The Time Factor in MOOCS
Time-on-Task, Interaction Temporal Patterns, and Time Perspectives in a MOOC

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Abstract: MOOCs are a current trend in Higher Education; universities around the world offer open courses for lifelong and geographically distributed learners. Nevertheless, there is a high drop-out rate on these courses. The temporal aspects related to learner Temporal Perspectives (TP), self-regulation of learning, and temporal patterns could be related to drop-out rates and motivations for following a MOOC. This study aims to analyse student objective and subjective times in order to better understand their relationships with MOOC participation. The paper describes the case study methodology proposed to explore this relation: a pilot MOOC course on entrepreneurship (IE MOOC) with a total of 30 Catalan students who were active during the two-week course. The study examines the motivation and active participation of students in these learning methodologies, and practical issues on the schedule and temporal pace of MOOCs. Results show how student actions decrease as the MOOC progresses. Students connect more during weekdays and early and late evenings. They are mostly future-oriented, which is classically related to higher performance and self-regulation. This exploratory study shows how research on learners' temporal patterns could help to advance in the understanding of MOOC students' profile, in order to increase the currently low completion ratios.

1 INTRODUCTION

Massive Online Open Courses (MOOCs) can be defined as online courses with free and open registration, a publicly shared curriculum, and open-ended outcomes (McAuley, Stewart, Cormier and Siemens, 2010). MOOCs are one of the major educational trends of the last four years (Pappano, 2012; Pence, 2012) and offer Higher Education (HE) courses to a massive number of participants. These participants are often lifelong learning students and frequently have no access to other courses due to their work and personal commitments.

MOOCs offer the possibility of learning online to many students and are free of charge (Pappano, 2012). A massive number of participants can enrol in MOOCs from anywhere, overcoming the limitations of traditional face to face classrooms and existing online courses. MOOCs enable practically anyone to engage in virtual education and have the potential to provide education on a global scale. In particular, they can enable the massive development of knowledge and skills among those adult learners who have enough motivation, self-regulation, and cognitive quality time to engage and thus succeed in online courses.

Nevertheless, MOOCs are not currently comparable to other online and onsite university courses, especially in terms of evaluation, personalisation, and certification (Cooper and Sahami, 2013). This massive methodology implies important changes in the range of times involved in the course; that is, in terms of student objective times (time-on-task patterns, temporal zones, time availabilities) and subjective times (time preferences and time perspectives, among others); the tutors' or facilitators' time; and last but not least, in instructional time, which must suit a larger audience than classical online courses. Understanding the MOOC time factor challenges could help in understanding the high dropout rates, which some studies have estimated at around 85% (Rodriguez, 2012). Adult student time availability is one factor in student participation and completion of MOOCs.

Furthermore, students in MOOCs report a high drop-out rate and usually only seven or eight per cent complete courses (Clarke, 2013; Little, 2013), with the majority leaving the course (due to time constraints) after a few weeks if they are not motivated or interested in the content. Two-thirds of respondents in the study by Carr (2013) affirm they would be more likely to complete a MOOC if an accreditation certificate was given. According to Vogel (2012), student number figures claimed by MOOCs are highly speculative, and could include students who may have had little more than curiosity rather than a real commitment to learn. In their present form, MOOCs can be challenging for the learners because they demand a serious commitment in terms of time and effort and strict self-regulation (Little, 2013).

This paper aims to analyse various time factor implications of MOOCs from an instructional perspective, both for objective and subjective learner time, and based on an analysis of the case study of the Introduction to Entrepreneurship (IE) MOOC.

2 TIME FACTOR IN MOOCS

In education, time is an implicit factor that some approaches have tried to make explicit by defining typologies of academic time. Time is an important factor for understanding learning activities (Barberà, Gros and Kirschner, 2012), especially in active and online learning methodologies such as MOOCs, where students have a central role in course development and in regulating study time. Following McAuley, Stewart, Siemens, and Cormier (2010), a MOOC builds on the active engagement of several hundred or several thousand students who self-organise their participation. Although sharing some of the conventions of an ordinary course, such as a predefined timeline and periodic topics, a MOOC generally carries no predefined expectations for participation.

In the following sections we will first discuss objective time, based on the ALT model, and focusing on time-on-task by students, and then we will define this variable in MOOCs. We will then study the subjective or intrapsychological time related to learning and focus on the Time Perspective (TP) of learners as one of the factors classically related to learning achievement (Usart and Romero, 2014). Finally, we will outline the prevailing challenges for MOOCs: both for objective and subjective student time.

2.1 Objective Time

Time is one of the dimensions that society uses to measure objectively and synchronise individual, collaborative, and social activities. Learning needs time, and the educational system has been organised to organise times for formal learning. The measure of time in learning has been studied and defined through different models and theories. In this study, we consider the Academic Learning Times (ALT) model (Fisher et al. 1980; Harnischfeger and Wiley, 1985). (cf. Figure 1). ALT has been used in face-to-face and online learning contexts (Romero, 2010) and focuses on time from instructional and student perspectives. Within the ALT model, students can devote more or less time to the learning activity (engaged time or time-on-task) within the bounds of the time allocated by the teacher (allocated time). Within this time range, students have an amount of effective learning time.

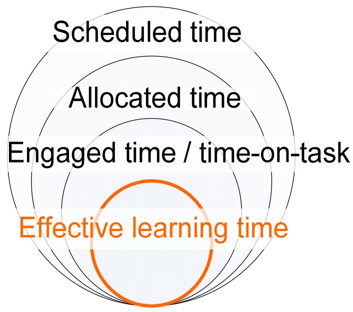

Figure 1: Academic learning times model.

The regularity and distribution of the different times can be observed as patterns. A temporal pattern refers to a structure appearing periodically within a given temporal rhythm, enabling the understanding of past events and anticipating future actions (Valax, 1986). Temporal patterns can be analysed at different levels of time such as the day, the week, and longer periods, such the duration of a learning activity of several weeks (Demeure, Romero, and Lambropoulos, 2010). The analysis of temporal MOOC patterns may help us understand student rhythms in these massive courses, and identify possible challenges such as high dropout rates.

In addition to the ALT categories, when technology is involved, we should also take into account the participants' e-competence and the complexity of the technology, and therefore consider the time required to learn how to use the learning technologies, which has been referred by McWilliams and Zilbermanfr (1996) as time of technology adoption.

2.1.1 MOOC Objective Time Challenges

Based on the ALT model, we can draw the temporal context for MOOCs. In a MOOC, scheduled time can be defined as the amount of time (usually weeks or even months) a course is open for users to access. However, MOOCs are by definition offered within a paced and time-dependent course model that could be limiting its supposed flexibility. The course structure represents a mix of open network models and traditional closed online models. If well designed, the speed and flexibility of MOOCs, together with ICT tools could help students interact without the constraints of space and time (McAuley et al., 2010).

After the first layer, allocated time can be measured as the changes in student objective time, understood both as the variety of time zones if students are geographically distributed; and their time availabilities as most students can only engage a few hours a day due to other commitments. Following McAuley, Stewart, Siemens, and Cormier (2010), individuals determine the extent of their own participation in a MOOC, defining their measure of success in the learning process. This apparent lack of schedules within the MOOC could turn against students if they lack self-regulation and do not know how to manage study time.

Changes in tutor time are also important. Being massive also demands a different role and time management system for the facilitator of the course. As McAuley et al., (2010) explain, although MOOC facilitators volunteer their time by guiding participants when necessary, it is expected that the other students will be the primary source of feedback during the course.

Finally, there are changes in the instructional time of the course needed to suit a large audience. Tasks and learning can take more time for students as they need to understand the rules and plan their own study. Furthermore, the time a student decides to invest in learning has been related to student engagement and motivation (Lewis, 2007; Wagner et al., 2008), two important assets that MOOC students hopefully acquire.

2.2 Subjective times

Human time is not only objective, but it also has a subjective dimension: intrapsychological time (Nuttin and Lens, 1985). This dimension of time is composed of individual variables related to the concept of time and how it is perceived. Three individual constructs are defined as the generators of psychological time: orientation to multitasking or polychronism; time orientation; and time perspective (TP; Zimbardo and Boyd, 1999). Polychronism is based on change and flexibility when attention is diverted among various possible activities, in contrast to monochronism (defined as the ability to concentrate on one activity at a time, with an emphasis on the development and adherence to schedules) (Hall and Hall, 1987). Polychronism is usually present in high-context cultures, where punctuality is less important, where flexibility and changes of activity are common and expected. Time orientation is described as being part of the wider TP context and is a one-dimensional trait that is independent of the situation or life domain.

Finally, TP is probably the aspect of psychological time that has been most related to learning processes and outcomes in formal education (Schmidt and Werner, 2007), and is defined as the manner in which individuals divide time into past, present, and future (Zimbardo and Boyd, 1999). In particular, they divide TP into 5 factors (see figure 2):

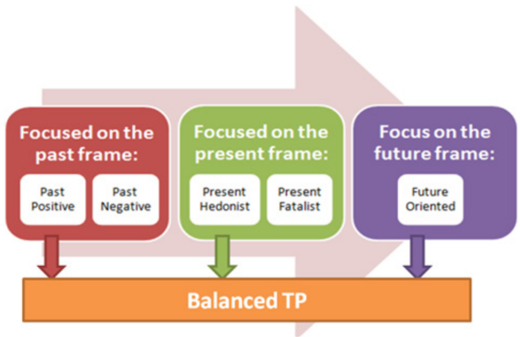

Figure 2: Time Perspective Factors.

These authors measured a correlation between higher education students and drop-out rates; present-oriented students tended to abandon university more than future-focused students. Furthermore, some authors have shown the relation between learners' future TP and learning achievement in e-learning (Usart and Romero, 2014); and also between future TP and self-regulation of learning by learners (de Bilde et al., 2011). Previous results show that, when learning activities are not compulsory, students with a high future TP tend to engage more in these learning tasks, as they foresee the future rewards of their present actions (Peetsma and Van der Veer, 2011). On the other hand, present-oriented students, in particular, present hedonists, tend to engage in social, instant-reward activities (Zimbardo and Boyd, 1999).

2.2.1 MOOC Subjective Time Challenges

Student TP has historically been studied in face-to-face contexts. There is a gap in the literature on the impact of TP on learning outcomes and processes in online learning (Usart and Romero, 2013). As MOOCs are based on different learning models, such as connectivism and constructivism (Brown, 2013; Siemens, 2009), and their participants have not always the self-regulation skills to be autonomous learners in MOOCs (Brown) it is important to study the temporal perspective of MOOC participants in order to understand the profile of adult entrepreneurship students enrolled in an open online course and study the possible relation with drop-out rates, learning achievement, self-regulation (Little, 2013), and motivation. Little, in the context of MOOCs, states that these courses can be challenging for learners because they demand a serious commitment in terms of time and effort, as well as strict self-regulation.

3 RESEARCH OBJECTIVES

To study both the temporal patterns of a MOOC and the temporal profile of students on these courses, we focussed on four aspects (hypotheses) of student objective and subjective times. Firstly, we posed a research question (RQ1) on student objective time. We aimed to study the temporal patterns of learners by focusing on three levels of interest: the global course (scheduled time); the day of the week (student time ties and self-regulation); and finally, the day periods (related to student time-on-task, self-regulation, and work and life bonds). MOOC temporal patterns are described and some aspects of student participation rates, both longitudinally and in terms of schedule, are quantitatively analysed.

RQ1: Which are the daily, weekly, and hourly patterns of the course?

The following hypotheses will help us specify this research question:

- H1. MOOC participants show a tendency to procrastinate as in face-to-face and e-learning programs (that is, we expect greater participation in the days nearer to the end of a task).
- H2. MOOCs are courses in which the participants are mainly lifelong learners who are professional adults with time constraints. We expect that students will participate more on weekends, when they have more leisure time, than during the weekdays, when they mostly work, as previously measured by Romero (2010).
- H3. MOOCS are aimed at adult participants with personal and professional ties, we expect that students will participate more during the late evenings than during the rest of day; nevertheless, we should keep in mind the large number of unemployed people in Spain, and this could influence results in this hypothesis.

We will also formulate a second research question (RQ2) to study learner subjective time, in particular, focusing on student TP. We have highlighted in the previous section that TP is usually related to diverse learning outcomes and individual differences such as self-regulation, and this is an important asset of MOOC students. To answer these questions, we conducted an exploratory study in the Introduction to Entrepreneurship (IE) MOOC.

RQ2: What is the TP profile of students in the IE MOOC?

- H4. We expect participants to be focused on future TP. This is due to the fact that existent literature on learning has related entrepreneurs and adult online student profiles with future TP as these students manage their time and are better self-regulated when studying.

4 METHODOLOGY

In this section we detail the case study methodology designed for analysing the objective and subjective times and their relationship with MOOC participation. Case studies are a research methodology attempting to examine a phenomenon in an authentic context. In particular, the real-life context chosen for analysing the MOOC participation in our study is an introductory course in entrepreneurship, the IE MOOC. In this section, the context of analysis of the IE MOOC course is described. We describe the study, the participants, and the main figures of the platform. Furthermore, we will focus on the specific methodologies for studying objective and subjective time factors, and the tools used for the quantitative analysis of objective and subjective time introduced in subsections 4.2 and 4.3.

4.1 Context of Analysis – MOOC in Entrepreneurship

The IE MOOC has been designed and implemented with the potentiality to be massive, but the first edition has had a total of 76 adults, registered through the IE MOOC form, available at a Google Site. The course has been only announced in the Catalan Chamber of Commerce for a month, which has limited the number of effective participants. Because the pilot nature of the IE MOOC, and its limited publicity, the number of participants does not allow to consider it as massive in terms of effective participation, but in terms of potentiality for future editions. We can refer to this MOOC as a "miniMOOC" in terms of Goldschmidt and Greene-Ryan (2013). Despite 76 Catalan participants registered this "miniMOOC", finally, 45 students accessed the LORE web of the course during the two weeks that the MOOC was active. There were 30 active participants during the two weeks of the course; 15 women and 15 men, with an average age of (M=31.8, SD=8.7). Only 13 participants completed the four mandatory activities proposed by the facilitators. Concerning their current occupation 5 of them declared to have an employment, and 2 of them admitted being unemployed. Because the question in relation to their occupation was not compulsory, the information of other participants' current status is missing. The proportion of unemployed participants in the IE MOOC (28%) is similar to the current unemployment rate in Spain, which has been estimated to be 26.7% according to EUROSTAT (October, 2013).

The IE MOOC was placed in the open platform LORE (www.lore.com), a web-based Virtual Learning Environment (VLE) that resembles a social network (see Figure 3). LORE was chosen because it looks like a social network and aims to help participants easily interact through the VLE, and also enables 'ICT non-experts' to create a MOOC. All the activities and references were accessible through the LORE discussion zone. The LORE platform initial studies allowed us to observe an irrelevant time of technology adoption (McWilliams, and Zilbermanfr, 1996) due to facility of use of the platform, and the normal to high level of e-competence of the participants enrolled in the IE MOOC.

The course schedule was divided into four topics: Topic 1, entitled *Presentation and Discussion*, was presented on the first day (Monday 13 May); Topic 2 was presented the same day to give faster students the opportunity make progress. The third topic was available on Tuesday, and the last topic on Wednesday. The course was active until the 23th May.

Figure 3: LORE discussion zone.

4.2 Methodology for Temporal Pattern Analysis

This study focuses on student participation during the whole course, therefore, it measures student activity both on the LORE platform and in the discussion zone; as well as measuring other tasks via the external logs from *Google forms* (for tasks 1, 2 and 5); and *LimeSurvey* data for task 3. Task 4 was reported by the students in the LORE platform. All time logs were recorded and prepared in an Excel file and analyzed with SPSS software.

The pace of the student actions was a relevant point: inside LORE students could post in the discussion zone, make (short) comments to posts, or press a 'like' button. Outside LORE, students had to perform different tasks and two serious games (completion of tests and game tasks). We therefore coded actions as *Post*, *Comment*, *Like* or *Task* outside LORE (P, C, L or T). In this study we did not differentiate among actions in the analysis, as the aim of our research questions and hypotheses is to study the activity and participation as a whole. These actions could be conducted during the 15 days of MOOC duration: the course started on 13 May and ended on 27 May. To analyse data and following Demeure, Romero, and Lambropoulos (2010) the comparison of the groups in the longitudinal activity level was conducted over three temporal periods: the beginning of the activity (days 1 to 5); the midterm of the activity (days 6 to 10); and the end of the activity (days 11 to 15). Secondly, these actions could be performed in a weekday or during the weekend, and finally, concerning the daily level, we follow the distribution used by Demeure, Romero and Lambropoulos, based on the Nie and Hillygus (2002) study, that divides the day into six time periods: night, early morning, late morning, afternoon, early evening and late evening. Thus, the times of these six periods are defined according to a standard working day: night for 2 am to 5 am; early morning for 6 am to 9 am; late morning for 10 am to 1 pm; afternoon for 2 pm to 5 pm; early evening for 6 pm to 9 pm; and late evening from 10 pm to 1 am.

4.3 Methodology for TP Analysis

The analysis of the student TP was conducted using the Zimbardo Time Perspective Inventory (ZTPI; Zimbardo and Boyd, 1999). This instrument presents 56 statements for the five theoretically independent factors described by Zimbardo and Boyd (Past Positive, Past Negative, Present Hedonism, Present Fatalism and Future). Each statement is rated using a 5-point Likert scale (1 = strongly disagree, and 5 = totally agree). Following these authors, individuals tend towards one of the five orientations or have a balanced TP. The Spanish version of the ZTPI was implemented in topic 3, as part of the MetaVals task. This instrument was previously validated through a psychometric study conducted by Díaz-Morales (2006) on a reliable sample of Spanish adults (N= 756) and was used in the present study to ensure consistency with the theoretical approach of the chosen TP definition.

5 RESULTS

A total of 30 students participated actively, and performed a total of 209 actions during the course. To study the H1, we focused on time patterns at a course level, operationalized as the number of student mean activities per day from 13 Monday to 27 Monday independently of the hour or day of week. By dividing the course into start, middle, and end (Demeure, Romero and Lambropoulos, 2010) we can observe from Figure 3 how participants showed a significant decrease in activity. We conducted a within subject ANOVA of each participant during the 15 days of the course, divided into three parts. Results show a significant difference between the last five days (M = 0.57, SD = 1.16) compared to the first (M = 3.07, SD = 2.80) and the second course periods (M = 2.63, SD = 3.31) [F (2,87) = 7.97, p = .001] .

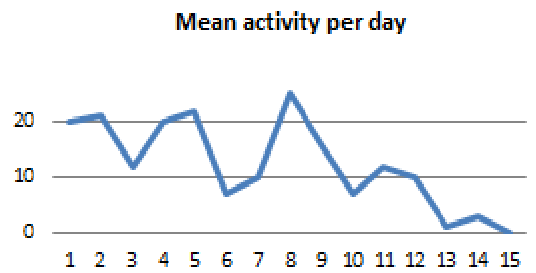

Figure 4: Students mean activity during the 15-day MOOC.

H2 aimed to study temporal pattern differences between the different days of the course. To explore more specifically the difference between weekdays and the weekend, we conducted a within subject ANOVA on the basis of the participation average of each participant during weekdays and weekends. Results show that participants in the IE MOOC tend to work more during weekdays, in particular Monday (M = 1.67, SD = 1.92), than during the weekend (M = 0.40, SD =0.96) [F(6,203) = 2.86, p = .011] .

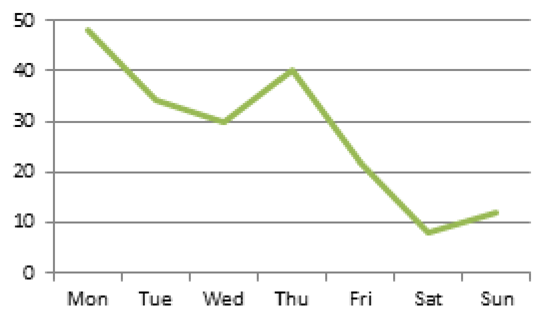

Figure 5: Participant actions per weekday.

H3 focuses on day periods. Differences among day periods were not found to be significant in the ANOVA study. However, students in the IE MOOC tended to participate more in late morning (M = 0.70, SD =0.84) and late evening (M = 0.67, SD =0.88) and less at night and early morning [F(5,174) = 2.15, p = .061]. Figure 6 shows results for this hypothesis.

H4: Student TP:

Only 12 students from the 30 active in the MOOC completed the ZTPI test. Of these students eight (66.67%) were future-oriented, two students were past negative (16.67%), one as past-positive, and another as present-hedonist. No students were classified as present-fatalists. Furthermore, all the participants had a high score in FTP (>3.3). The average TP pattern for the students in the IE MOOC can be seen in the figure below.

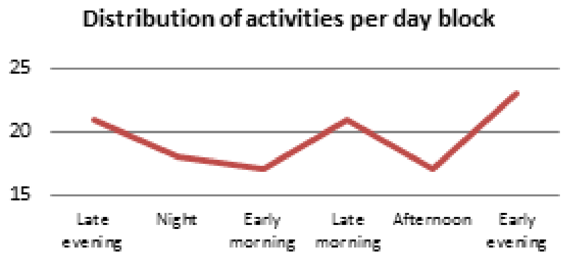

Figure 6: Student task distribution during the day.

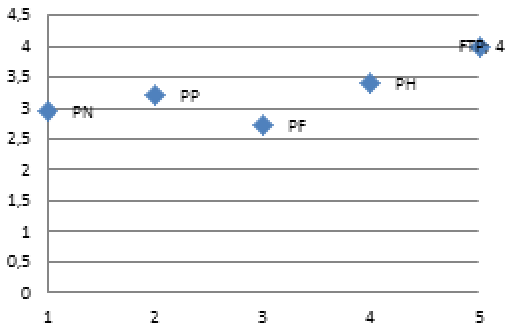

Figure 7: Student average TP.

6 DISCUSSION

Results for the course longitudinal activity (H1) show a significant decrease in the mean activity for IE MOOC students. This enables us to affirm that, following Clarke (2013), students tend to lose motivation during the course. Nevertheless, taking a look at the scheduled activities and the content of the facilitator messages, we can see that the 'day 8' peak is probably due to the reminder issued in the LORE forum of the MOOC rules. This course was designed with a gamification approach (Romero and Usart, 2013) that enabled participants to add scores to their task results, and finally win a competition within the MOOC. Course designers aimed to foster participation with this contest, and, from the quantitative results (Figure 4) students peaked when they were reminded of these rules. To the best of the authors' knowledge, no previous studies have focused on the quantitative analysis of this longitudinal pattern in MOOCs. However, following the Demeure, Romero and Lambropoulus (2010) study in e-learning tasks, a tool that could help students in a group to become acquainted with each other (such as the LORE discussion zone and presentation) could enhance the time allocated to the learning task itself, and thus improve e-learner performance and leveraging procrastination. This is consistent with our results.

Finally, as Carr (2013) showed, some students need a final accreditation in MOOC to further their participation in the course. The implementation of a contest or gamification could be another solution for this issue, as the results for longitudinal participation demonstrate in our case. Some researchers claim there is a need to develop interactive MOOCs to engage learners and keep them sufficiently interested during the whole course to complete it. Little (2013) suggests the inclusion of games or simulations to help students engage in these learning environments.

Concerning the differences among weekday and weekends (H2), we have shown that students tend to participate significantly more on Mondays, as it coincides with the MOOC starting day, and on Thursdays, when students were reminded of the rules of the course by the facilitators. Furthermore, weekends show lower participation rates, contrary to what could be expected for lifelong learners, and students prefer to spend their weekends in other activities and study while they work during the week. This is in accordance with Romero's (2010) results that students in adult e-learning activities use their residual time to work on learning tasks. As the author reports, helping students to organise themselves in other life aspects could help them to free better quality time for the learning task; but this is not the focus of our study.

In light of the results from day period analysis (H3), we have observed a higher activity ratio in early and late evening, despite the results are not statically significant. Linking this to previous hypothesis results (weekends are not used by learners), we can relate this to the fact that students are lifelong adult learners who have work and family commitments during the 'conventional' time of the day, and take advantage of other time periods to engage in learning activities such as the MOOC. Nevertheless, there is a peak of activity in the late morning that seems to be in accord with Demeure, Romero and Lambropoulus (2010). Students could be using their job-breaks during lunch time to connect to the MOOC, but it is also possible that some students are unemployed and study all the day. A possible solution to the reported daily and weekly time constraints could be mobile access to MOOCS. As de Waard and colleagues (2011) state, participants in MOOCs indicate that they prefer to use their mobile devices to access course materials because they can participate whenever they wish, that is, they positively evaluate temporal independence. In our case, students could make posts, post short comments, or post likes to other comments via Smartphones.

H4. Student TP was highly oriented to the future, and this factor was high even in students with other perspectives. This can be explained in face-to-face learning activities; students with a high future TP usually engage in the learning process and are more active (Peetsma and Van der Veer, 2011) because they care about the future implications of their investment in study. Following Clarke (2013), MOOCs build on the engagement of learners who self-organise their participation according to learning goals, and prior knowledge, skills, and common interests.

Future TP students showed a higher academic engagement (Fourez, 2009). Furthermore, these temporal profiles are correlated with self-regulated learners (de Bilde, Vansteenkiste, Lens, 2011), and we have seen that a MOOC demands high levels of self-regulation to succeed in an open learning context where there is little direction by the facilitator – and much of the learning is provided by interaction with peers. The fact that no present-fatalist students completed the ZTPI could be related to their profile characteristics; individuals with a fatalist TP tend to be passive and less engaged in learning as they believe the future is written (Zimbardo and Boyd, 1999). Finally, the fact that only one present-hedonist student was found in the sample could agree with Zimbardo and Boyd's results among undergraduate students: present-hedonists show higher drop-out rates due to their lack of consideration of future consequences.

The results of the case study show the challenge integrating lifelong learning to the already complicated equation of Work Life Balance (WLB). We observed that the learners of the IE MOOC use their evenings for participating in the course and the first days of the weekdays when returning to their daily routines. When considering their TP, we observe a better engagement of future oriented students, a result that should be taken into consideration in order to promote social activities where future oriented students are mixed to other TP students to promote their engagement.

7 CONCLUSIONS

MOOCs offer a new approach for lifelong adult learners who aim to pursue a course with fewer time and space constraints than classic face-to-face and online courses. However, this methodology demands high levels of self-regulation and commitment. We have studied objective and subjective learner temporal patterns. Results show a continuing decline in activity during the whole course, probably because personal and work bonds do not allow students enough time. Students increase their level of activity when reminded of the rules of the MOOC in a gamification context. This could be very useful for engaging students during this period. Time during the week and within a day was analysed quantitatively. Students prefer to access the MOOC at night and connect less on weekends. This aspect should be further studied, as we suggest that night time study may be of poor quality and students should be helped to connect at weekends. Finally, students show a clear future orientation; this is in accordance with previous studies on learning and TP; students who are focused on the future tend to be more self-regulated, and invest more time studying in expectation of future benefits. We recommend MOOC designers learn about the TP of their audience and thus design more active and 'mobile' MOOCs that could help students with present or past-perspectives engage in the MOOC with an instant-reward activity. The number of participants of this first edition of the IE MOOC entails some limits to the external validity towards other MOOC studies. Nevertheless, this "miniMOOC" study has advanced in the methodology of the analysis of the time factor in MOOCs, and opened the possibilities for extending this study in future editions of the course. More research is needed in the field of time factor in MOOC contexts. In particular, qualitative analysis and focus on the types of actions (posting a *like* in LORE does not demand the same effort as making a long presentation post or task) could give us more details about the temporal patterns of participants and the quality of their time spent learning.

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