring the interaction of the learner in educational games, such Intelligent Tutoring System (ITS) and Adaptive Educational System (AES). The use of ZPD in ITS has been investigated in Fenza e Orciuoli 2016; Fenza, Orciuoli & Sampson 2017; Capuano et al., 2008; Adorni et al., 2010.

To this purpose, the intelligent tutoring approach, developed in the context of Inf@nzia Digitales 3.6, aims to automatically adapt tutoring actions to learning needs and progresses of children, providing the benefits of one-to-one instruction. It can be articulated in these operational phases:

1. *Modelling* (Bandura,1969), or the initial execution of task by the expert, represented by a character guide;
2. *Scaffolding*. The character guide assists the child by providing suggestions and adapts feedback related to the task performance, ensuring him support to exercise his competence. This support, however, will be progressively reduced to allow the latter to develop operational autonomy (fading).
3. *Reflection*. When there are several difficulties and mistakes in proceeding, child's performance is compared to that of the expert through a guided reflection;
4. *Restructuring and cognitive expansion* by the integration of old and new interdisciplinary learning contents.

3 Application: Bigfoot the Pedestrian

The AR application is an educational game that refers to interdisciplinary learning activities situated in a (smart) city. Led by an intelligent tutor, called *Bigfoot the pedestrian* (fig.2), children can recognize the meaning of different road signs and their geometric shapes, to group and sort objects and materials according to different criteria.

Bigfoot is a 3D virtual child with a lively, cheerful and friendly character capable of arousing empathy, curiosity and interest, modelled by using LightWave

3D software[2]. He guides and supports children through the phases analyzed in 2.3, in order to the increase autonomy and self-esteem, trust, responsibility and safety. The educational objectives of the game are: i) recognizing road signs in the real world, also by analogy with known geometrical shapes; ii) stimulating children with a 3D character able to move and talk; iii) allowing touch interaction and voice commands (Speech Recognition); iv) presenting a user-friendly layout to reduce comprehension and interaction efforts. In this way, the completed experience allows the growth of new knowledge through the restructuring and rearrangement of the previous one. Below, it is possible to see a summary table (tab.1) that links the phases of the game scenario with their description.

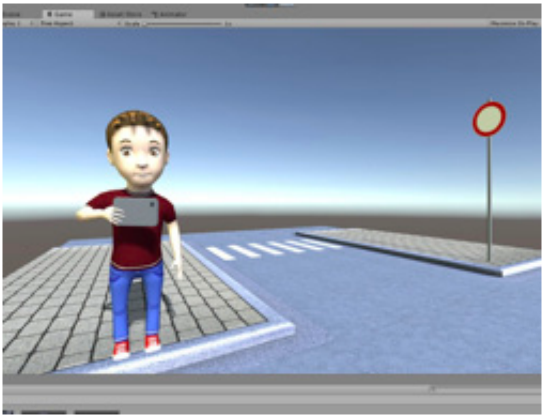

Fig. 2 - Bigfoot the pedestrian

The application has been developed by using Unity 3D and the AR engine Vuforia[3] that recognizes and tracks planar images targets, simple and complex 3D objects and models targets in real-time. In this specific case, if a tablet (or a smartphone) focuses on, through their camera, a road sign, the proposed application recognizes and tracks the sign in real-time and an educational game is generated and rendered automatically and contextually. Therefore, when the child starts the game and moves in the city, Bigfoot appears on the device screen, greets the user, introduces himself and invites the child to play the game and find out the meaning of the road signs. The game is presented by visualizing Bigfoot who asks a question about the signal and the corresponding shape. Now, the child can use the UI (User Interface) buttons for making her/his selection, typically, in a multiple-choice test (fig. 3).

[2] https://www.newtek.com/lightwave/2019/

[3] https://engine.vuforia.com/engine

Table 1
PHASES OF SCENARIO

Phase	Description	Main characteristics
Introduction	Tutor's storytelling Introduction to the game	Digital storytelling
Presentation	Recall, by the tutor, of the cultural objects present in the city	Reference to the cognitive matrix of children
Expert performance	Explanation, by the tutor, of the game mechanisms	Observational learning (modelling)
Child performance	Learning task request	Verification of prerequisites
Consolidation of learning contents	Interactive game Tutor suggestions and intervention in case of correct and / or incorrect answers from the child.	Scaffolding Increase of ZSP Adapted feedback Positive reinforcement Symbolism/Realism Active research of contents present in the environment
Expansion and transfer	Presentation of additional disciplinary and interdisciplinary contents	Transfer of learning

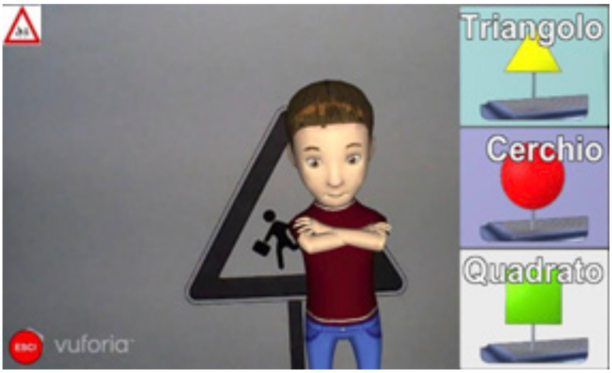

Fig.3 - Example of a multiple choice

4 Exploratory research: first results

An exploratory research has been conducted from May to June 2018, with the aim of detecting first results about the acceptability of a first trial of the developed application deployed at an Android Tablet, the degree of satisfaction and involvement of the learners, as well as the achievement of the learning objectives associated with the game activity.

This study involved 107 children (six years old) from first classes of two Educational Institutions in the province of Salerno (Italy), through a pre-experimental design with one-group and post-test only (Cohen et al, 2002).

The phases of the experimentation were the following:

- Preliminary interviews with the executives and teachers of the involved Institutions;
- Verification of the Three-year Training Offer Plan (PTOF) of the involved Institutions;
- Preparation of the learning environment and the materials for the experimental activity;
- Game activity carried out in the laboratory in the presence of the experimenter, the observer and, where possible, of the class teacher (fig.4). A structured children's observation grid has been compiled during the game by experimenters, in order to verify the acceptability of the tool (application) and the engagement among students;
- Execution of a short structured questionnaire (six items), by the students, on the degree of satisfaction and involvement during the game. Some of these items are adapted from the System Usability Scale (SUS) (Brooke, 1996). The questionnaire has also collected additional data such like children gender, age and their use of tablet at home.
- Execution of a final learning task by the students. In this task, children individually answered five questions concerning the meaning of some road signs, one of which related to the recognition of the geometric shape present in one of the signals.

Fig.4 - Children involved in the execution of the game

The planned activities had, for each participating class, the duration of a school day. In fact, children have been divided into small groups in order to increase their engagement.

Analysing the collected data of the short structured questionnaire, it is possible to affirm that there is a certain gender equality among the participants (50.4% male; 48.6% female). Moreover, the majority of the trial participants own a tablet (81.3%) and the 66.3% of them admitted to use it frequently. This means that the use of tablets is widespread among children and is largely a great attraction even in the school context, especially if associated with a strong interactivity, provided by specific applications, such as that provided by AR.

With respect of the level of engagement expressed during the game, almost all of the children provided positive opinions (94.3%), confirming the pleasantness of the game experience. In fact, the large majority of children (92.5%) affirm they have pleasantly acquired the proposed contents, and a majority of them (89.7%) state that they would like to have this *special* application in their school daily. The results of the observation and the interviews with the teachers also revealed that children with special educational needs had no difficulties to focus their attention during the learning experience, if compared to a traditional learning activity (e.g., frontal lesson of a teacher), favoring the inclusion of children in the 89% of cases.

The analysis of the answers coming from the final learning task is generally positive, despite we do not have greater certainty about the consequentiality between the introduction of game and the learning outcomes (given the lack of an initial pre-test and a control group). Around 51.4% of children answered correctly to at least four (of the five) questions, while those who made no mistakes were about the 34.5%. Furthermore, no pupil scored less than the two correct answers (of the five) (fig.5).

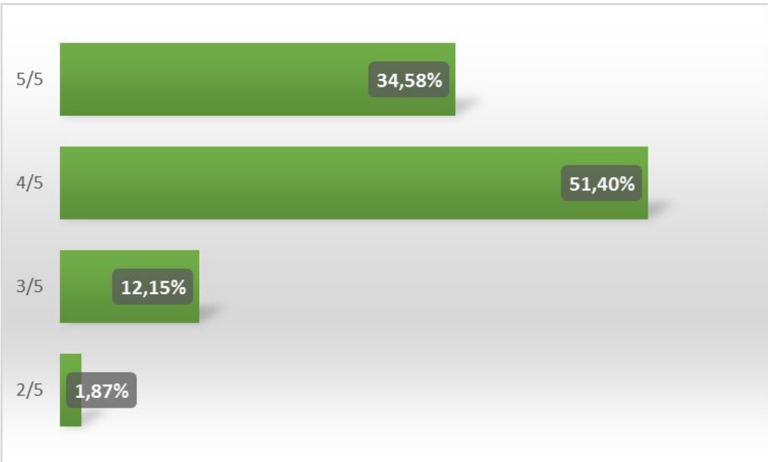

Fig.5 - Percentage of correct answers.

In addition, the application is also been presented and used, besides this formal experimentation, at Giffoni Film Festival 2018[4], in the context of a Showcase on Innovation dedicated to new technologies for human learning. At Giffoni, children used smart glasses to live an even more engaging game experience (fig.6). Thus a porting of the application onto Microsoft HoloLens has been realized to accomplish the objectives of the aforementioned Showcase.

Fig.6 - The Giffoni Film Festival experience.

Conclusion and future works

The AR-based interactive situated learning experience allows children to enjoy a learning moment involving different senses. Sense and movement, in fact, are fundamental for the development of the child and provide her/him with fruitful ways of exploring the environment and constructing abstract thought (Montessori, 1948). For these reasons, it is possible to envision the use, in classroom, of multisensory applications that put together digital tools and physical materials, thus fostering motivation and engagement of students, also with special educational needs (Miglino et al. 2014; Ponticorvo et al., 2018).

Of course, it is needed to re-think and re-model the traditional learning spaces in order to adapt them for the use of such new tools based, for instance, on AR. An example of is the one realized during the aforementioned experimental activity. Such laboratory has been constructed in order to provide students with the capability of exploring the surrounding learning environment, full of stimuli, both independently and under the guidance of the adult (e.g., tutor, teacher, etc.).

The role of the intelligent tutor has been represented, in the game, by a

[4] Giffoni Film Festival is a film festival for children and young people that takes place every year, in the month of July, for about ten days, in the city of Giffoni Valle Piana (Salerno, Italy). https://www.giffonifilmfestival.it/

character guide. The presence of a virtual tutor, however, does not exclude the involvement of peers and adults in the learning process. During the experimental activities, in fact, the support action did not take place only between child and virtual tutor, but also between different children and between the child and one or more adults, to emphasize the situated nature of learning. Even in this case, new technologies augment the real world but do not replace it.

Definitely, the proposed didactic re-mediation model is based on the idea that the numerous information sources (generated by heterogeneous points of interest) of the (smart) city can be used to build situated learning experiences. Such experiences can be implemented, in the future, through both integration and alignment of multiple educational scenarios.

Acknowledgments

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IMPROVING SCHOOL SETTINGS AND CLIMATE: WHAT ROLE FOR THE NATIONAL OPERATIVE PROGRAMME? INSIGHTS FROM A LEARNING ANALYTICS PERSPECTIVE

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Keywords: Learning analytics; Students' behaviours; Educational activities; Teacher-student relationship; Probability models; Multivariate analysis techniques

Although students are increasingly involved in extra learning activities aimed at enriching the attributes and the contents of conventional educational programmes, still little is known on the main implications of these initiatives. Embracing a Learning Analytics (LA) perspective, the article sheds light on the effects triggered by students' involvement in innovative educational activities and learning processes co-financed by the Call no. 10862/2016 issued by the National Operative Programme (PON) 2014/2020. We implemented a three-step study design, which consisted of: 1) a descriptive analysis; 2) a principal component analysis; and 3) a discrete choice regression analysis. Our findings pointed out that educational activities and learning processes were especially effective in improving social relationships at school; moreover, they contributed in increasing the students' willingness to expand their horizons.

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1 Introduction

1.1 The growing relevance of learning analytics

The New Media Consortium (NMC) "Horizon" report issued in 2014 (Johnson *et al.*, 2014) identified schools and, in general, educational settings as fertile grounds to implement Learning Analytics (LA) tools and approaches. In fact, LA has been variously understood as a timely and relevant opportunity to: 1) enhance pedagogical and educational theories and models; 2) assess and improve learning processes; and 3) shed light on the factors that are more likely to affect the students' behaviour and performances (Siemens, 2013; Roll & Winne, 2015). This is especially true as far as disadvantaged students are concerned, including those who show greatest risks of dropout due to either economic or social frailties (Coates, 2017).

LA is intended to enhance the methodologies and the tools used in the educational context (Fulantelli & Taibi, 2014). In fact, it is defined as "... *the measurement, collection, analysis and reporting of data about learners and their contexts, for the purpose of understanding and optimizing learning and the environments in which it occurs*" (Siemens & Baker, 2012, pp. 252-253). It makes an effort to merge data mining (Baker & Inventado, 2014), information retrieval (Berland *et al.*, 2014), and technology-mediated learning (Gašević *et al.*, 2015), in order to turn educational research in a data-driven science (Knight *et al.*, 2014). In other words, LA is aimed at enhancing the ability of educational institutions to make decisions in light of reliable evidence obtained by dependable data analysis; this paves the way for the advancement of students' experiences and, consequently, for a better functioning of the educational system (Lockyer *et al.*, 2013).

In an epoch which has triggered the process of "data explosion" in the educational context (McIntosh, 1979: p. 82) – with the increasing growth of online learning, big data analytics and digital technologies applied to learning processes – educational institutions have to reframe their strategies, organizational models and management approaches, in an attempt to deal with the challenge of complexity. Sticking to these considerations, the Educational Data Mining field is gradually emerging as a research stream concerning the development and implementation of tailored methods directed, on the one hand, at investigating quantitative data about the educational contexts and, on the other hand, at exploiting these data to better understand the students' expectations (Slater *et al.*, 2017) and to enhance the quality of educational services (Romero & Ventura, 2010).

In this research field, LA primarily concerns the appropriate use of smart data – directly produced by schools, teachers, students or by other sources of information – to shed light on social issues affecting learning processes, performances and dynamics (Baker & Inventado, 2014). Even though LA includes a variety of streams and developments, conceptual and practical challenges are still to be overcome in order to unravel and realize the full potential of LA in improving the functioning of educational institutions (Aldowah & Al-Samarraie, 2019).

1.2 Research context

The study launched by the Italian National Institute of Documentation, Innovation and Educational Research (INDIRE) in 2015 – that is intended to comprehensively assess the performances of the whole national educational system – can be contextualized in the theoretical background depicted above. INDIRE introduced a brand new management system – labelled GPU "Gestione della Programmazione Unitaria" – to support the Italian Ministry of Education, University and Research (MIUR) in its role of management authority for the governance of the National Operative Programme (PON) 2014-2020 "For the School: competencies and environments for development". PON should be understood as a strategic plan, whose institutional aim is to pave the way for a high quality educational system and for excellence in learning.

PON is entirely financed by the European Structural Funds. It is addressed to all the schools operating in Italy and, therefore, to the whole population of students and teaching staff of Italian public educational institutions. Its main purpose is to enhance the quality, the timeliness and the effectiveness of educational activities, in order to facilitate the achievement of the key strategic aims listed in the strategic framework for European cooperation in education and training: 1) curb the rate of early leavers from education and training aged 18-24 below 10%; 2) encourage at least 40% of people aged 30-34 to complete some form of higher education; 3) bring at least 20 million people above the poverty line and/or outside conditions of social exclusion.

Contributing in the achievement of such goals, GPU fosters the involvement of schools, students, and teachers in initiatives that are financed either by the European Social Fund (ESF) – in the case of soft interventions focussing on educational activities – or by the European Regional Development Fund (ERDF) – in the case of hard, infrastructural interventions. From a methodological point of view, GPU is established on the Deming Cycle, *i.e.* an iterative management model including four main steps (PDCA) (Chen, 2012):

- *Plan*: definition and agreement of objectives and processes;
- *Do*: implementation of the plan;
- *Check*: evaluation and assessment of data and/or information collected during the "Do" step;

- *Act*: amendment of problems and inconsistencies and improvement of strengths identified during the "Check" step.

By accessing the GPU platform, schools have the opportunity to submit their proposals to the calls issued by the Management Authority. They formalize their submission and, if their project is approved, they are enabled to manage and assess on-line their project. Employing the PDCA scheme, GPU allows schools to thoroughly manage and oversee the progress of implemented activities and to constantly improve educational processes.

1.3 State of the art and research questions

The results achieved in the period 2007/2013 were encouraging: in fact, the educational institutions operating in the "Convergence" Italian regions (Calabria, Campania, Apulia and Sicily) managed more than 30.000 project financed by ERFD (intended, inter alia, to co-finance the acquisition of innovative technologies, the design of advanced teaching laboratories and the upgrading of existing learning structures) and more than 60.000 ESF projects (aimed at the design and implementation of innovative learning activities and educational processes). About 2.5 million people – including both students and teachers – participated in more than 200.000 interventions that have been financed by PON and managed through GPU.

This article specifically looks at the Call no. 10862/2016 of the PON 2014/2020, labelled "Social Inclusion and fight to deprivation". This call promotes positive actions intended to prevent school dropouts. More than 600.000 students coming from about 4.400 schools established in the Italian Peninsula have been involved in the projects submitted to the call. Data about the activities implemented were collected from the observation cards, which are filled by educational tutors in two circumstances: 1) before the beginning of the project; and 2) at the end of the project. These cards allow illuminating changes in students' behaviours and performances that are strictly related with the project to which they participated. Such data are stored in the GPU platform.

Table 1 and Figure 1 summarize the sources that have been accessed to collect the data examined in this study. Our main purpose was to obtain and discuss some evidence about the effectiveness of interventions financed by the Call no. 10862/2016 to minimize the occurrence of schools' dropouts and to prevent social exclusion. Two research questions triggered our study:

- *R.Q. 1*: What are the main factors influencing students' behaviours and educational performances?
- *R. Q. 2*: What kind of strategic and management initiatives can be implemented to increase the students' willingness to actively participate in innovative learning processes and educational activities?

We exploited LA to provide a tentative answer to these research questions. The article is organized as follows: Section 2 depicts the research design and methods; Section 3 reports the study findings, shedding light on the main implications of initiatives co-financed by the Call no. 10862/2016; Section 4 critically discusses the study results, paving the way for some conceptual and practical insights inspiring further developments.

2 Methods

2.1 Research Strategy

To meet the purposes of this paper, we accessed primary data from GPU. GPU is owned by INDIRE and it is currently part of the Axis IV "Technical Assistance to the Management Authority of the Italian Ministry of Education, University, and Research" of the PON 2014/2020 (CP: 4.1.4A-FSEPON-INDIRE-2015-2; CUP: B55I15000470007). One of the main aim of GPU is to improve the efficiency, the effectiveness and the quality of financed interventions, as well as to contribute in the assessment of the outputs and outcomes of implemented projects.

Table 1
DATA SOURCES

Source	Type of information
Observation cards	They allow to assess changes in the students' behaviours and educational performances
Evaluations	They allow to gauge the effects of interventions on students' school performances
Project indicators	They concern the expected outcomes as formalized in the project submission
Transversal indicators	They include output and outcome indicators yearly provided to the European Commission and to the Italian National Inspectorate for the financial relationships with EU
Self-assessment	Educational managers self-assess the achievement of project indicators and transversal objectives
Satisfaction survey	They measure the students' satisfaction with the contents of the initiatives realized

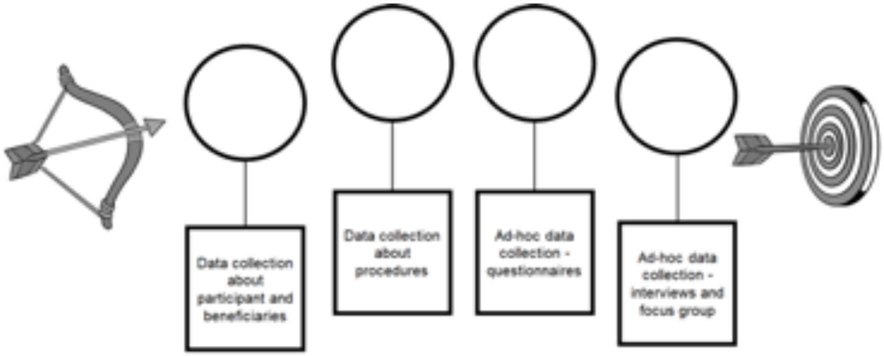

Fig. 1 - The process of data collection.

Most of data used in this study were collected through Lime Survey, an on-line open source survey software that is embedded in the GPU platform. Lime Survey allowed us to administer ad-hoc questionnaires to the educational tutors of each educational activity implemented within the Call no. 10862/2016 of the PON. More specifically, the survey was aimed at eliciting the respondents' considerations and insights into the behaviours and approaches of students who participated in the financed educational activities.

The items included in the survey concerned six main themes:

- *Relationships with peers*: this theme allowed us to understand how students established and nurtured inter-personal relationships with their peers; inter alia, we examined the implications of interpersonal relationships on the development of soft skills and social competencies;
- *Relations with teachers*: this theme sheds light on the educational, social and cultural approach employed by teachers;
- *Ability to reflect on negative school experiences*: this theme permitted us to assess how students critically reflected on failures as an important growth opportunity;
- *Extra-curricular motivation*: this theme was useful to early detect the increasing needs and expectations held by students;
- *Awareness and respect for rules*: this theme – which has been usually underestimated both in theory and in practice – is crucial to gauge the growth of students and their ability to effectively perform in the society;
- *Ability to manage emotional sphere*: this theme is essential to assess the students' self-esteem and awareness of their contribution to the society.

The educational tutors were asked to self-rate – at the best of their knowledge – the items included in each of the six themes reported above; obviously, an individual score was reported for each of the students who participated in the initiatives financed by the Call no. 10862/2016. A 10-points Likert scale was attached to each item: "1" indicated that the event reported in the item was not relevant or that it did not occur; conversely, "10" indicated that the event reported in the item was highly relevant or that it occurred frequently. The interviewees provided a huge amount of data, which concerned more the 1 million students.

2.2 Study Design

In light of the huge number of observations and the large amount of data available, we decided to use a mixed study design, which was consistent with the distinguishing nature and the specific purposes of this research. More specifically, our study was articulated in three steps. Firstly, we performed a preliminary, descriptive analysis; this preliminary investigation was useful to shed light on the main issues which were obtained from the filled questionnaires. We used both measures of position and variability for this purpose. Secondly, we implemented a multivariate statistical analysis, which was aimed at pinpointing the principal components included in the collected questionnaires, in an attempt to illuminate – embracing an *ex post* perspective – potential areas of improvement. Thirdly, we arranged a binomial logistic analysis, in order to gauge the positive or negative effects of the educational initiatives on the behaviours and performances of students.

2.3 Statistical models

As previously anticipated, the principal component analysis was useful to curb the number of variables in our large and complex data set. The reduction of dimensions was inspired by the purpose of eliciting the most relevant and/ or most significant factors contemplated in the analysis, which explained most of the variances of responses for each theme investigated. A brief overview of the approach used to implement PCA follows. Define **C** as a correlation matrix with covariance "*p x p*", where:

$$\mathbf{C} = \mathbf{V\Lambda V'} = \sum_{i=1}^{p} \lambda_i \, \mathbf{v}_i \mathbf{v}_i'$$

$$\mathbf{v}_i' \mathbf{v}_j = \boldsymbol{\delta}_{ij} \text{ (orthonormality)}$$

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$$

Eigenvectors vi represent the principal components. The direction (*i.e.* the sign) of principal components cannot be identified. In fact, principal components are estimated to allow that $1'\mathbf{v}_i > 0$. The sum of variances is:

$$\text{trace}\ (\mathbf{C}) = \sum \boldsymbol{\lambda}_j$$

The asymptotic distribution of eigenvalues $\hat{\mathbf{v}}_i$ and $\hat{\lambda}_i$ of the covariance matrix **S** for a sample with a multivariate normal distribution $\boldsymbol{N}(\mu, \Sigma)$ has been proposed by Girshick (1939). Readers who are interested in additional details, can make reference to Anderson (1963), Jackson (1991), and Lawley (1956), Besides, Tyler (1981) provides some insights into the elliptic distribution. We preferred to use an elliptic distribution rather than an exact one to avoid complex computations, which are related to the latter (Muirhead, 1982).

As reported in the introductory section, we were especially interested in assessing the likelihood that the participation and the involvement in an educational initiative financed by the Call no. 10862/2016 produced a change (in either positive or negative terms) in the emotional, social, relational, and educational spheres of students. For this purpose, we identified both the nature and the direction of the principal factors, which were more effective in explaining the change in the students' behaviours and performances. A cross-section sample of 1,143,681 students distributed in the Italian context was involved in the analysis.

We designed a probability model to investigate our dummy dependent variable as a function of a set of explicative variables (*i.e.* regressors) and parameters. The regressors concerned the thematic areas reported above, which were assessed both *ex ante* and *ex post*: this permitted us to shed light on the evolution of students' behaviours and performances. The parameters measured the effects that such variables generated either at the beginning of educational activities (*ex ante*) or at the end of the educational activities (*ex post*) for each student involved in the analysis.

Alongside the regressors, which were run in the analysis, we also included in our statistical model a variable concerning the geographical area where the students lived and accomplished their educational activities: this was useful to take into account potential territorial effects on the object of our analysis.

The logistic regression model arranged for the purpose of this research can be described as follows:

$$y_i^* = x_i\beta + \epsilon_i, i = 1, \dots, N$$

Where:

- y_i^* is a latent variable;
- The observed variable is a binary variable y_i, which is equal to 1 if $y_i^* \geq 0$, and equal to 0 if $y_i^* < 0$.
- The estimated value of y_i implies the likelihood that one of the two available alternatives occurs;
- x_i is a vector with "*1 x K*" regressors;
- β is a vector with "*K x 1*" parameters;
- and ε_i is the error term.

3 Findings

3.1 Descriptive statistics

Table 2 and Table 3 provide an overview of the items, which were included in this study, reporting average values and standard deviations. We found that the average values of the *ex ante* situation were higher than those concerning the *ex post* situation only concerning two items: 1) "she/he is willing to ask peers for help"; and 2) "she/he is willing to help others". It is worth noting that the relationships with peers generally improved as a result of educational activities. Moreover, the respondents reported a drop of several negative shades of students' relationship with others, such as: 1) "she/he prefers to stay alone"; 2) "she/he only interacts with a few students"; 3) "she/he is willing to only interact with older peers"; 4) "she/he is not interested in socializing with others"; 5) "she/he is likely to be humiliated by peers"; 6) "she/he is considered to be aggressive by peers". Interestingly, we did not detect perceivable variations in the item "she/he is considered to be a leader by peers". In sum, we found a sort of improvement of relationships between students as a result of educational activities. In fact, several negative dynamics – such as social exclusion, bullying, and social isolation – were less common in the *ex post* situation than in the *ex ante* one.

Most of items which concerned the relationship between students and teachers improved at the end of the learning process. This was especially true for those items which concerned the delivery of educational activities: at the end of the initiatives, students were more likely to ask for explanation to better understand topics dealt with during the lessons and to pass written exams. Besides, they were more prone to collaborate with peers to meet the teachers' assignments. However, several items were found to be lower in the *ex post* situation, such as: 1) "she/he is willing to take position against the teachers' instructions", and 2) "she/he tends willing to be dependent on teachers".

Students were found to be more willing to ask teachers for help to understand their wrongdoings and to achieve greater awareness of the errors made during written exams in the *ex post* situation. Whilst, the students did not seem to be attracted by innovative topics (*i.e.* arguments not included in conventional educational programmes), they were collaborative in performing extra learning activities. It is worth noting that, in the *ex post* situation, we detected a slight worsening of the students' relationship with rules. Lastly, students showed a greater ability to manage social and performance stressors during the everyday school activities after the completion of educational activities.

3.2 Principal component analysis

The 31 items investigated in this research were run in a principal component analysis in order to point out the factors, which concomitantly contributed in illuminating the implications of the educational activities co-financed by the Call no. 10862/2016. As summarized in Table 4, we identified three principal components, which explained slightly more of half of the total variance (50.2%). To increase the amount of total variance explained, we included a forth component, which allowed us to cover about 60% of the total variance. Since the differences between eigenvalues of the following components were marginal, we decided to stick to 4 components.

Table 2
RELATIONSHIP OF STUDENTS WITH PEERS AND TEACHERS BEFORE AND AFTER THE DELIVERY OF EDUCATIONAL ACTIVITIES (N=1,140,705)

Observation cards	***ex ante***		***ex post***	
Relationship with peers	**Mean**	**S.D.**	**Mean**	**S.D.**
She/he prefers to stay alone	4.11	2.91	3.44	2.73
She/he only interacts with a few students	4.55	2.92	3.84	2.79
She/he is willing to only interact with older peers	4.01	3.30	3.42	3.01
She/he is willing to report peers' wrongdoings to peers	5.13	2.97	5.03	3.02
She/he is not interested in socializing with others	3.93	2.90	3.41	2.77
She/he is willing to ask peers for help	5.74	2.54	5.91	2.58
She/he is willing to help others	6.27	2.66	6.53	2.74
She/he is likely to be humiliated by peers	4.31	3.01	4.37	3.04
She/he is seen by peers as a potential victim of bullying	3.43	2.83	2.97	2.67
She/he is considered to be aggressive by peers	2.75	2.54	2.42	2.36
She/he is seen by other students as a peer	6.45	2.97	6.40	3.19
Relationship with teachers	**Mean**	**S.D.**	**Mean**	**S.D.**
She/he is willing to ask for explanations to better understand topics dealt with a lesson	6.58	2.56	6.97	2.60

She/he is willing to ask for explanations to pass written exams	6.49	2.64	6.94	2.64
She/he is willing to ask teachers for help to avoid peers' mistreatment	4.93	2.90	5.16	3.01
She/he is willing to positively deal with the teachers’ instructions	6.41	2.77	6.62	2.93
She/he is willing to take position against the teachers’ instructions	3.06	2.59	2.73	2.49
She/he tends willing to be dependent on teachers	4.28	2.80	4.02	2.81

Table 3

SOCIAL, MOTIVATIONAL, CIVIC, AND EMOTIONAL BEHAVIORS OF STUDENTS BEFORE AND AFTER THE DELIVERY OF EDUCATIONAL ACTIVITIES (N = 1,140,705)

Observation cards	***ex ante***		***ex post***	
Ability to reflect on negative school experiences	**Mean**	**S.D.**	**Mean**	**S.D.**
She/he is willing to ask teachers for help to understand her/his own wrongdoings	6.49	2.55	6.94	2.60
She/he is aware of the errors made during written exams	6.82	2.50	7.12	2.65
She/he is aware of the meaning of negative evaluations achieved	6.95	2.57	7.16	2.74
Motivation for additional learning activities	**Mean**	**S.D.**	**Mean**	**S.D.**
She/he is interested for topics which are not included in conventional educational curricula	7.03	2.68	7.01	2.97
She/he is interested towards new topics	6.90	2.70	6.95	2.96
She/he is collaborative in performing extra learning activities	7.08	2.77	6.86	3.12
Relationship with rules	**Mean**	**S.D.**	**Mean**	**S.D.**
She/he is aware of school rules	6.79	3.01	6.64	3.30
She/he agrees with the school rules	6.86	2.95	6.72	3.25
She/he complies with the school rules	6.82	2.93	6.69	3.23
She/he is aware of guidelines set in the classroom	6.86	2.98	6.68	3.29
She/he agrees with the guidelines set in the classroom	6.89	2.94	6.74	3.25
She/he complies with the guidelines set in the classroom	6.85	2.92	6.71	3.23
Ability to manage the emotional sphere	**Mean**	**S.D.**	**Mean**	**S.D.**
She/he is able to manage emotions and social stress during oral exams	6.70	2.29	7.41	2.43
She/he is able to manage emotions and performance stress during written exams	6.02	2.30	7.12	2.40

Table 4
MAIN OUTPUT OF THE PRINCIPAL COMPONENT ANALYSIS

	Eigenvalues	Δ	% of variance	Cum % of variance
Comp1	9.21	5.24	27.92%	27.92%
Comp2	3.98	0.59	12.05%	39.97%
Comp3	3.38	1.25	10.25%	50.22%
Comp4	2.14	0.62	6.48%	56.70%
Comp5	1.51	0.25	4.59%	61.28%
Comp6	1.27	0.26	3.83%	65.11%
Comp7	1.01	0.05	3.06%	68.17%
Comp...	...	...	...	...
Comp28	0.20	0.05	0.59%	99.09%
Comp29	0.14	0.05	0.42%	99.51%
Comp30	0.09	0.01	0.26%	99.78%
Comp31	0.07	0.07	0.22%	100%
No. Of observations	1,140,704			
No. Of components	4			
Trace	31			
▯	0.57			

Table 5 shows the variance and covariance matrix, which allows us to identify the four components, which resulted from the analysis. We only included in each component those items, which mostly contributed in explaining the variance of the related construct; for this reason, items whose eigenvalues exceeded the third quartile (Q3) were assumed to be part of each construct. The first component is composed by concordant variables and is labelled "self-management": in fact, it mainly concerns the students' ability to acknowledge, agree, and stick to the rules and the guidelines, which regulate individual and collective behaviours at schools. This is an important finding, since the Call no. 19862/2016 is targeted to fragile people, who generally live in suburbs and experience cultural, social, and economic disadvantage.

The second component concern the students' "emotional distress": the items included in this component focussed on the negative interactions established by students with their peers and teachers, including the willingness to challenge the instructions of the teachers and the propensity to social isolation and to aggressiveness towards peers. Since poor interpersonal relations might undermine the effectiveness of educational activities, they should be properly handled to minimize their drawbacks.

The third component involved the students' "relationality", *i.e.* the willingness of students to ask peers for help, to seek explanation in order to improve their understanding, and the propensity to establish peer-to-peer relationships with other students. Good relationships with other people in the classroom and the establishment of a friendly environment foster learning processes, paving the way for a fair atmosphere, which enhances the students' desire of learning. Conversely, poor relationships at school hinder the learning experience, creating a disempowering environment.

Table 5

FACTOR LOADINGS FOR EACH PRINCIPAL COMPONENT

Item	Components				
	Self-Management	Emotional maturity		Interest in learning	N.E.
She/he is aware of guidelines set in the classroom	0.2443	-0.1463	-0.2406	-0.1568	0.1164
She/he agrees with the school rules	0.2437	-0.1512	-0.2302	-0.1549	0.1316
She/he agrees with the guidelines set in the classroom	0.2434	-0.1525	-0.2358	-0.1621	0.1175
She/he is aware of school rules	0.2430	-0.1414	-0.2310	-0.1436	0.1518
She/he complies with the school rules	0.2389	-0.1543	-0.2261	-0.1611	0.1510
She/he complies with the guidelines set in the classroom	0.2384	-0.1544	-0.2274	-0.1640	0.1494
She/he is interested towards new topics	0.2083	-0.1122	0.0598	0.2036	0.4496
She/he is interested for topics which are not included in conventional educational curricula	0.2073	-0.1060	0.0376	0.1988	0.4702
She/he is aware of the errors made during written exams	0.2039	-0.1083	0.1776	0.2087	0.3705
She/he is collaborative in performing extra learning activities	0.2031	-0.0973	-0.0048	0.1712	0.5197
She/he is aware of the meaning of negative evaluations achieved	0.2006	-0.1008	0.1328	0.1928	0.4499
She/he is willing to positively deal with the teachers' instructions	0.2003	-0.0730	0.0967	0.1142	0.5497
She/he is willing to ask for explanations to better understand topics dealt with at lesson	0.1898	-0.0647	0.2264	0.1546	0.4269
She/he is willing to ask teachers for help to understand her/his own wrongdoings	0.1893	-0.0758	0.2337	0.1613	0.4067
She/he is willing to ask for explanations to pass written exams	0.1861	-0.0573	0.2359	0.1548	0.4283
She/he is willing to help others	0.1653	0.0080	0.2055	-0.0470	0.6005
She/he is willing to ask peers for help	0.1617	0.1904	0.2626	-0.3901	0.0566

She/he is seen by other students as a peer	0.1539	0.0124	-0.0157	0.0447	0.7760
She/he is likely to be humiliated by peers	0.1536	0.1514	0.0953	0.0229	0.6598
She/he is able to manage emotions and social stress during oral exams	0.1426	-0.0889	0.1537	0.1086	0.6761
She/he tends willing to be dependent on teachers	0.1257	0.2275	-0.0645	0.0655	0.6254
She/he is willing to report peers' wrongdoings to teachers	0.1217	0.1950	-0.0668	-0.0389	0.6941
She/he is willing to take position against the teachers' instructions	0.1127	0.2675	-0.1201	0.0979	0.5292
She/he is seen by peers as a potential victim of bullying	0.1094	0.2729	-0.0973	0.0623	0.5534
She/he is considered to be aggressive by peers	0.1093	0.2909	-0.1048	0.0957	0.4968
She/he prefers to stay alone	0.1059	0.2806	-0.1652	0.1236	0.4587
She/he is willing to only interact with older peers	0.0990	0.2577	-0.1222	0.1013	0.5732
She/he is seen by peers as a leader	0.0980	0.1348	0.0905	0.0167	0.8109
She/he is not interested in socializing with others	0.0951	0.2841	-0.1956	0.1467	0.4202
She/he only interacts with a few students	0.0936	0.2847	-0.193	0.1469	0.4248
She/he is able to manage emotions and performance stress during written exams	0.0613	0.0760	0.026	0.0592	0.9327

The fourth and last component – labelled "interest in learning" – involves the students' willingness to expand their horizon dealing with new topics and issues and striving for understanding errors made during written and oral exams. Since the increased interest towards educational activities and the students' engagement are two critical ingredients of the recipe for curbing social dropouts, this component is especially relevant for the purpose of this research. In fact, the interest, curiosity and desire to learn are crucial steps of the individual personal and educational growth.

3.3 Discrete Choice Regression Model

Table 6 summarizes the main findings of the multivariate regression analysis. We found that the item "She/he is willing to ask peers for help" (β=0.016) showed a statistically significant and positive coefficient: this suggested that – as an outcome of the educational initiatives – students were more likely to rely on their peers to successfully deal with the learning activities. In addition, we found that the educational activities implemented within the Call no. 10862/2016 contributed in increasing the students' ability to face social distress during written and oral exams (β=0.029) and in enhancing their willingness to establish peer to peer relationships at school (β=0.001). In sum, it can be argued that the educational activities were successful in ameliorating the school climate, which is essential in triggering better school performances.

We also found that the educational activities financed by PON had a positive effect on the student-teacher relationship. At the end of the educational activities, students were more willing to ask teachers for: 1) help to avoid peers' mistreatment (β=0.035), 2) help to understand wrongdoings (β=0.035), 3) explanations to pass written exams (β=0.016), and 4) explanations to better understand topics dealt with a lesson (β=0.014). In other words, the initiatives financed by PON were effective in triggering greater trust of students towards teachers, making the former more willing to establish a co-creating partnership with the latter.

Lastly, yet importantly, the logistic regression analysis suggested that the educational activities had a positive and significant effect both on the students' awareness and on respect for rules and on their willingness to expand their horizons, paving the way for a more effective and smoother learning process.

Table 6

THE RESULTS OF THE DISCRETE CHOICE REGRESSION ANALYSIS

Item	Coeff	Sig	S.E.	z	P>|z|
She/he prefers to stay alone	-0,0287	***	0,0012	-24,86	0,000
She/he only interacts with a few students	-0,0370	***	0,0011	-32,92	0,000
She/he is willing to only interact with older peers	-0,0262	***	0,0007	-35,21	0,000
She/he is willing to report peers' wrongdoings to peers	-0,0123	***	0,0008	-16,07	0,000
She/he is not interested in socializing with others	-0,0071	***	0,0009	-7,46	0,000
She/he is willing to ask peers for help	0,0156	***	0,0009	17,58	0,000
She/he is willing to help others	0,0062	***	0,0009	7,07	0,000
She/he is seen by others as a leader	-0,0041	***	0,0007	-5,57	0,000
She/he is likely to be humiliated by peers	-0,0381	***	0,0009	-41,65	0,000
She/he is considered to be aggressive by peers	-0,0102	***	0,0012	-8,68	0,000
She/he is seen by other students as a peer	0,0019	**	0,0007	2,71	0,007
She/he is willing to ask for explanations to better understand topics dealt with a lesson	0,0145	***	0,0012	12,03	0,000
She/he is willing to ask for explanations to pass written exams	0,0159	***	0,0012	13,52	0,000
She/he is willing to ask teachers for help to avoid peers' mistreatment	0,0351	***	0,0008	42,95	0,000
She/he is willing to positively deal with the teachers' instructions	0,0103	***	0,0009	11,8	0,000
She/he is willing to take position against the teachers' instructions	-0,0167	***	0,0011	-15,65	0,000
She/he tends willing to be dependent on teachers	-0,0096	***	0,0008	-11,47	0,000

She/he is willing to ask teachers for help to understand her/his own wrongdoings	0,0349	***	0,0011	31,38	0,000
She/he is aware of the errors made during written exams	0,0053	***	0,0013	4,08	0,000
She/he is aware of the meaning of negative evaluations achieved	-0,0058	***	0,0012	-5,03	0,000
She/he is interested for topics which are not included in conventional educational curricula	-0,0033	**	0,0013	-2,65	0,008
She/he is interested towards new topics	0,0109	***	0,0013	8,7	0,000
She/he is collaborative in performing extra learning activities	-0,0498	***	0,0010	-47,77	0,000
She/he is aware of school rules	0,0091	***	0,0015	5,95	0,000
She/he agrees with the school rules	-0,0034	*	0,0016	-2,11	0,035
She/he complies with the school rules	0,0009	*	0,0016	0,6	0,500
She/he is aware of guidelines set in the classroom	-0,0117	***	0,0017	-6,84	0,000
She/he agrees with the guidelines set in the classroom	-0,0040	*	0,0018	-2,28	0,023
She/he complies with the guidelines set in the classroom	-0,0092	***	0,0017	-5,59	0,000
She/he is able to manage emotions and social stress during oral exams	0,0290	***	0,0010	30,38	0,000
She/he is able to manage emotions and performance stress during written exams	0,0002	***	0,0010	0,19	0,000

Concluding remarks

The study findings should be read in light of the limitations, which affected this research. First, we only focussed on the Call no. 10862/2016; therefore, the breadth of our analysis was limited. In addition, our research exclusively contemplated Italian students; hence, it is not possible to argue for the generalizability of the study results at the international level. Lastly, we adopted a static perspective, which did not allow us to time after time detect the evolution of the students' behaviours and performances throughout the educational activities.

In spite of these limitations, we collected several intriguing evidence, which push forward our understanding of the potential implications of innovative educational activities delivered alongside conventional learning processes. The students involved in this study were consistent in showing an increased interest in interacting with others (both teachers and peers) to grasp with the issues and topics dealt with in the classroom. In addition, they were found to be more aware of the rules guiding individual and collective actions. From this standpoint, it can be argued that the PON performs as an effective tool to improve students' engagement with educational activities and to enhance their ability to establish fair and fruitful interactions in the classroom. This may lead to lower risks of social exclusion in the educational context and, consequently, to reduced rates of school failures and dropouts. Embracing a LA perspective, the research findings stress that, to support students' positive behaviors and enhance their educational performance, learning contexts need to be reframed following two main trajectories: first, they should contribute in boosting the emotional maturity and the relationality of students, involving them in "social learning" practices; second, they should raise the students' interest in learning, nourishing their self-management skills and their self-awareness of individual skills and capabilities.

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WHICH LEARNING ANALYTICS FOR A SOCIO-CONSTRUCTIVIST TEACHING AND LEARNING BLENDED EXPERIENCE

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The contribution describes and problematizes the use of learning analytics within a blended university course based on a socio-constructivist approach and aimed at constructing artefacts and knowledge. Specifically, the authors focus on the assessment system adopted in the course, deliberately inspired by the principles of formative assessment: an ongoing assessment in the form of feedback shared with the students, and which integrates the teacher's assessment with self-assessment and peer-assessment. This system obviously requires the integration of qualitative procedures - from teachers and tutors - and quantitative - managed through the reporting functions of the LMS and online tools used for the course. The contribution ends with a reflection on the possibilities of technological development of learning analytics within the learning environment, such as to better support constructivist teaching: Learning Analytics that comes closest to social LA techniques providing the teacher with a richer picture of the student's behaviour and learning processes.

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1 Introduction

Introducing technology in learning can take place in different ways depending on different pedagogical approaches, moving along a continuum that goes from more transmissive models to more interactionist and constructivist models. From the model depends, of course, the type of assessment: to a transmissive pattern generally corresponds a summative assessment, based on the attribution of scores / ratings by the teacher at the end of the path; if, on the other hand, the model envisages learning not only as an acquisition of knowledge, but as an active construction, the assessment method will try to take into account the complex underlying dynamics and observe, rather than the mere results, the processes of construction of knowledge and social participation implemented both at individual and at group level. From this point of view, the classical assessment systems - oral test, test, written paper - are not sufficient, as they mainly aim to verify the acquired knowledge and, as such, do not allow to reflect and bring out those processes. To this end, it is necessary to adopt forms of observation and monitoring - rather than just final assessment - and then use them *in itinere*, so that students can grasp the adequacy and efficacy of the learning strategies they put in place while building knowledge. In short, it is a matter of passing from a summative assessment to a formative one, using multiple assessment tools at different times of the learning path (Dochy & McDowell, 1997). This type of assessment allows students to be actively involved, to consider and enhance numerous skills and competences, and to value both the processes and the products of learning (Sambell, McDowell, & Brown, 1997). In fact, if the assessment is introduced within a course, rather than just at the end, it directly calls into question the students, pushing them to reflect on their own path and on how they learn (Gielen, Dochy, & Dierick, 2003): the feedback offered *in itinere* allows both to recognize the validity of what has been done up to that point, and to develop meta-cognitive skills, useful for reorganizing one's own knowledge. Moreover, this type of assessment, in addition to reflecting what really happens in the learning context, supports the individual taking of responsibility (Zimmerman, 2001) and sense of belonging to the group (Ligorio & Sansone, 2016), as well as self-regulation (Brown & Harris, 2013). That is to say that it genuinely reflects the socio-constructivist approach here presented. Taken together, the pedagogical approach and its corresponding assessment generates a huge amount of data within the digital environments used: from MOOC platforms to Learning Management Systems, from collaborative writing tools to shared drawing boards, from discussion forums to repositories of online resources. Each of these tools hosting activities, functions and roles for individual and groups to be performed. Hence the development of a new area of research in the field of educational sciences, the Learning Analytics (LA) that Siemens (2010) defines as the use of data produced by the student and the analysis models to discover information and social connections, and to predict and give advice on learning. LA applications use data generated by student activities that can be roughly summarized in number of click, participation to discussion forums, formative assessment based on computer – assisted technology. These data can be used to monitor learning outcomes and improve them, if we adopt approaches and analysis tools consistent with the pedagogical model. Unfortunately, this practice is not yet widespread, as it requires the joint work of several stakeholders. That is, it is necessary that researchers, operators and developers work together around factors such as development of new tools, definition of target activities to analyse and care for ethical aspects related to privacy.

Recently, however, a new perspective about LA has emerged. It is called Social Learning Analytics and it includes analysis techniques which are strongly rooted in learning theories and focus its attention on the crucial aspects of active online participation (Ferguson & Buckingham Shum, 2012). The social LA includes: social network analysis and discourse analysis (De Liddo *et al.*, 2011; Ferguson & Buckingham Shum, 2011) with reference to exploratory dialogue (Mercer & Wegerif, 1999; Mercer, 2000), latent semantic analysis (Landauer, Foltz, & Laham, 1998) and computer-supported argumentation (Thomason & Rider, 2008). The development of Social Learning Analytics represents a progressive shifting from a data-driven inquiry to a learning theory-based research that increasingly concerns the complexity of lifelong learning that occurs in a variety of contexts. In this sense, these analytics would seem more capable of achieving objectives such as: guiding training interventions, providing automatic but personalized feedback, encouraging reflection and interaction in students, and identifying the best practices to follow.

2 The experience

The course in Experimental Pedagogy of the graduate course in Psychology and Health Sapienza University of Rome) takes place, since its establishment, in a blended mode, stimulating the students to carry out an experience of collaborative knowledge building (Scardamalia & Bereiter, 2006), through group-work both face-to-face in the classroom as well as online on the Moodle platform. About 80 students participate in the course each year, divided in groups of 8-9 students each. Over the years, the pedagogical design of the course has become more refined, following, as its main theoretical reference, the Trialogical Learning Approach (TLA, Paavola & Kakkarainen, 2014;). This approach aims to integrate the monological vision of learning - which emphasizes the individual activity of knowledge acquisition -, and the dialogical one - which stresses the importance of the interaction in knowledge construction -, with a third element, represented by the use of mediation tools with the aim of constructing artefacts (tangible objects or knowledge objects) resulting from collaborative work. TLA authors provide a series of guidelines, the so-called design principles (Paavola *et al.*, 2011; Cesareni, Ligorio & Sansone, 2019), supporting the creation of pedagogical scenarios that, in line with the trialogical approach, are aimed at the collaborative construction of artefacts through the mediation of technologies. The design principles focus teachers' attention on some specific aspects of the educational planning: promoting collective agency together with individual agency; stimulate "contaminations" between practices of different disciplines and between professional and academic contexts; support the continuous advancement of knowledge and artefacts; facilitate reflection and metacognitive processes; provide flexible mediation tools to the learning group. In this sense, this approach hardly conceives learning as an acquisition of knowledge, rather as an active construction of it which lead to the development of crucial skills.

In summary, what characterizes a trialogical course is the organization of the activity around the creation of knowledge objects that have a real and concrete utility, that can convey the didactic contents of the discipline and that are realized in a collaborative way, through continuous improvements. The object chosen for the course of Experimental Pedagogy is a "pedagogical scenario", i.e. the conception and writing of an educational project to be carried out in a school or in a university classroom. Since the course of Experimental Pedagogy focuses on collaborative learning and on how technologies can support communities that build knowledge, the pedagogical scenarios need to capitalize on what was presented and discussed during the course, imagining a didactic unit based on an active and collaborative use of technologies to favour the construction of knowledge.

Around and before the final object, the course includes a series of steps to be completed in groups and individually.

First, students are divided into working groups of 8-9 people with a MOODLE course each, in which to discuss, build products, share resources, access to learning contents. Moodle is integrated with the Google Drive suite for collaborative writing and drawing (Google docs and Google drawing). The course is divided into 3 modules lasting three or four weeks, in which two different online activities take place. Each module ends with the creation of an object, reflecting the class contents and preparatory to the construction of the final object. Thus, for example, in the first module the lecture activities concern the different theories of learning ("*how to teach, how to learn")* which are addressed through lectures, movie watching, reading and discussing transcripts of educational activities; at the same time, in their Moodle course, groups discuss on the figure of the "*Good teacher*" and then discuss the teacher's behaviour that they are asked to observe through a short online video. At the end of this module, the object to be collaboratively built by each group will be a conceptual map on the figure of the "*Good teacher*". A peer-review activity will follow in which each group will provide two other groups with advices on how to improve the map, so that a revised version of the object is produced and then presented to the classmates. The same process of lessons-forum discussions-object building-peer-review and final object improvement is followed for the other two modules.

To support collaboration and active knowledge creation in the group, in each module six scripted roles are assigned (Cesareni, Cacciamani & Fujita, 2016), that students play in turn. The roles can change from one to another module.

3.1 The contribution of Learning Analytics for a formative assessment in a socio-constructivist course

As mentioned before, a crucial aspect of a socio-constructivist course is assessment which cannot be merely of a summative type, instead requires a continuous analysis of students' participation and activities during the course so to provide them with formative feedback. Ongoing monitoring helps reflection and guides the students towards a better participation in the subsequent activities.

The question we asked ourselves is how learning analytics can help the teacher to perform such an assessment, including quantitative and qualitative data and analysis. How the learning analytics can support socio-constructivist teaching and learning approaches? That is why we focus on the recent framework of the Social Learning Analytics (Ferguson & Buckingham Shum, 2012) which seemed to us as a suitable way to take into account the set of processes activated, and the number of objects created from the students, individually and in groups.

Searching for these answers, we now explain how we performed the assessment in the course here described.

The feedback model adopted in this course, at the end of each module, provide students with an overall assessment of their online work. In fact, following the literature suggestions (Gielen, Dochy, & Dierick, 2003), when the assessment is introduced within a course, rather than just at the end, it pushes students to reflect on their own path and to develop meta-cognitive skills, useful for reorganizing their own knowledge.

The feedback model considers 4 different aspects: a) participation in the first module activity, b) participation in the second module activity, c) continuity in commitment to group work, c) role taking in the service of the group activity

(Tab.1).

Table 1
EXAMPLE OF FEEDBACK-ASSESSMENT PROVIDED TO THE STUDENTS OF A SINGLE GROUP-WORK AT THE END OF A MODULE

NAME	First Activity: Discussion about Learning with Technologies	Second Activity: Analysis and discussion on research articles	Continuity in commitment	Roles	Second Module Assessment
M..	very good	excellent	excellent	excellent	excellent
M.	good	very good	satisfactory		good / very good
R.	very good	excellent	excellent	excellent	excellent
A.	excellent	-	good		good / very good
E.	very good	-	satisfactory	good	good
C.	good	-	satisfactory		more than sufficient
R.	very good	excellent	very good	good	very good / excellent
C.	very good	excellent	good / very good	good	very good
A.	excellent	excellent	very good	excellent	excellent

To build this multi-dimensional feedback, the teacher and her collaborators first use the learning analytics provided by Moodle in order to create summary tables of each student's quantitative participation in the activities. These tables are then integrated with a qualitative assessment of the interventions that students write in the forums and of how they performed their assigned role (Tab.2).

Table 2
SUMMARY TABLE OF THE QUANTITATIVE AND QUALITATIVE DATA USED TO BUILD THE FEEDBACK FOR A SINGLE GROUP-WORK

	First Activity			Second Activity					
Name	Notes n°	Quality	Level 0/5	Notes n°	Quality	Level 0/5	Continuity	Role	Role assessment
Cl.	7	excellent	5	1	good	3	excellent	Skeptic	Excellent
Fr.	4	very good	4	0	-	0	good	-	
Re.	4	very good	4	1	good	3	fair	Synthesizer 2	Good
Em.	1	fair/good	2	2	good / very good	4	good	-	
Cl.	7	excellent	5	1	good	3	excellent	Synthesizer 1	Excellent

Th.	4	excellent	5	1	good	3	good	Map presenter	Very good
But.	8	excellent	5	1	good	3	excellent	Observer	excellent
Fl.	4	very good	4	0	-	0	fair	Social tutor	Fair
There.	3	excellent	5	0	-	0	good	-	

Specifically, to perform the qualitative assessment, once again it is necessary to use some sort of LA. In this sense, Moodle provides some functions to keep track of both the overall work of the group as well as of the individual work. By querying the database – using specific masks within the "report" function -, you can get a complete report of all the activities the student has conducted in the online course. Starting from this report, the teacher can evaluate the quality of the interventions based on previously defined criteria: the level of argumentation, the theoretical references to the classroom contents, the originality of the intervention and the connections to others' ideas. This last aspect is the one defining the level of collaborative knowledge building: keeping in mind others' ideas to improve them means actively contributing to the increasing of the group knowledge and to the refining of the collective products. This is the concept of *continuous improvement of ideas* proposed by Scardamalia and Bereiter (2006) when illustrating their theories about the communities that build knowledge, and which is made evident in the Knowledge Forum[1] through the summary notes called "*Build on*".

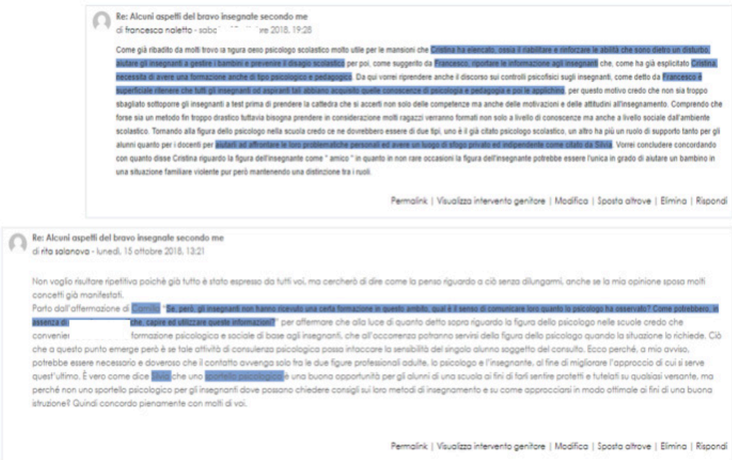

Fig. 1 - the connections to groupmates' ideas highlighted the students in their interventions.

[1] Knowledge Forum is the educational software designed to help and support knowledge building communities (http://www.knowledgeforum.com/).

At the moment, Moodle does not allow us to trace connections between different interventions, so to compensate for this lack, the students of this course are asked they themselves to highlight the concepts taken up by their colleagues which they intend to expand or correct (Fig.1).

It is worth saying that, while on the one hand the request for highlighting was created to compensate for a limitation of the platform, on the other, it promotes students' awareness, as it makes them understand the importance of reading others' interventions taking them into consideration, thus modelling such behaviour. Ultimately, this action helps the teacher in the assessment of the collaborative knowledge building. Starting from the already highlighted connections, the teacher can focus on the assessment of the subsequent parts of the speech, evaluating the level and quality to which they extend others' ideas.

Another important feature in a knowledge building community is how to maintain an adequate continuity and consistency in students' commitment. Writing several interventions at the beginning of the activity and then taking no more interest in what the others say cannot possibly lead to a general advancement of knowledge. A continuous commitment, reading and commenting on the groupmates' interventions is rather a matter to be recognized with a positive assessment. Moodle LA can help in this assessment. Access tracking ("log") allows you to see how the student's engagement is distributed. In the case reported in figure 2, the effort is concentrated only in the first part of the course: this student expressed his ideas only in the beginning of the activities - probably for "absolving the task" - but then he showed no more interest in the progress of the discussion in his group. Thus, the log transcripts represent a further support to evaluate students' interventions and, more generally, their commitment.

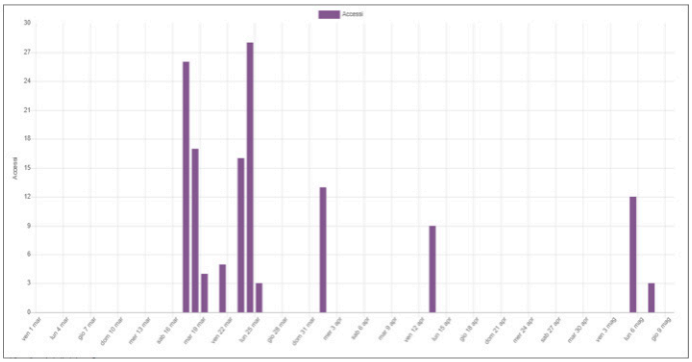

Fig. 2 - Example of log tracking to assess the continuity and consistency in students' commitment.

The role taking in service to the advancement of the group knowledge is the last aspect we consider in formative assessment. In this case too, a good help is provided by the LA, since they show the actions and activities carried out by the students who covered a role, which will be subsequently qualitatively assessed. For example, after having defined the contribution of those who played the role of the skeptic, the teacher can assess whether she/he acted consistently with this role, *avoiding commonplace ideas in the group discussion in order to generate prolific doubts* (Cesareni, Cacciamani & Fujita, 2016).

The online activity of this course does not end within the Moodle platform but, as already mentioned, it also includes the Google Drive Suite for collaborative writing of texts. The final object, the intermediate products, as well as the peer-feedback sheets, they are all created in through Google Documents which are then linked in the Moodle course of each group. Just like Moodle, the Drive documents can track the activities performed on them. Going back to the different versions of the text, the contributions provided by the various participants who have logged into the document itself are highlighted in different colours. The teacher can, in this way, observe the growing of the ideas in the document, as well as the contribution of the different authors. That is how he/she can take into account the complex underlying dynamics and observe, rather than the mere results, the processes of construction of knowledge

3 Reflections and conclusions

In the previous paragraph we described the assessment system adopted and defined in the course of Experimental Pedagogy. It is an assessment model intentionally inspired by the principles of formative assessment: an ongoing assessment in the form of feedback - and not just judgments / scores - shared with the students, and teacher's and peer's assessment. This system requires the integration of qualitative procedures - managed by the teacher and her collaborators - and quantitative data mining - managed through the reporting functions of the LMS and tools used for the course, Moodle and Google Drive. This operation has not been easy, as Moodle has shown some gaps in tracing elements useful for allowing the assessment of a socio-constructivist course. First, when it comes to assessing the quality of the interventions in the forums, the only contribution the platform provides is the possibility of grouping them into a single file (the complete "report") to be evaluated. In the same way, no analysis or even tracking is possible at the level of collaborative knowledge building, where it would be very helpful to automatically highlight those parts of text which are present in several interventions and the subsequent arguments that come to constitute the added knowledge.

A type of LA that comes closest to social LA techniques would reflect the socio-constructivist learning here proposed in a more coherent way, providing the teacher with a richer picture of the student's behaviour and learning processes. We all know very well that just accessing a resource or being connected for a considerable amount of time does not mean having really acquired knowledge or in-depth concepts. An interpretative mediation of these quantitative data is always necessary, both by the teacher and within the group of students itself, especially if we consider that, in a blended course, not all the work takes place online.

The correct interpretation and placement of the quantitative data, as well as a suitable integration of qualitative and quantitative data is what is required on the one hand by the teachers, on the other by the learning software and the LA techniques, which must necessarily be developed in close connection with the pedagogical assumptions. To this aim, the reflection on the assessment must precede the planning and implementation of the measurement.

Ultimately, we believe that the direction to follow should start from a global understanding of how learning can be facilitated and its socio-relational factors supported, to arrive at personalized reporting and visualization methods that are made available to students and clearly linked to mechanisms for improving their learning.

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