Analysis of completion and dropout rates in EduOpen MOOCs
Analisi di tassi di completamento e abbandono nei MOOC di EduOpen

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The completion rate of massive open online courses (MOOCs) is generally less than 10% of participants. This is due to several factors, many of which cannot be eliminated: spontaneous enrolment, participants' extreme heterogeneity, self-regulated processes and differences in motivational and cultural profiles. One of the factors that can affect the rate of completing a MOOC is the modality of delivery. The active presence of the teacher and of other support figures in MOOCs, even where criticality is linked to the number of students and the management of the dynamics present in the online learning environment, can qualitatively and quantitatively affect both the levels of interaction and participation of the users and the completion percentages of the course itself. The MOOCs published on the EduOpen Portal provide two specific methods of use: self-paced and tutoring. The choice of modality, which is defined in the design phase, "impacts" the structure and timing of the course itself, its learning objectives and the types of teaching resources. Consequently, the levels of interaction and evaluation processes are also "calibrated" in relation to the "presence or absence" of support figures in the online environment. The contribution, starting from the first data generated by the Learning Analytics system of the Portal, focuses on analysis of the percentage of the completion/ dropout rate recorded for the entire group of MOOCs published in relation to the delivery methods defined in the design phase of the various courses. In July 2019 there were 247 courses in the catalogue with more than 55,000 users. The final objective of the analysis is to include in the guidelines for the design of a MOOC the results of this first study.

Keywords: MOOCs; learning analytics; self-regulated processes; instructional design; dropout rate

Il tasso di completamento di MOOCs e generalmente inferiore al 10% degli iscritti. Questo a causa di diversi fattori, molti non eliminabili, quali: reclutamento spontaneo, estrema eterogeneità degli iscritti, processi di autoregolazione, differenze nei profili motivazionali e culturali. Uno dei fattori che può incidere sul tasso di completamento di un MOOC e rappresentato dalla modalità di erogazione. La presenza attiva del docente e di altre figure di supporto in corsi MOOCs, se pur con le evidenti criticità legate alla numerosità degli studenti e alla gestione delle dinamiche presenti dall'ambiente di apprendimento online,

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può incidere (qualitativamente e quantitativamente) sia sui livelli di interazione e partecipazione degli utenti sia sulle percentuali di completamento del corso stesso. I MOOCs pubblicati sul Portale EduOpen prevedono nello specifico due modalità di fruizione: autoapprendimento e tutorata. La scelta della modalità - definita in fase progettuale - "impatta" sulla struttura e sulle tempistiche stesse del corso, sugli obiettivi di apprendimento e sulla tipologia delle risorse didattiche. Di conseguenza, i livelli di interazione e i processi di valutazione sono "calibrati" anche in relazione "alla presenza o all'assenza" di figure di supporto nell'ambiente online. Il contributo, a partire dai primi dati generati dal sistema di Learning Analytics del portale, si focalizza sull'analisi delle percentuali di completamento/tasso di abbandono registrate sull'intero insieme di MOOCs pubblicati in relazione alle modalità di erogazione definite nella fase di progettazione dei vari corsi. A luglio 2019 i corsi presenti nel catalogo sono 247 con un numero di utenti superiore a 55000 utenti. L'obiettivo finale dell'analisi e quello di includere nelle linee guida alla progettazione dei MOOCs i risultati emersi da questa prima ricerca.

Parole chiave: MOOCs; learning analytics; processi di autoregolazione; progettazione didattica; tassi di abbandono.

1. Introduction

Recent growing academic interest in massive open online courses (MOOCs) – described as a disruptive technology that challenges traditional educational models (Bozkurt et al., 2017; Yu et al., 2017) – is linked to their ability to influence and increase the spread of higher education provision (Jung, Lee, 2018), to foster the flexibility of the learning process and to provide access to "disadvantaged" students.

However, to be successful in a MOOC environment, greater literacy (and not merely digital) is often required (Jordan, 2014). As described in the latest report published by the International Council for Open and Distance Education (ICDE) entitled *Global quality in online, open, flexible and technology enhanced education,* strengths and weaknesses related to the spread of technology-enhanced learning and digital learning environments coexist. Concerning the European context, what emerges from the report can be summarised in three points:

1. "Within European universities, digital learning environments maintain a strong presence and there seems to be more acceptance related to the value of learning in these modalities.
2. The development of blended and online learning does not always appear to be developed through a systematic approach. Instead development may rely on the interest and commitment of individuals resulting in slow and limited implementation.
3. There is a need to build competence and expertise in blended and online learning design by offering professional development on re-

levant topics. However, there may be challenges within academic environments where the culture does not encourage innovation" (p. 8).

Common points, both in Europe and internationally, are linked to the quality and construction of a "quality framework", to professional development in terms of strengthening the skills of teachers and students, and finally to the social perception linked to the relationship between distance and traditional learning (ICDE, 2018).

With respect to this scenario, the spread of MOOCs has contributed to a wider "awareness and acceptance of the added value of blended and online education" (ICDE, 2018, p. 32). However, as anticipated, there are still forms of "stigma" and critical issues related to the "quality" of content and educational design, and in particular to high rates of abandonment. In many cases, the completion rate of MOOCs is generally less than 10% of participants (Jordan, 2014, 2015; Onah et al., 2014; Bozkurt et al., 2017) due to several interrelated factors, many of which cannot be eliminated, for example spontaneous recruitment, the extreme heterogeneity of learners, self-regulated processes and differences in motivational and cultural profiles. One of the factors that may affect the completion rate of a MOOC is how it is delivered. The active presence of the teacher and other support figures in MOOCs, even where the criticalities are linked to the number of students and the management of the dynamics present in the online learning environment, can influence both the levels of interaction and participation of users and the completion rates of the course itself.

Numerous studies have investigated the relationship between tutoring systems, student motivation, support tools/resources present in training courses and training success (Tait, 2003; Loizzo et al., 2017; Khalil, 2014). One example is the Open University, which since its inception in 1969 has established a system of support/tutoring for students: a personal tutor follows and works with a group of students not exceeding 25 people (Tait, 2003). Other studies and research underline the importance of the teacher's presence in relation to significant effects recorded in terms of "learning commitment"; however, "to increase learners' participation in MOOCs, instructor-centered learning activities should focus on supporting learners with feedback and having the learning contents well organized" (Jung, Lee, 2018, p. 19). This result is also explained by voluntary participation in these courses, "if learners do not experience presence during the course, their participation and involvement become lower, and the probability of dropping out would be higher" (p. 19). Jung and Lee (2018) define the concept of teaching presence "as the degree to which learners perceive that instructors facilitate learning by designing and organizing content and supporting them" (p. 11).

The relationship between dropout levels and "support" offered to students has an impact not only in relation to the learning processes, but also regarding the possibility of strengthening the student's sense of self-efficacy, self-esteem and motivation (Kizilcec & Schneider, 2015), as well as the levels of completion of planned training activities (Tait, 2003).

Owing to the numerous variables involved, if the first experiments related to the development of models and intelligent tutoring systems (even in open mode) that provide for the presence of integrated systems by which to structure teaching materials, with the possibility of receiving feedback from the teacher and other support figures, research in recent years has focused on the development of "predictive" tools that exploit recent systems of learning analytics (LA) with the ability to act in "real time" and with direct repercussions on the "process" of designing the courses.

2. Instructional Design of the EduOpen MOOCs

Numerous researches have deepened the link between course design and dropout rates (Yousef et al., 2014; Margaryan et al., 2015; Kim, 2016). According to Yousef and colleagues (2014), despite a large number of criteria available for successful design, not all models can be used in the context of MOOCs due to their unique characteristics.

According to Margaryan and colleagues (2015), if the learning experiences are fundamental, the quality of the didactic design of a course is also a critical indicator and prerequisite of the potential of the course with respect to the effectiveness of learning in terms of course complement. A "unique format" in the design of MOOCs can negatively affect the completion of courses and the learning process owing to the different backgrounds of students (Onah et al., 2014).

As far as the design and production of EduOpen[1] MOOCs is concerned, the starting point is the "EduOpen Guidelines". The workflow for producing an EduOpen MOOC can be simplified in the following actions (EduOpen Guidelines):

1 EduOpen Portal (https://learn.eduopen.org).

1. Presentation of the general project (title only, general description, objectives, certification structure and duration estimate);
2. Educational Macro-Design;
3. Educational Microdesign;
4. Recording of video content;
5. Production of teaching materials;
6. Structuring of the course and/or pathways on the EduOpen Portal;
7. Technical validation and quality standards;
8. Validation by the working group;
9. Publication of the course and/or pathways on the EduOpen Portal;
10. Delivery of the course and/or pathways (course planner);
11. Ex-post evaluation of the course.

With the drafting of the guidelines for the design of MOOCs and the development of the online learning environment – the result of the joint effort of the entire network of EduOpen – we set ourselves the goal of supporting teachers and other professionals involved in the design of training content while also facilitating the process of learning and act on self-regulated learning. Good design is essential to "accompany" and "orient" the user in the choice of courses and towards the completion of the training course undertaken. This last aspect increases its importance when the MOOC offer opens the user up to certified courses linked to academic courses and which may involve the issue of university credits (CFU).

The process of hybridisation between "formal" training paths and open and "informal" environments involves a rethinking of previous models, as described by García-Peñalvo (2018): "it is necessary to design specific technological frameworks for the MOOC context to take advantage of the massification, diversity, and multiculturalism they present; generate new pedagogical approaches" (p. 1020). Previous research (De Santis et al., 2019) has shown that EduOpen MOOC participants pursue different learning objectives, as "EduOpen learners are to be found in a personal training needs and curiosity/interest in the topics of the courses" (p. 363), as confirmed by other studies that show that MOOCs participants not only have different academic objectives, but present extremely heterogeneous age groups and educational levels (García-Peñalvo et al., 2018). Some studies have focused attention precisely on the link and the ways in which the "instructional conditions influence the prediction of academic success" (Gašević et al., 2016, p. 70). The same author suggests "that it is imperative for learning analytics research to account for the diverse ways technology is adopted and applied in course-specific contexts" (Ivi, p. 81), with a particular attention for learning design.

With respect to this complex scenario, the choice made at the design stage of the course delivery method cannot be random, because it "impacts" on the structure and timing of the course itself, the learning objectives and the type of teaching resources. Consequently, the levels of interaction and evaluation processes are also "calibrated" in relation to the "presence or absence" of support figures in the online environment and in close relation to the life cycle of MOOCs (Fig. 1).

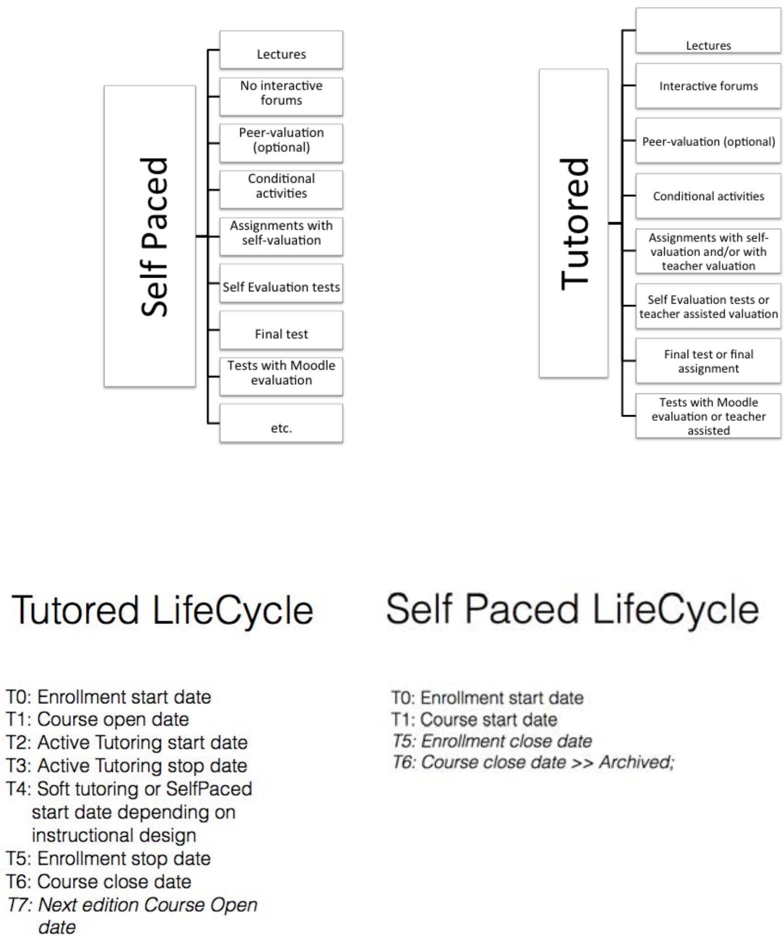

Fig. 1: Course life cycle

The design guidelines also apply to the development and design of the pathways, a sequence of courses that define a single set of training objectives and ending with a capstone course (Fig. 2). The capstone (final course of the pathway) includes the final activities associated with the entire path, for example the final evaluation of all the individual MOOCs that make up the pathway, which may also be linked to Master's and advanced courses and so forth. Specifically, the EduOpen MOOCs provide two modes of use: self-paced and tutoring.

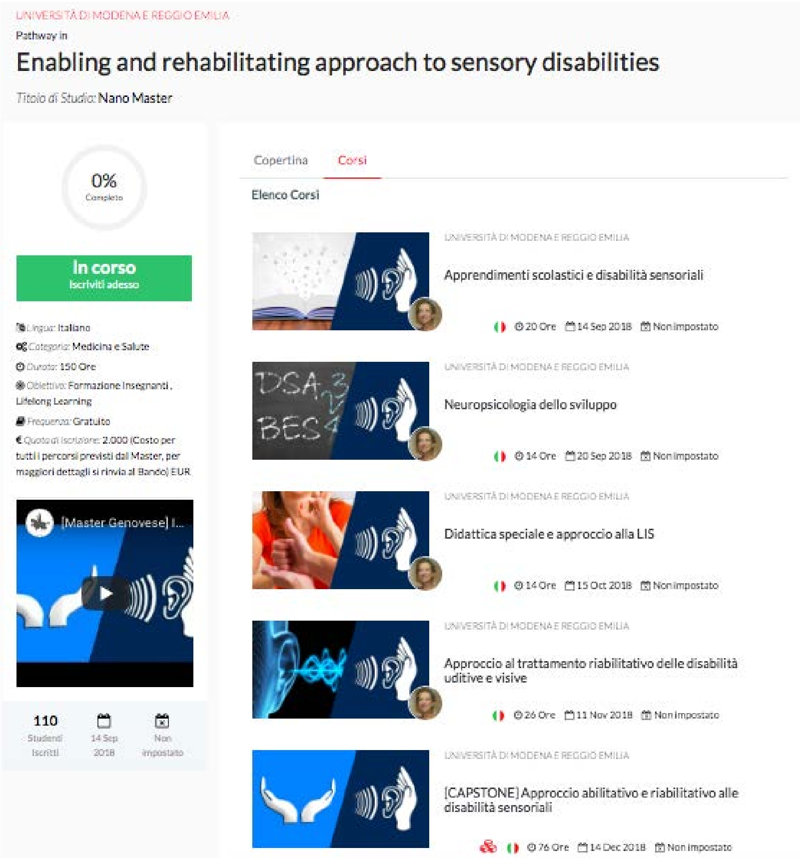

Fig. 2: Example of the structure of a pathway on EduOpen

In the tutoring modality, the courses provide for a more structured temporal scan of the training activities, and the course life cycle provides in most courses for the indication of a pre-established date for the conclusion of the activities and a closing date of the MOOCs (Fig. 3). After the closing of the course, it is possible for the students to access the didactic resources, but it is not possible to obtain the certificate of participation and consequently consider the course completed. In addition, in this mode the presence of support figures (the same teacher of the course or tutor) with whom one can interact and ask questions related to the topics covered in the MOOCs is offered. In the self-paced mode there are neither tutors nor the possibility to interact or ask questions to the teacher of the course, but there are still discussion forums (news forums, thematic forums and so on) in which participants can interact with one another or receive communication from the referents of the technical support of the Portal (example alerts on the closing date of the course, etc.). Moreover, in this mode the course calendar (Fig. 3) may not include at the time of opening the MOOCs indication of a default closing date of the course and training activities.

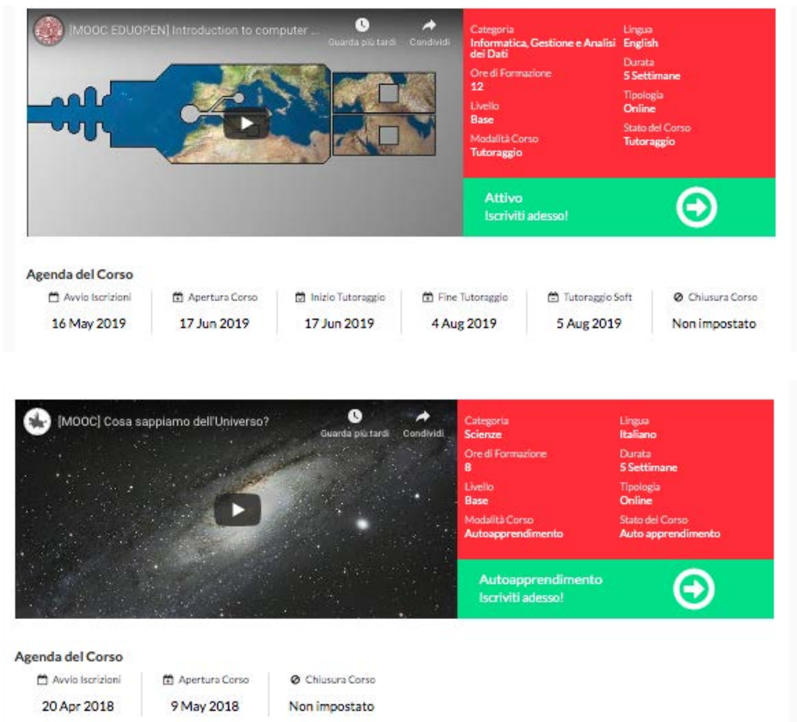

Fig. 3: Example of a course schedule in tutoring mode and in self-paced mode

These are central elements in the design process of the MOOCs, from which this research, analysing course delivery methods, was developed.

3. Materials and Methods

This empirical study, realised from data produced by the learning analytics system of the EduOpen Portal, focused on analysing the percentage of the completion/abandonment rate recorded on the whole set of MOOCs published on EduOpen, differentiated on the basis of the delivery mode defined in the design phase. In July 2019 there were 247 courses in the catalogue with more than 55,000 users. This contribution answers the following research question:

- can the way in which the courses are delivered – self-paced and tutoring – influence the levels of completion of the courses?

The purpose of the research is to determine any differences in the completion rates of the courses with respect to the mode of delivery chosen. The results of the research can be integrated into the process of instructional design of MOOCs on EduOpen.

3.1. *Data Set*

Our data set is composed of 195 MOOCs published on the EduOpen Portal, selected from the entire set of published courses (247). Of the total number of courses, 66 are part of one or more pathways, while the number of active pathways is 30. Compared to the categories present on EduOpen (arts and humanities, computer and data sciences, health and pharmacology, science, social science, technology/design and engineering) the highest percentage of courses falls into the social science category (42%) (Fig. 4).

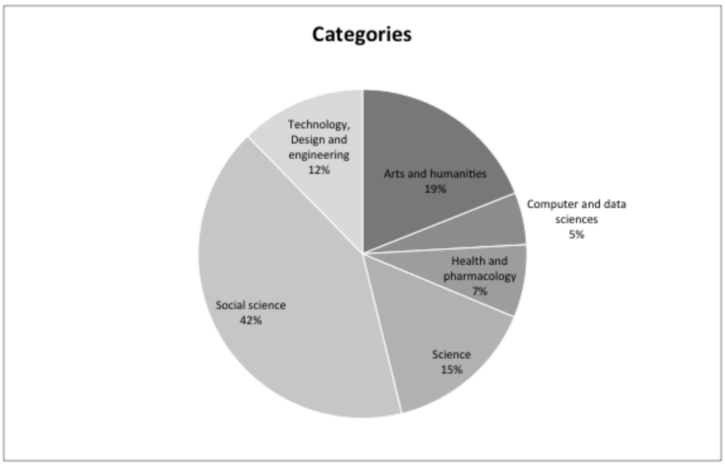

Fig. 4: Categories used on the EduOpen Portal

Data on the number of enrolments and completions were collected through the LA system and produced by the LMS of the EduOpen Portal.

The total number of MOOCs published excludes "capstone" courses, whose life cycles were incomplete with respect to the dates envisaged for their delivery (for example, courses running for fewer weeks than those envisaged for the completion of training activities, as indicated in the presentation form of the MOOCs). In fact, the choice of courses took into account the life cycles of the MOOCs linked to the mode of delivery of the same, as described above. In addition, courses closely linked to university courses whose levels of completion are by nature high have been excluded. The data collected and associated with the individual courses are related, in addition to the mode of delivery, to:

– the state of the course, which may differ from the mode of supply indicated by the date of the MOOCs' opening (Fig.3). In this case we can find courses in self-paced, tutoring, archived, in closing, etc.;
– hours of training and duration (indicated in weeks);
– the course category, the reference university and indication of the possible pathway to which the MOOCs are linked;
– the opening date of the course, the start/end date of the tutoring (if any), the closing date of the enrolment, the closing date of the course (if stability);
– the number of users enrolled in the course and the number of users who completed it (obtaining the certificate of participation).

For self-paced courses the average training hours associated with each individual course is equal to 13.45 hours and the average duration in the week is equal to 4.5 hours; while in the tutoring courses the average duration in training hours is equal to 16 hours and the average duration in the week is, as for self-paced courses, equal to 4.5 hours.

The selected sample is made up of 93 courses in "Self-paced" mode (S), 82 courses in "Tutoring" mode (T) and 20 courses in "Undefined Type" (U). The latter includes MOOCS that for reasons related to the course agenda and the change in delivery mode (e.g. the change from Tutoring mode to Self-paced) it was not possible to associate with one of the two modes indicated (S or T).

The full data set and R Markdown file are available as an attachment.

3.2 *Method*

To verify the differences between the three distributions related to the three groups identified within the sample, we used the tools of descriptive statistics, identifying the mean, standard deviation and quartiles.

We focused in particular on the calculated averages and, in order to verify if the differences between them were statistically significant, we found the possible overlapping of the confidence intervals for each of the three groups; the normality of the distributions was verified through the Shapiro-Wilk test. The t-test was used to verify the reliability of our assumptions.

4. Analysis and Findings

We started from the description of the three course samples, calculating the central trend measurements for each (Tab. 1) to check if the course completion trend in the three subsamples exhibited any differences.

As shown in Table 2, the average of group S is slightly higher than that of the other two groups, which differ by a few tenths. The boxplots (Fig. 4) show a significant superposition.

Course status	N courses	Average % completion	DEV.ST
Self-paced (S)	93	25.75	13.01
Tutoring (T)	82	22.83	11.52
Undefined type (U)	20	22.22	9.13

Tab. 1: Average and standard deviation of the percentages of completion in the three subsamples

Course status	N courses	MIN	1st Qu.	Median	3st Qu.	MAX
Self-paced (S)	93	2.03	16.19	23.84	34.34	56.00
Tutoring (T)	82	2.42	14.96	22.39	29.28	50.67
Undefined type (U)	20	6.46	15.66	22.14	27.97	40.20

Tab. 2: Quartiles in the three groups

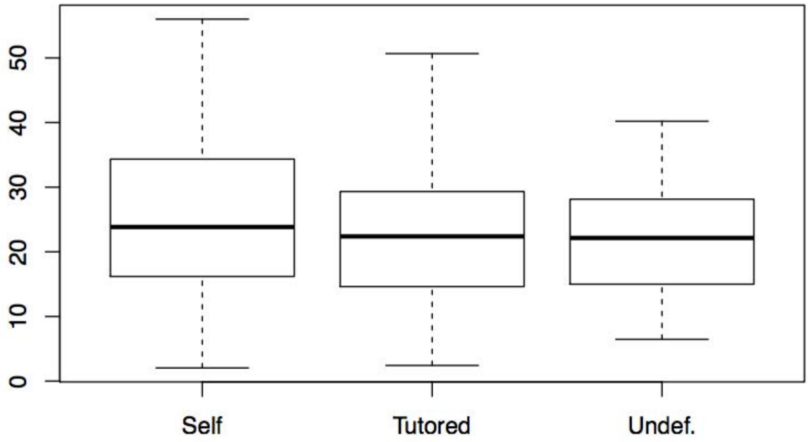

Fig. 5: Boxplot of the three samples of courses

We sought to evaluate the confidence intervals to check for differences or overlaps.

First, we needed to test the normality distribution of the samples referred to the completion rate (Rate). We used the Shapiro-Wilk normality test (H0: distribution is normal). In the three cases we attained a value of $p>0.05$, and so at 95% we could not refuse the NULL hypothesis and hence considered the three distributions as normal.

We moved on to evaluate confidence intervals for the means in the three samples (if CIs were not disjointed we gained some indication that the means were not statistically different). As can be seen in Tab. 4 and Fig. 5, the three CIs were not disjointed, so there was evidence that the three means were not statistically different.

	inf	**sup**
Confidence intervals for the mean of the completion rate in tutored courses	20.34	25.32
Confidence intervals for the mean of the completion rate in self-paced courses	23.10	28.39
Confidence intervals for the mean of the completion rate in undefined courses	18.22	26.22

Tab. 3: Confidence interval

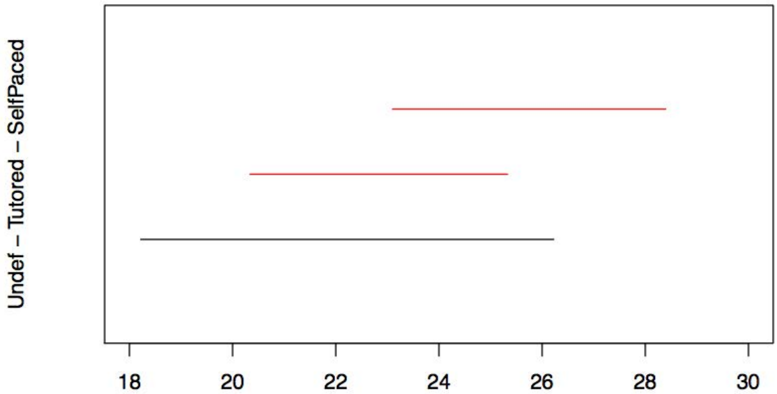

Fig. 6: Confidence intervals

Lastly, we evaluated the *t-test* for the NULL hypothesis "Difference is generated by casuality" against the H1 "Difference is generated by the tutoring". We compared only tutored courses versus self-paced courses.

The *p-value* was 0.12 > 0.05, so we could not refuse the NULL hypothesis. This implied the two means were not statistically different and thus we could conclude that tutored courses or self-paced courses showed statistically similar behaviour in terms of completion rate. We applied the same methodology appending undefined courses to tutored (case 1) and self-paced (case 2) courses, obtaining the same results.

The data analysis revealed that tutoring a course does not increase its completion rate.

5. Conclusions

The aim of the research was to determine the differences in the completion rates of courses in MOOCs with their delivery methods. The results of the study showed that the completion rates of tutoring courses do not increase compared to self-paced courses.

The next step of the research will consider the instructional design process of EduOpen's MOOCs focusing on rethinking the tutoring and the interaction modality in the online learning environment. It is possible to identify future areas of research related to the need to investigate the effects of the data emerging from the study, with respect to:

– the didactic design process of the MOOCs, and how to reconsider the tutoring modality in the courses. Does the presence of support figures in MOOCs qualitatively and quantitatively affect the levels of user interaction and participation beyond the levels of completion?

– the analysis of the "reasons" for abandonment from a student's perspective in relation to the processes of self-regulated learning (Crosslin, 2018); in fact, several studies associate to the limited self-regulating abilities of learners one of the possible causes leading to dropout (Maldonado-Mahauad et al., 2018a, 2018b). In a digital learning environment, significant self-regulation capabilities are required, with obvious repercussions on completation rates. As Van Laer and Elen (2017) have highlighted, every learning environment, but especially digital, differs considerably in terms of the technologies and didactic methodologies adopted: just as these environments are created, they *challenge* the processes of self-regulation of learners. It is therefore necessary to move towards different analysis approaches, such as "study of learning analytics to better understand students' performance in digital environments" (Gil-Jaurena et al., 2018, p. 53).

If the presence of support figures does not affect the completion rates, it is not possible to disregard the importance linked to the presence of the instructor (or other professional figures) with respect to the significant effects recorded in terms of "learning engagement", the quality of the formative activity and the levels of interaction of the learners. The focus is on perceptions, motivation and learning attitudes (Saadé et al. 2017). If certain conditions – e.g. instructional design and in EduOpen this aspect is linked to the guidelines already mentioned - are met "MOOC participants can and do experience engaged, high quality learning" (Wintrup et al., 2015, p. 4). In agreement with Michele Pellerey (2006) it becomes fundamental to identify analysis and intervention tools to act on self-determination and self-regulation in learning processes, to investigate the role played by motivations in promoting personal, cultural and professional development. These processes are also enhanced by the spread of MOOCs in academia and in formal learning contexts.

As of for this complex educational scenario, the role and support offered by the learning analytics system is not limited only to the collection and monitoring of data – associated in this study with levels of completion and rates of dropout that are still two elements to which instructors look carefully to evaluate the outcome of learning processes and instructional design – but it is the resource from which (re)start to (re)think the processes of personalization of learning environments: in relation to the course and curriculum design of MOOCs (Haras et al., 2017) and to the experience of the learners.

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