

Exploring MOOC User Behaviors Beyond Platforms

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Abstract—MOOC user behavior is generally studied using the data collected within platform interactions in the learning system or via outside social media platforms. It is important to understand the root causes of anomalies in MOOCs, such as the 80% attrition, less interactions within platforms and what causing the reflected behaviors beyond platforms. We study MOOC student behaviors outside the platform using ethnographic methods, mainly focusing on diary study and interviews. Two groups, 11 extreme users who have completed many MOOCs and 10 who never completed MOOC have been used to collect data. The log sheets data and interviews were analyzed using Epistemic Network Analysis (ENA) method to explore if there is a significance between these 2 groups and other qualitative comparisons to explore behavioral patterns. Our results indicated 4 behavioral patterns with insights into significant level of learner's habits between extreme and novice users' behaviors leading to completion or dropping. This reflects the design gaps of MOOC platforms and based on the behavioral patterns, we provide recommendations to meet the learners' needs.

Keywords—MOOC, User behaviors, diary study, epistemic network analytics

1 Introduction

Massive Open Online Courses (MOOCs) are a phenomenal education technology consist of short videos, peer graded or self-graded assignments and forum to interact. Despite being advantages, MOOCs face challenges, such as the high drop-out rate which has been constant between 80 – 90% from the total enrollments [30]. Researchers argue number of completions may not be ideal metrics for measuring success but other factors such as percentages from those who watch all the content, take quizzes/assignment and engage in the MOOC [18]. Such MOOC behaviors being measured in many platforms to understand and improve learner experience and retention. Especially many MOOC data traces learners' clicks, views, assignment submissions and forum entries investigate various aspects of MOOC learning, such as the effect of lecture video types on learner engagement [20], the introduction of gamification [11], the impact of instructor involvement [37] and the significance of peer learning [12].

Apart from the data generated within the MOOC platform itself, few data-driven research works go beyond. Such as exploring the learners' traces on the wider Web, in particular the Social Web, to gain understanding of learner behavior in a distributed learning ecosystem. Billions of users are active on the larger Social Web platforms such as Twitter and existing research has shown that detailed user profiles can be built from those traces, covering dimensions such as age [27], interests [2], personality [3], location [21] and occupation [31]. However, data within MOOCs and social platforms may provide certain behavior without knowing causes triggering to the interactions or the reason causing the behaviors. Such as, some users may never log into continue assignments and platform logs only provide evidence that they did not log, but would not support "why". However, by tracing the learner experience within the time and context leads to understand the root causes of certain behaviors and anomalies. Participate in pre-course surveys or learner interactions in system offer only a snapshot-based perspective as learners drop out or retention, but little is known about the user experience that leads up to take part and learning in MOOC and how it should be best supported. It is extremely important to bring learning analytic to the data gathered beyond the platforms. We aim to examine and understand the journey of the MOOC participant which may lead to retain or drop off. Thereby uncover gaps in the user experience and then take actions to optimize the experience. We aimed to get insights from situations like "where" or the "context" of the learner who take part in the MOOC, what emotions or state of mind at various learning tasks during the course, what life responsibilities they have, how they manage the daily responsibilities and what support and motivation they get could significantly influence to the drop off or retain in a MOOC. At the same time, we particularly interested to understand if there is a behavioral difference between those who conveniently complete MOOCs and those who struggle to finish.

It is crucial to understand that MOOC student behavior in a learning platform or on the Social Web cannot provide us with a source of diverse, fine-grained and longitudinal learner traces which let us to be empathetic about contextual understanding of user behaviors and experiences over time. Our main objective is to understand the learners: i) Learning habits of extreme and novice users ii) MOOC usage scenarios such as primary tasks they perform in a course. iii) Changes in learning behavior.

In the course over the time with their perception and resonate the changes and examine the gaps by understanding the learners journey towards taking the MOOC. We aimed to provide design insights to close the gaps in the MOOC learning experience. To do this, we gathered our data using ethnographic methods specifically following diary study. Large amount of longitudinal data was collected from 21 participants over a period of 1 year. Participants were gathered using snow ball method, where we first searched web and also inquired from personal networks for participants who have at least finished 10 MOOCs. We called them extreme users of MOOCs, then found relevant referrals to who they might know with similar capacity. First author of this research is an extreme MOOC user and belongs to many MOOC communities who actively gathered network to provide data. Considering the ethical compliance's and to educate the participants about expectations and to complete the process of our data collection, selected 21 participants were explained via a short induction meeting. In

this, we clearly stated that they can opt out of this commitment. It is mainly because, in a diary study user are request to provide many data as much as possible voluntarily which takes extra effort and consumes huge amount of time commitment and may include privacy data.

We used quantitative ethnography method Epistemic Network Analysis (ENA) to analyze the large amount of qualitative data gathered through the diary study while observing the patterns of MOOC behaviors under the lenses of extreme MOOC users and non-extreme MOOC users to understand if there is a significance in the behavioral patterns in experiencing MOOC. As key findings, extreme users change their daily habits to cater to MOOCing yet sometimes face challenges to complete tasks due to platform design gaps.

Extensive mobile usage and MOOCs pedagogical limitations to be supportive in continuing the course using the mobile was well visible in results. Non extreme users face mainly motivational issues. While they perform tasks, keeping their level of interest is key factor in the journey. In the next sections, we illustrate in details of background of previous research, methods of this research. Next, detail analysis with discussion followed by conclusions and finally, the future directions which need to change in design to cater inclusive design to learner habits and lifestyle of 21st century is depicted.

2 Related Work

2.1 Learner behavior and motivations

Learner behavior, motivation and engagement patterns are important factors in understanding the success of MOOCs. In order to understand this, researchers have been using many qualitative, quantitative or mixed methods. Reviewing the literature, we found research base on analyzing the MOOC platform data [8, 39] or other social platform data [9] pre-post course survey [25], interviewing the participants [38], matching the system data to participant survey data [32] as common methods to understand behaviors, motivation and engagement of MOOC participants. Some research argued need of mix methods to understand the deep reason to engage in MOOCs or keep the motivations. They conducted survey questionnaire followed up by interviews [24].

Results in many of those research reveals a snapshot of the problems in the usage. For example, based on the analysis of Coursera platform data patterns of engagement and disengagement in three MOOCs, [25] has found 4 categories of user behaviors: 1) Completing, the learners completed the majority of assessments. 2) Auditing, learners watched most of the videos but completed assessments infrequently. 3) Disengaging, learners completed assessments at the start of the course, then reduced their engagement. 4) Sampling, learners explored some course videos

They suggest interventions should be targeted these categories of users to increase the engagement. Similarly, [14] has analyzed learner engagement from 4 MOOCs in

Futurelearn platform data set stating that learning is a social activity which engagement patterns will be different in Futurelearn than Coursera, since it is based Social Constructivist pedagogy. In such a platform learner found to be collectively learn by discussing and engaging. Replicating the same method in [25] and found only 'Completing' and 'Sampling' clusters, but not 'Disengaging' and 'Auditing'. However, our argument lays on the fact that these patterns have been identified based on the engagement in the platform yet learner background, their context information, reasons for any changes between clusters were uncovered. Identifying the reasons on what triggers anyone to transit from one state to another will bring important insights in controlling these transitions.

Many survey data reveals that motivation and engagement in a course is based on the perceived factors such as Extrinsic factors (relevance to study and lifestyle interest) and Intrinsic factors (improve themselves) [24]. This will be based on the questionnaire design but will not provide significant insight to the actual behavior within the context over the time. Detail analyses of learner behaviors using in-depth qualitative study recommended to uncover the reasons which affects course completion rate [23]. Research in this tandem followed focus groups which students describe their experience taking a course of what they like and dislike and qualitative method with interviewing the learner has been commonly practiced. However, interviewing the learner over a period of time has not been commonly practiced due to nature of heavy time and resources requirement. Yet, key qualitative method "Grounded theory" has been used to understand user's perception towards a success of a MOOC [17], which found 10 dimension that MOOC need improvement based on the data collection through observations on forum postings, social media postings, formal and informal interviews [16]. However, these qualitative results does not support clear evidence of learner behaviors change over time based on the task and what are their experiences towards particular tasks. Therefore, we used diary study yet more effective systematically design version incorporated with media which participants were requested to take pictures of their context in ease of recalling the memories of the experience. This integration has proven to be significant in producing more accurate and insightful than user just repeating what they experience during the follow up interview [6].

2.2 User experience with diary study

Studying user behavior in the CHI, CSCW and LAK communities lately created a buzz namely User Experience (UX). As such method, Diary Study has been widely used method and accepted to understand user behaviors with temporal contexts. Research to password usage in daily life [22], use of paper in everyday students life [28] and studies of understanding mobile internet use [10] has extensively used Dairy studies. In these studies, most commonly used observations, questionnaires in collecting data. Further, qualitative methods from HCI involve talking directly with users, such as semi-structured interviews, focus groups and open interviews, as well as procedures such as user observation, analysis of video recordings and diaries used [4]. Yet the diary study is used less common due to the time it takes, high commitment needs from the participants and also the time it takes in analyzing complex data. Nev-

ertheless, in this research we used Diary study and immediate follow-up interviews as the method to collect data. Our objective was to collect longitudinal data capturing contextual understanding of MOOC user behaviors and experiences over time. It mostly helps us to gain insights of learner habits, usage scenarios and related motivational levels and changing behaviors which can be very difficult in a lab setting to gather. Thus, Diary studies are useful for understanding long-term behaviors, yet time-consuming and may be expensive. According to [36], although diary study may be expensive and time consuming, it results the most effective than usability test and interviewing. To improve the effect of diary study, [6], investigate the use of media in capturing context affects the diary study method. They suggested modifications to traditional diary techniques that enable annotation and review of captured media incorporation as a variation on the diary study more appropriate for researchers using digital capture media. In other words, taking a picture and describing the event in follow up interviews were found be more effective than keeping a log data.

2.3 Quantitative ethnography by ENA

Epistemic Network Analysis (ENA) method has been widely used in Learning Analytics (LA) communities lately. Specifically the recent analysis of meta research on understanding to increasing the Impact of Learning Analytics used ENA in to explore the relationships between the dimensions Focus, Purpose, Scale, Data, and Settings extracted from LAK conferences and JLA used this method in quantifying the relationship with the use of binary occurrence of codes with in the corpus [13], [26]. In order to make sense in the deluge of information in the digital age, using this kind of new science of Quantitative Ethnography make potential to bring boundaries between qualitative data, In this case we used to understand the difference between novice and extreme users behaviors using qualitative data but processed by quantifying according to ENA. This dissolves the boundaries between quantitative and qualitative research and give researchers tools for studying the human side of big data [34]. Although our intention in this research is to analyze log files and interviews generated in diary study using ENA, method itself is widely applicable with well-defined process. Explaining the process is beyond our research and page limits, therefore, we recommend readers to be familiar with the process in a worked example by Shaffer who brought the concept to the LA community [33].

3 Methodology

3.1 Diary study

We used Diary study with in-situ as the main method of understanding the MOOC participants learning habits, primary tasks they perform in a course, time and context they perform these tasks, attitudes and motivations in performing those tasks, changes in learning behaviors in the course over the time with their perception. By identifying those, we resonate the changes and examine the gaps by understanding the learners'

journey towards taking the MOOC. We incorporated media where participants were requested to support any audio, video or image of the context to recall the memory. At the same time, we structured our diary study in to a 5-step process where we invest in time to make frequent engaging weekly meetings with 1-2 participants at a time with post study meeting in the end. This involvement helps to keep interest high and reminds participants of the importance of the diary entry in data collection. We introduced a calibrated Logging sheet to facilitate in-situ logging method which cover the 24 hours with the data which we are interest in analyzing. It included easy way for the user to fill the activities, log the moods and context and specifically we crafted to highlight the MOOC activities which we are interest in examining.

3.2 Participants

Since we were intending to understand the behaviors of MOOC users, our recruitment needed to narrow on the aspect whether the target participants have taken MOOCs and willing to take a course during this study. At the same time, we constrained to seek extreme users (those who have completed at least 10 MOOCs) and novice to MOOCs (those who has not completed a single course) intending to find if there are behavioral changes between two groups. Sample collected using snowball method where one user find similar users in their network [5]. Having been in the field of MOOCs for a few years, we first used our own network to find extreme users. We also used search engines to find extreme users and found many who completed considerable number of MOOCs keeps internet records in blogs and social media and often keep best practices advises. Then, we found non-extreme users, the type commonly found and easily accessible through posting in forums of usual MOOCs. We used our enrolled Coursera and edX courses forum to spread the word and also used twitter. Based on our criteria 21 participants were finally selected to study. Table 1 explains the demography of the participants.

Table 1. Participants demography of the study with the coun-try they live, the course platforms they have taken courses and willing to take during the study with the user type of Extreme (EX) or Novice (NC). Among these 9 are females and 12 are Males while 6 participants with 8-5 job, 8 with Freelance and 7 with flexible jobs

Participants	Country	Course Platforms	User type
P1	USA	Coursera, edX, OpenSAP	EX
P2	USA	Coursera, edX	EX
P3	Germany	Coursera, edX	EX
P4	India	Coursera, edX	EX
P5	Sri Lanka	Cousera, edX	EX
P6	India	Coursera, edX	EX
P7	India	Coursera, edX	EX
P8	USA	Coursera, edX	EX
P9	India	Coursera, edX	EX
P10	USA	Coursera, edX	EX
P11	Australia	Coursera, edX	NC

P12	Russia	Coursera, edX	NC
P13	Sri Lanka	Coursera, edX, Udacity	NC
P14	Sri Lanka	Coursera, edX	NC
P15	Sri Lanka	Coursera, edX	NC
P16	Finland	Coursera, edX, EMMA	NC
P17	Sri Lanka	Coursera, edX	NC
P18	USA	Coursera, edX, Udacity	NC
P19	USA	Coursera, edX	NC
P20	Germany	Coursera, edX	NC
P21	South Africa	Coursera, edX	NC

3.3 Procedure

Conducting a diary study is time consuming and expensive, yet we planned our study, using resources and time effectively. We structured the diary study process to 5 steps.

During **Step 1**, planned the entire diary study holistically as in timeline, what need to be done and how. Based on literature [7, 19] and our own experience, we identified key tasks that we focus in changing behaviors in MOOCs such as watching video, taking quiz, completing assignments, take part in the forum, and online meetings. Next, we created a logging sheet to maximize the effectiveness of data collection which covered 24 hours of activities, the context of the activity and level of motivation or feeling at the context. At this step, a sample participant was searched, got confirmation agreements for follow up meeting times, payment methods, expectations, payment terms and guided the communication channels. This was a paramount step for us as participants were spread over the globe with different time zones, different expectations and accepting methods. For example, few participants faced issues such as amazon gift cards values were not found useful, issues with bank accounts, unavailability of payment method PayPal. For each participant, we agreed to compensate accordingly. At the same time, we created a comprehensive orientation plan in useful web guide to explain our intentions and to be clear up front on what is expected and how we expect it linking all the contact channels, communication updates and follow up chart.

In **Step 2**, scheduled orientation calls with the confirmed participants in a common Google hangout based on their availability gathered in step 1. We ended up having to organize 4 of the meeting due to time zones and availability of users. During orientation, each participant was given a time to meet us every week individually. This is a one-to-one follow up interview at every end of week of the course they are taking part during the study. During the orientation call, we demonstrated how to use the log sheet and how to incorporate media to provide us rich data, how to reach us and how to upload their daily log sheets.

During **Step 3**, each participant is taking part in a course of their interest MOOC platform. In this case, participants randomly took courses from OpenSAP, Coursera, futurelearn and edX with similar instructional design, 4-5 weeks courses in Humanity, Energy and Entrepreneurship. They are meeting us individually every end week of the course schedule. Normally, a MOOC schedule their activities per week and we meet

the participant in end of the weekly cycle. This process is highly depending on the course schedules; therefore, it took nearly 300 days to completed 21 participants as we fully focused only 1-2 participants at a time. This helped us to get to know more of the participant, give more attention and collect rich data set while keeping them motivated to continue the study until we reach our expectation. The participants took courses between 2017 January to 2017 Oct.

Step 4, was somewhat similar to step 2 as we gathered all the participants who provided the log sheets to reflect their insights as a group. For example, those who took part in a course during May-June 2017 were gathered in July for closing-up meeting to provide us more information of how the overall course experience felt and the course expectations in the respective MOOC platforms they followed.

In **Step 5**, which is the final stage, we made sure all the participants were compensated and cleaned the data for the purpose of analyzing. At the end of this step, we were able to structure, code and summarize the finding to be able to build ENA diagrams and journey maps while preparing context summaries.

Once we collected all the log sheets and transcribed the interviews on each participant, we coded these qualitative details based on previous literature indications of MOOCs behaviors, many participants are either conducting a cognitive task (where their activities based on cognitive behaviors or individual thinks) or social task (based on collective ideas and conversations) [29]. Based on those and convergent by the data, we define 7 codes: 1) Cognitive behaviors of watching video(C.watch Video), 2) Cognitive type of Taking Quizzes(C.Quizzes),3) Cognitive Course Assignments (C. Assignment), 4) Cognitive behavior of Forum usage (C.Forum) Forum Activity, 5) Cognitive type of Meeting and online discussions (C.Discussions) 6) Social Behavior of Forum usage (S.Forum), and 7) Social type of online meeting and discussions (S.Discussions).

ENA was conducted to identify if there are behavioral similarities between extreme users and novice users. The ENA tool [1] was used where its algorithm uses a moving window to construct a network model for each line in the data, showing how codes in the current line are connected to codes that occur within the recent temporal context [15], defined as 1 lines (each line plus the previous lines) within a given conversation. The resulting networks are aggregated for all lines for each unit of analysis in the model. In this model, we aggregated networks using a binary summation in which the networks for a given line reflect the presence or absence of the co-occurrence of each pair of codes. The ENA model included the 7 codes as mentioned and we defined conversations as all lines of data associated with a single value of Participant type where experience or a novice subset by Participant number, C.Watching.video, C.Quizzes, C.Assignment, C.Forum, S.Forum, C.Meeting Discussion, and S.Meeting Discussion. The ENA model normalized the networks for all units of analysis before they were subjected to a dimensional reduction, which accounts for the fact that different units of analysis may have different amounts of coded lines in the data. For the dimensional reduction, we used a singular value decomposition, which produces orthogonal dimensions that maximize the variance explained by each dimension. (See Shaffer et al.,[35] for a more detailed explanation of the mathematics).

In addition, to understand the behavior patterns, logging sheets were analyzed and graphed based on 3 key attributes as: 1) Context (the situation of the participant). 2) Logging time 3) The key tasks performed in the MOOC.

4 Results and Discussion

Our study generated 665 logging sheet entries including context information and motivation levels during the task performed in courses they took part. This is 31.6 sheet entries per person which reflected 89% success compared to overall expected entries per person. Text entries during the interviews were coded using 2 researchers with an inter-rater reliability Cohen Kappa's 0.87.

ENA networks were visualized using network graphs where nodes correspond to the codes, and edges reflect the relative frequency of co-occurrence, or connection, between two codes. Our model had co-registration correlations of 0.96 (Pearson) and 0.96 (Spearman) for the first dimension and co-registration correlations of 0.99 (Pearson) and 0.99 (Spearman) for the second. These measures indicate that there is a strong goodness of fit between the visualization and the original model which intended to see the difference of MOOC behaviors.

At the same time, we plotted behavioral graph based on the 3 attributes which reflect the patterns of behaviors in the usage of MOOCs. Next sections will derive the outcome of the ENA graph which indicate the differences in MOOC extreme vs non extreme users and also type of behavioral patterns.

4.1 MOOC user habits and usage of extreme and novice

Habits are the behavioral patterns visible during time, which will be directly correlating with time of the day and frequency of tasks. Such as "What time of day do users engage in MOOCs? Context of this engagement and weight of the engagement in terms of number of hours spent". Usage can be explained as key tasks perform at the time of engagement where we defined as 7 codes. To test for differences of these behaviors between experienced extreme used and novice, we applied a Mann-Whitney test to the location of points in the projected ENA space for units in Novice and Extreme experienced MOOC participants. The results along the X axis (MR1), a Mann-Whitney test showed that Extreme experienced participants (Mdn=0.52, N=10) was statistically significantly different at the alpha=0.05 level from Novice (Mdn=-0.36, N=11 U=9.50, p=0.00, r=0.83).

Other than these main tasks, occasional log sheet entries with programming, reading books and articles were found. During our follow up interviews, we clarified that those tasks were relating to course assignments. As a key finding, we present that MOOC usage heavily weighted on watching videos (52%). Assignments (25%), quizzes (11%) and least in the forum's (9%) activity and rarely on the online synchronous meetings discussions relating to MOOC (3%). Fig. 1 reflect the specific Extreme experienced participants, Novice participants and compression of 2 groups.

Connection between watching video and use of forum was the highest yet Novice had a weight of 3.21 and Extreme 3.15. Using social type forum and Videos, Novice weighted as 2.53 and Extreme 2.99. In watching video and doing assignments, Novice was 1.78 and Extreme is at 2.46, video and quizzes, Novice was 1.73 while Extreme weighted at 2.00. The graph containing the difference (bottom of Fig 1) indicate the key tasks conducted by extreme users. The results of this behavior in other words proves the previous course survey conducted in OpenHPI platform inquiring perceived helpful features in MOOC which describe 63.7% of students highly satisfied with videos [19]. This indicates that Extreme users are more often complete assignments and quizzes whereas Novice more tend to watch the videos in MOOCs but comparatively less engage in other activities.

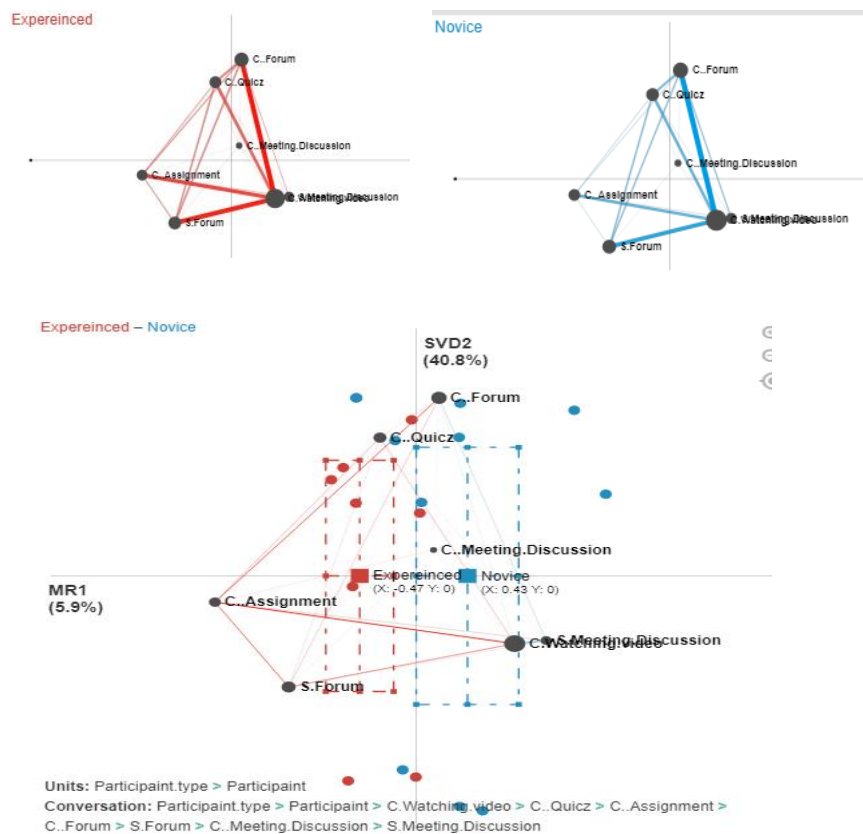


Fig. 1. ENA graphs on Extreme (Red), Novice (Blue) and in the bottom the compression on both groups which indicate the significant lines in red

However, we also scrutinized and map the participants time of the logging, devices they use and context environment at the time of logging. As a key finding, we were

able to classify 4 behavioral patterns based on the user styles. It is presented in the Fig. 2 where based on context, usage task and time of logging its categories into 4 patterns. The green is the use of Mobile device and orange is use of Notebook or PC device to use MOOCs while each pattern has following patterns:

Pattern 1: Active in early morning, logging accessed via a desktop or notebook, used to attempt or complete assignments, reading materials. These are mostly the tasks need high cognitional and both hands in typing, designing, writing, accessing data in own repositories or other.

Pattern 2: Active in mid-morning to afternoon, access via Mobile /portable devices and some with desktops. Mainly consumed content while commuting or unsettled seating environments, such as on the move which hands and legs will be occupied for short roams and activities. This time particularly used to watch / listen videos or short quizzes.

Pattern 3: Active in evening, majority access via Mobile or portable devices, commute in traffic conditions or distance, Major task is watching or listing to the MOOC content video.

Pattern 4: Active in the night to late night, access via Desktop or Notebook, some forum activity, assignment related activities combined with retrospection of overall tasks are commonly practiced.

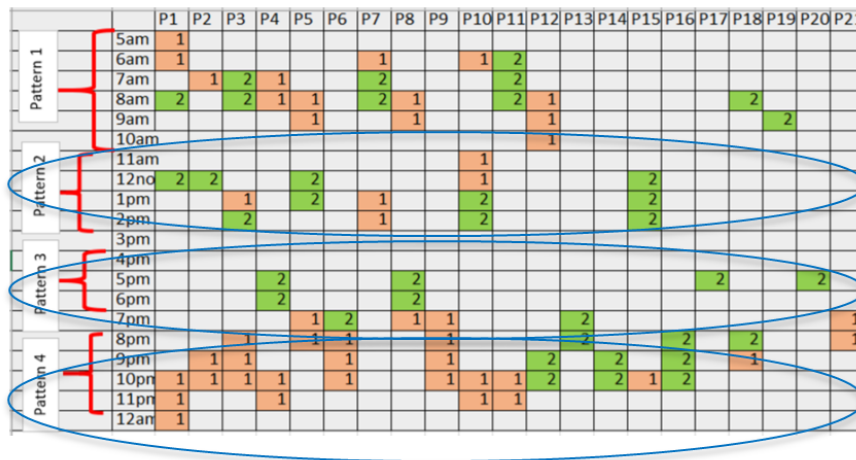


Fig. 2. Behavior based on context, logging time and MOOC tasks of the users identified 4 significant patterns

4.2 Implications of the behavioral patterns

During the study, we not only focused the behavioral patterns, but also the knowhow of the occurrence of these patterns. Majority of video consumption was occurring at the time of users are mostly on the move or in situations such as when they are spent on waiting for something, travelling to daily work or a usual free time

but not enough time to spend related to chores of day. Video consumption mostly incorporated mobiles and other portable devices to access the content. This implies that Short videos commonly practiced in MOOCs and need only short time stamp that can continue any time and context. Participants well adjust MOOC primary task of watching videos in their daily rituals.

We observed that extreme MOOC users have daily rituals cooperating with primary tasks of MOOCs, such as the participant has habits of watching or listening to video while traveling to work, exercise or any other leisure activity. But non extreme users mainly reflect the pattern of “lookers” who mostly spend only on watching video's yet time investment of other activities were limited. Their daily lifestyle carried somewhat unpredictable rituals. We found that P11, P13, P17, P19 and P21 occupied in daily jobs with dramatic changes of workloads such as children's school work, office new project assignments and sudden business travels. They lose track of the MOOCs by missing deadlines where most of MOOCs follow strict deadlines in completing courses. Majority (72%) of the participants indicated the use of MOOCs as a supplement to the knowledge enhancement and less view it as a compulsory livelihood enhancement certificate for work or lifestyle. Participants perceived source of knowledge is the video content in the MOOCs. They explained that, completion of MOOCs has no direct impact, however, if they miss their time of work due to MOOC tasks, it is high likely to meet a direct (negative) impact. Therefore, the least effort's and best outcome perceived as acquiring knowledge by watching video as it is structured more instructive similar to typical university course with easy to follow than self-discovering learners.

Although we observed high video consumption, we found less forum activities (9%) or online or on-site meetings relating to MOOCs (3%). Forum is the main feature of being social and interact with other students in a MOOC. Scrutinizing in to more data in participants social behavior, surprisingly, our results (log entry details) reflected that they are socially active in their physical world which reflected significant social activities such as initiating and having team meeting, friends gathering or even other social activities online such as social media interactions with friends yet none of those characters reflect in their MOOC activity profile. We specifically followed up if they have a log entry with using social media and if it has anything to do with a MOOC friend or group. In other words, we never found log entrees attempting set up a team for study on MOOCs or not even if any participant initiates discussions about the MOOC they follow with immediate family, friends or gusts in the physical world. We were unable to find any significant evidence to MOOC social interactions. However, the log entries with forum, we found that email notifications triggered most of the forum activities to take part and encouraging to interact with each other. Only 2 extreme MOOC participants joined meetings which the course has facilitated. We identified that those participants keep their calendar entries reserved and tracked the timing of the meeting well in advance. Log entry P1.3.2 (participant 1's 3rd week day 2 log entry), P3.1.2, P19.1.3 revealed that forum participation rather an activity they do as a result of the course instructions to introduce themselves. When a user use forum, we made sure to ask if they were requesting some help, socially moving with getting to know each other or any other specific related things in discussion. We

found that none of the social interactions with conversations in “getting and doing things together” were occurred as collective artifacts or building community with sense of belonging. 79% of the forum task were relating to requesting help in technical matters or assignment related matters.

During the task relating to quizzes, participants were able to quickly finish with less cognitive load and just clicking interactions. This interaction is well supported in Mobile by many MOOC providers. We believe, many MOOC platforms provide quiz facility with in the video itself which users must interact to move further. Most occasions, quizzes are light weight reflections from the directly supporting pedagogical concept mastery base learning. In order to complete quizzes, many users use the continuous time of watching video at any context. In other words, as a habit, many users attempt quizzes during the time of watching videos.

Assignments and other related things were highly depended on the participants availability of the time to sit in a relax mode of environment. Overall, only 7% of time used for Assignments. Mostly accessed in the early morning or in the night where users need comfortable typing gestures and comfortable seating positions. Requirement of special context and interactions such as heavy typing, designing or building needed for assignments. Interaction designs beyond typical gestures are needed to build an inclusive user culture.

4.3 MOOC user motivations, changes of behaviors and perception

We examined the participants activities, level of motivation over the period of time from start of the course date to end. Some of the data points in the log entries were confusing to understand as why it was less or high motivating, yet during follow-up interviews we were elaborated comprehensively.

We identified that many users are experiencing significant motivational decrements over time. Experience gaps were well visible towards later stages of the journey of the course. Most commonly, being isolated without a cohort which feels less sense of belonging, they lose interest to continue. Although we observe self-regulated skill in extreme users, they demonstrated experience difficulties in managing time with the daily rituals or unexpected events occurring in the daily life. One other major finding was that user experience difficulties in compatibility of the devices, such as the content is not mobile friendly or the interactions need in MOOC is not usable on a mobile device. Many tasks of the MOOCs required typing actions which mobiles does not provide optimal interface and it is less supportive in providing a better user experience.

At the same time, we found that learners missing deadlines due to loose track of the course, no support from any other learner and sudden changes to daily life rituals affected lot in the motivations and how they experience the course. Once recovering from time disturbances, participants face missing deadlines which has nothing to do with the course quality or learner skills, but merely the learner capacity will ultimately log in system as failures. Therefore, it is vital to understand the experience gaps of MOOC participants to design user centered interventions. Overall, we reveal 2 cate-

gories of experience gaps in the journey of MOOC. These are system gaps and learner gaps.

System gaps: In the MOOC usage, we identified users are shifting devices base on the context. Such as while travelling, users much depend on the mobile, yet only few MOOCs provide the ability to fully function in mobile. Options to access light weight audio files with minimum user interactions were expected at time in this context.

Learner gaps: Participants ability to self- regulate the time consumption effectively and ability to be versatile in any context was much expected.

4.4 Laminations and recommendations

Diary studies usually contain rich data, yet it has the limitation of analyzing biases. At the same time, during this study, we requested participants to take part in a course of their choice in any platform. Although most of the courses in MOOC platforms follow similar structure, changes in course pedagogy and platform features may have affected the leaner experience and behavioral patterns. We revealed that MOOC users may encounter difference learning experience and belong to different behavioral patterns. At the same time, they experience system gaps and learner gaps during the journey of MOOCs. Based on that, our recommendations are 2 folds, Platform recommendations and pedagogical recommendations based on habits and experience gaps.

Micro/Pico completion modes: Pedagogical: Participants required to be able to complete at Micro or Pico learning stages than expectation of completing the weekly cycles such as 4-5 weeks in normal MOOCs. Learning need to be identified as objects which can be combined in creating modules where students will be able to accumulate based on time demands and volatile time availability of each learner. This will benefit learners who demonstrated each behavioral pattern. Currently, if student complete the course work early in the week, it does not impact to the overall completion. However, if students could finish modules and return at next stage to continue, complete and if it is measured by how many modules were completed oppose to requirement spending all 4-5 weeks, will demonstrate the effective use of volatile time of the participants. Therefore, we recommend success as not the competition rates at the end of the course but Micro / Pico levels over the time.

Device independence on tasks: Platform: Many MOOC participants use different devices based on the task, such as portable devices for watching videos. Much rarely participants use Mobile devices to contribute to forum or assignment submissions. The space is wide open for designers to understand on-the-go users and implement interactions catering to the needs. Such as, while unable to use the typing, how might the user complete other tasks? Is typing required using fingers? Such temporal considerations have been device driven, not work driven. In contrast, less research has been undertaken in understanding of temporal factors of the social and organizational environment that shape work. We recommend to explore user centered contextual driven interaction techniques for MOOCs to incorporate in Primary tasks,

5 Conclusion

We claimed that MOOC users behavioral habits have been analyzed using surveys, system analytic with in the MOOC platform and some in out side the platform using social media. User behaviors in the systems will provide limited knowledge of learner behavioral changes over the time. Mainly it does not capture learner motivations, context of the learner and learner experience at the time of the tasks. To identify learner behaviors with context over time, we used user experience method diary study. We strategically design the diary study into 5 step process and conducted the study using 21 MOOC participants spending 4-5 weeks with each participant. With the use of effective strategies such as in-situ logging, designed logging sheet, defined and useful communication and compensation mechanism we completed the study analysing log data and interviews using ENA methods. Identifying MOOC habits, usage and behavioral changes over time beyond the system or social media, Our results indicated 4 behavioral patterns depending on time, context and device. At the same time gaps in the experience was found as system and learner gaps while extreme user behaviors significant to novice users of MOOC. Based on the findings, we provide 2 recommendations. Although it is not the only possibility to enhance user experience, we anticipate more studies over the time to understand more users and promote user centered design for MOOC users.

6 References

- [1] ENA Epistemic Network Analysis Tool. <https://app.epistemicnetwork.org>. Accessed: 2019-09-30.
- [2] Fabian Abel, Qi Gao, Geert-Jan Houben, and Ke Tao. 2011. Semantic enrichment of twitter posts for user profile construction on the social web. In Extended semantic web conference. Springer, 375–389. https://doi.org/10.1007/978-3-642-21064-8_26
- [3] Yoram Bachrach, Michal Kosinski, Thore Graepel, Pushmeet Kohli, and David Stillwell. 2012. Personality and patterns of Facebook usage. In Proceedings of the 4th annual ACM web science conference. ACM, 24–32. <https://doi.org/10.1145/2380718.2380722>
- [4] Javier A Bargas-Avila and Kasper Hornbæk. 2011. Old wine in new bottles or novel challenges: a critical analysis of empirical studies of user experience. In Proceedings of the SIGCHI conference on human factors in computing systems. ACM, 2689–2698. <https://doi.org/10.1145/1978942.1979336>
- [5] Patrick Biernacki and Dan Waldorf. 1981. Snowball sampling: Problems and techniques of chain referral sampling. *Sociological methods & research* 10, 2 (1981), 141–163. <https://doi.org/10.1177/004912418101000205>
- [6] Scott Carter and Jennifer Mankoff. 2005. When participants do the capturing: the role of media in diary studies. In Proceedings of the SIGCHI conference on Human factors in computing systems. ACM, 899–908. <https://doi.org/10.1145/1054972.1055098>
- [7] John Champaign, Kimberly F. Colvin, Alwina Liu, Colin Fredericks, Daniel Seaton, and David E. Pritchard. 2014. Correlating Skill and Improvement in 2 MOOCs with a Student's Time on Tasks. In Proceedings of the First ACM Conference on Learning @ Scale Conference (L@S '14). ACM, New York, NY, USA, 11–20. <https://doi.org/10.1145/2556325.2566250>

- [8] Bodong Chen, Yizhou Fan, Guogang Zhang, and Qiong Wang. 2017. Examining motivations and self-regulated learning strategies of returning MOOCs learners. In Proceedings of the Seventh International Learning Analytics & Knowledge Conference. ACM, 542–543. <https://doi.org/10.1145/3027385.3029448>
- [9] Guanliang Chen, Dan Davis, Jun Lin, Claudia Hauff, and Geert-Jan Houben. 2016. Beyond the MOOC platform: gaining insights about learners from the social web. In Proceedings of the 8th ACM Conference on Web Science. ACM, 15–24. <https://doi.org/10.1145/2908131.2908145>
- [10] Karen Church and Barry Smyth. 2008. Understanding Mobile Information Needs. In Proceedings of the 10th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '08). ACM, New York, NY, USA, 493–494. <https://doi.org/10.1145/1409240.1409325>
- [11] Derrick Coetzee, Armando Fox, Marti A Hearst, and Björn Hartmann. 2014. Should your MOOC forum use a reputation system?. In Proceedings of the 17th ACM conference on Computer supported cooperativework & social computing. ACM, 1176–1187. <https://doi.org/10.1145/2531602.2531657>
- [12] Derrick Coetzee, Seongtaek Lim, Armando Fox, Bjorn Hartmann, and Marti A Hearst. 2015. Structuring interactions for large-scale synchronous peer learning. In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing. ACM, 1139–1152. <https://doi.org/10.1145/2675133.2675251>
- [13] Shane Dawson, Srecko Joksimovic, Oleksandra Poquet, and George Siemens. 2019. Increasing the Impact of Learning Analytics. In Proceedings of the 9th International Conference on Learning Analytics & Knowledge (LAK19). ACM, New York, NY, USA, 446–455. <https://doi.org/10.1145/3303772.3303784>
- [14] Rebecca Ferguson and Doug Clow. 2015. Examining Engagement Analysing Learner Subpopulations in Massive Open Online Courses (MOOCs). In Proceedings of the Fifth International Conference on Learning Analytics And Knowledge (LAK '15). ACM, New York, NY, USA, 51–58. <https://doi.org/10.1145/2723576.2723606>
- [15] Simon Skov Foug, Amanda Siebert-Evenstone, Brendan Eagan, Sara Tabatabai, and Morten Misfeldt. 2018. Epistemic Network Analysis of Students' Longer Written Assignments As Formative/Summative Evaluation. In Proceedings of the 8th International Conference on Learning Analytics and Knowledge (LAK '18). ACM, New York, NY, USA, 126–130. <https://doi.org/10.1145/3170358.3170414>
- [16] Dilrukshi Gamage, Shantha Fernando, and Indika Perera. 2015. Effectiveness of elearning: Grounded theory approach. In Moratuwa Engineering Research Conference (MERCOn), 2015. IEEE, 336–341. <https://doi.org/10.1109/mercon.2015.7112369>
- [17] Dilrukshi Gamage, Shantha Fernando, and Indika Perera. 2015. Factors leading to an effective MOOC from participants perspective. In Ubi-Media Computing (UMEDIA), 2015 8th International Conference on. IEEE, 230–235. <https://doi.org/10.1109/umedia.2015.7297460>
- [18] Dragan Gasevic, Vitomir Kovanovic, Srecko Joksimovic, and George Siemens. 2014. Where is research on massive open online courses headed? A data analysis of the MOOC Research Initiative. The International Review of Research in Open and Distributed Learning 15, 5 (2014). <https://doi.org/10.19173/irrodl.v15i5.1954>
- [19] Franka Grünewald, Christoph Meinel, Michael Totschnig, and Christian Willems. 2013. Designing MOOCs for the support of multiple learning styles. In European Conference on Technology Enhanced Learning. Springer, 371–382. https://doi.org/10.1007/978-3-642-40814-4_29

- [20] Philip J Guo, Juho Kim, and Rob Rubin. 2014. How video production affects student engagement: an empirical study of MOOC videos. In Proceedings of the first ACM conference on Learning@ scale conference. ACM, 41–50. <https://doi.org/10.1145/2556325.2566239>
- [21] Bo Han, Paul Cook, and Timothy Baldwin. 2014. Text-based twitter user geolocation prediction. *Journal of Artificial Intelligence Research* 49 (2014), 451–500. <https://doi.org/10.1613/jair.4200>
- [22] Eiji Hayashi and Jason Hong. 2011. A Diary Study of Password Usage in Daily Life. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11). ACM, New York, NY, USA, 2627–2630. <https://doi.org/10.1145/1978942.1979326>
- [23] Kate S Hone and Ghada R El Said. 2016. Exploring the factors affecting MOOC retention: A survey study. *Computers & Education* 98 (2016), 157–168. <https://doi.org/10.1016/j.compedu.2016.03.016>
- [24] Biyun Huang and Khe Foon Hew. 2017. Factors Influencing Learning and Factors Influencing Persistence: A Mixed-method Study of MOOC Learners' Motivation. In Proceedings of the 2017 International Conference on Information System and Data Mining. ACM, 103–110. <https://doi.org/10.1145/3077584.3077610>
- [25] René F Kizilcec, Chris Piech, and Emily Schneider. 2013. Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. In Proceedings of the third international conference on learning analytics and knowledge. ACM, 170–179. <https://doi.org/10.1145/2460296.2460330>
- [26] Lisa Lim, Shane Dawson, Srečko Joksimovic, and Dragan Gašević. 2019. Exploring Students' Sensemaking of Learning Analytics Dashboards: Does Frame of Reference Make a Difference?. In Proceedings of the 9th International Conference on Learning Analytics & Knowledge (LAK19). ACM, New York, NY, USA, 250–259. <https://doi.org/10.1145/3303772.3303804>
- [27] Dong Nguyen, Rilana Gravel, Dolf Trieschnigg, and Theo Meder. 2013. "How Old Do You Think I Am?" A Study of Language and Age in Twitter.. In ICWSM.
- [28] David M. Nichols and Sally Jo Cunningham. 2009. The Use of Paper in Everyday Student Life. In Proceedings of the 10th International Conference NZ Chapter of the ACM's Special Interest Group on Human-Computer Interaction (CHINZ '09). ACM, New York, NY, USA, 65–68. <https://doi.org/10.1145/1577782.1577794>
- [29] Poquet Oleksandra and Dawson Shane. 2016. Untangling MOOC Learner Networks. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge (LAK '16). ACM, New York, NY, USA, 208–212. <https://doi.org/10.1145/2883851.2883919>
- [30] Daniel FO Onah, Jane Sinclair, and Russell Boyatt. 2014. Dropout rates of massive open online courses: behavioural patterns. *EDULEARN14 proceedings* (2014), 5825–5834.
- [31] Daniel Preoțiu-Pietro, Vasileios Lampos, and Nikolaos Aletras. 2015. An analysis of the user occupational class through Twitter content. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), Vol. 1. 1754–1764. <https://doi.org/10.3115/v1/p15-1169>
- [32] Emily Schneider and René F. Kizilcec. 2014. "Why Did You Enroll in This Course?": Developing a Standardized Survey Question for Reasons to Enroll. In Proceedings of the First ACM Conference on Learning @ Scale Conference (L@S '14). ACM, New York, NY, USA, 147–148. <https://doi.org/10.1145/2556325.2567852>

- [33] D Shaffer and A Ruis. 2017. Epistemic network analysis: A worked example of theory-based learning analytics. *Handbook of learning analytics* (2017). <https://doi.org/10.18608/hla17.015>
- [34] David Williamson Shaffer. 2017. *Quantitative ethnography*. Lulu. com.
- [35] David Williamson Shaffer, Wesley Collier, and AR Ruis. 2016. A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics* 3, 3 (2016), 9–45. <https://doi.org/10.18608/jla.2016.33.3>
- [36] Anjali Singh and Sareeka Malhotra. 2013. A researcher’s guide to running diary studies. In *Proceedings of the 11th Asia Pacific Conference on Computer Human Interaction*. ACM, 296–300. <https://doi.org/10.1145/2525194.2525261>
- [37] Jonathan H Tomkin and Donna Charlevoix. 2014. Do professors mat-ter?: Using an a/b test to evaluate the impact of instructor involvement on MOOC student outcomes. In *Proceedings of the first ACM conference on Learning@ scale conference*. ACM, 71–78. <https://doi.org/10.1145/2556325.2566245>
- [38] George Veletsianos, Amy Collier, and Emily Schneider. 2015. Digging deeper into learners’ experiences in MOOC s: Participation in social networks outside of MOOC s, notetaking and contexts surrounding content consumption. *British Journal of Educational Technology* 46, 3 (2015), 570–587. <https://doi.org/10.1111/bjet.12297>
- [39] Yue Zhao, Dan Davis, Guanliang Chen, Christoph Lofi, Claudia Hauff, and Geert-Jan Houben. 2017. Certificate Achievement Unlocked: How Does MOOC Learners’ Behaviour Change?. In *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*. ACM, 83–88. <https://doi.org/10.1145/3099023.3099063>

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