MOOC Learner Behaviors by Country and Culture; an Exploratory Analysis

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ABSTRACT

The advent of Massive Online Open Courses (MOOCs) has led to the availability of large educational datasets collected from diverse international audiences. Little work has been done on the impact of cultural and geographic factors on student performance in MOOCs. In this paper, we analyze national and cultural differences in students' performance in a large-scale MOOC. We situate our analysis in the context of existing theoretical frameworks for cultural analysis. We focus on three dimensions of learner behavior: course activity profiles; quiz activity profiles; and most connected forum peer or best friends. We conclude that countries or associated cultural clusters are associated with differences in all three dimensions. These findings stress the need for more research on the internationalization in online education and greater intercultural awareness among MOOC designers.

1. INTRODUCTION

Over the past decade there has been a substantial increase in the study of cross-cultural behaviors in e-learning systems. Prior researchers have shown that learners from different cultures behave differently when using educational systems, particularly in terms of their off-task behaviors [25, 21], help-seeking [21], and collaboration [22, 16]. The cultural differences uncovered in these studies suggest that designers of future e-learning platforms would benefit from a better understanding of their distinct target populations and distinct cultures.

Large-scale MOOCs typically attract diverse international audiences. The course we discuss here, for example, attracted students from 172 countries on 5 continents. Despite this acknowledged diversity, most MOOCs take a one-size fits-all approach to designing and structuring the course. The materials are typically offered in a single format and language, or via direct translations that preserve the structure, pacing, and content.

Prior researchers have shown that country of origin affects students' performance in MOOCs. Nesterko et al. [19] found that non-American students were more prone to complete MOOCs and to seek certification than their U.S. counterparts. Guo and Reinecke [12] found that a student's country of origin significantly predicted the amount of content that they would cover and the amount of time that they spent reviewing prior course content. Kizilcec [17] found that there was a significant correlation between a country's level on the Human Development Index and the number of students from that country who completed a majority of the assignments. In each of these studies, however, nationality was treated as a single independent factor. No substantive comparisons were made between countries or cultures, nor did the authors frame their conclusions in the context of prior theoretical work on cultural differences in learning

A deeper understanding of how students differ both within and across cultures will help us to design and deploy more effective, and truly international MOOCs. And this understanding will be enriched by relating these differences to the rich existing literature on cross-cultural education such as Hofstede's cultural dimensions theory [13] and the Cultural Dimensions of Learning Framework (CDLF). In this paper we will address this need through our analysis of crosscultural student behaviors in an existing MOOC. This was an open course with a total enrollment of 29,149 students drawn from 172 countries and 5 continents. We found clear inter-country and inter-cultural differences in the observed stu-

dent behaviors and in the distribution of user categories. We also found that these differences can be evaluated in the context of existing theoretical frameworks and that they are consistent with prior educational literature.

2. LITERATURE REVIEW

2.1 Culture & Educational Technology

Advances in educational technology have enabled educators to incorporate technologies at larger scale and to collect richer and more diverse educational data than ever before. This has, in turn, substantially increased interest in studying variations in the use of e-learning tools across cultures

One approach to understanding the impact of culture on learning is through field observation. Rodrigo et al. [25] coded U.S. and Filipino students' on- and off-task behaviors when using three ITSs. They found that Filipino students spent more time on task than their U.S. counterparts on all three systems. They also found that the Filipino students gamed some systems more than others. Similarly, Ogan et al. [22] coded the on-task behaviors and interaction of similar students in Chile. They found that the Chilean students had a higher proportion of on-task interactions than the U.S. students studied previously.

Another approach is through educational data mining. Ogan et al. [21] generated student models from ITS logs collected in three countries: Costa Rica, The Philippines, and the U.S. Their goal in this work was to predict effective helpseeking behaviors. They found that it was possible to generalize the U.S. model to Filipino students but not to students from Costa Rica. Saarela and Karkkainen [27] applied a hierarchical clustering algorithm to data collected from the PISA, a worldwide assessment of 15-year old students covering reading, mathematics, and science. They found that students' performance on the test clustered by country, suggesting cultural influences.

While these studies found interesting cross-cultural differences, we have little understanding of why these differences occur, or of how they relate to more general cross-cultural variation. Learning behaviors are influenced by a complex set of factors and cross-cultural comparisons may help us deepen our understanding of this phenomenon and highlight ways to remediate or accommodate it. In this paper, we explore the logs of student activity in a MOOC, with an eye toward how culture may relate to differences in behavior.

2.2 MOOC Research

MOOCs represent both opportunities and challenges for educators. On the one hand they involve large numbers of users working in highly instrumented systems which can, in turn, provide deep insights. On the other hand, however, MOOCs have high dropout rates, wide variation in levels of engagement, and MOOC users have extremely diverse motivations and demographic backgrounds. Thus any insights are qualified by the noisy nature of the data. Researchers have therefore focused their efforts on better understanding MOOC users and their differing behavior patterns.

One approach to understanding MOOC students is to build predictive behavior models based upon their clickstream data,

such as mining sequences of actions for analysis [29, 5]. These induced models are highly accurate but are not always readily interpretable. Other work has focused on improving our understanding of engagement and dropouts by detecting key subgroups. In this work, researchers have used hierarchical clustering to identify groups of students with similar patterns of engagement, such as those who viewed many lectures but rarely attempted quizzes, and those who balanced their activities equally [17, 10, 4, 1]. Kizilcec et al. [17] and Ferguson et al. [10], for example, clustered students by engagement factors such as the number of lectures viewed and quizzes attempted. Anderson et al. [1] likewise used lecture views and considered the ratio of lectures to assignments while Bergner et al. [4] focuses solely on assignments attempted. These studies served to highlight the distinct behavioral patterns of different subgroups.

Researchers have also begun to study students' diverse backgrounds through voluntary surveys with the goal of understanding how their incoming motivation [28, 2] and demographic features [19, 17, 12] affect their observed behaviors. Both Nesterko [19] and Deboer [9] found that participation (as indicated by survey responses) and certificate attainment rates differed across countries, continents, and genders; they did not, however, delve deeper into students' in-system behaviors as logged by the learning environment. Wang and Baker [28], by contrast, found that learners receiving course certificates tended to be more interested in course content, while students not receiving certificates often stated that they were seeking a new type of learning experience.

Few of these researchers however, have focused on the relationship between geographic information and observed behaviors. Guo and Reinecke [12] applied linear regression to correlate some demographic features such as years of education to geographic data. They found that a students' country of origin was significantly related to their coverage of the course content overall and the extent to which they reviewed prior content, called backjumps. They attributed this diversity to varying student-to-teacher ratios. They found that countries with a higher ratio had a higher frequency of backjumps suggesting more time on review. In related work Kizilcec focused on partitioning countries into tiers based upon the Human Development Index (HDI). They found that as the HDI tier increased, so to did the proportion of students who completed the course. While these results are instructive, however, the authors made no attempt to situate these results in the context of existing theoretical models of cross-cultural learning.

Thus the results from prior MOOC research show that understanding students' diverse backgrounds can be essential to the development of effective educational interventions, and to providing useful support for student engagement and participation. Geographical location, considered as a set of economic, cultural, and educational differences, may play a crucial role in understanding, supporting, and appealing to the increasing population of MOOC users.

2.3 Theoretical Frameworks

MOOCs and educational technologies allow us to collect robust information about cross-cultural differences in user behaviors. Yet we face challenges in interpreting and explain-

ing these results in a consistent theoretical framework.

Prior educational researchers have worked to identify related cultural dimensions and values, and to examine how they vary across cultures. One common framework is Hofstede's Cultural Dimensions Theory [13, 14]. Hofstede analyzed a set of 117,000 attitude surveys collected by IBM from their international workforce and synthesized a set of 7 general cultural dimensions: a) power distance; b) collectivism vs. individualism; c) femininity vs. masculinity; d) uncertainty avoidance; e) long/short term orientation; and f) indulgence vs. restraint. Hofstede then calculated scores for each culture within these dimensions.

Hofstede's dimensions have been used to analyze and explain differences in collaboration across cultures [16], as well as differences in help-seeking and off-task behavior in educational technology [21, 25]. However these studies have suggested that the cultural dimensions framework has some limitations in explaining these findings. Many of the key differences in the observed behaviors do not correspond to the differences that Hofstede's theory suggests. In particular, variations in collectivism and collaboration/help-seeking strategies do not seem to relate well to Hofstede's underlying dimensions. Therefore we will combine this with the Cultural Dimensions Learning Framework (CDLF).

The CDLF framework, designed by Parrish et al. in 2010 [24], defines eight cultural parameters regarding social relationships, epistemological beliefs, and temporal perceptions, and how they manifest in learning situations. The CDLF has been used to guide the design and analysis of e-learning across cultures [23, 15]. For the purposes of our analysis we will focus on the intersection of the CDLF and the Hofstede dimensions. We will use this hybrid framework to group countries into cultural clusters, and to interpret the observed behavioral differences between them. Table 1 provides an overview of the shared dimensions.

While these frameworks may help to explain observed behaviors, it is worth noting that learner behaviors in MOOCs can be affected by many other factors such as personal motivation. Wang and Baker [28], for example, surveyed the motivations of incoming students on a later version of the course we study here and found that learners who obtained course certificates tended to be more interested in course content than those who took the MOOC in order to test the learning experience. While this highlights the importance of individual differences, our analysis below we will focus on inter-country differences and cultural factors.

3. DATA

The data used in this study was collected from Big Data in Education (BDE), an 8-week long MOOC offered by the Teacher's College at Columbia University on the Coursera platform [28]. The BDE curriculum included video lectures, discussion forums, and 8 weekly assignments or quizzes. The lectures covered key methods for educational data analysis. The assignments required students to analyze existing data (typically real data collected from educational settings) and to answer questions about their results. All of the assignments were automatically graded via numeric or multiplechoice questions. Students were given between 3 and 5

Table 1: Intersection of Hofstede Dimensions and the Cultural Dimensions of Learning Framework.

Hofstede Dimension [13]	Selected Interpretations in CDLF [24]
Power Distance: the extent to which the less powerful members expect and accept unequal/unfair situations.	Countries with high power distance view teacher as an unchallenged authority and the primary communicator, not as a fallible peer.
Individualism: the degree of interdependence a society maintains among its members	Highly individualist students are more prone to speak up in class, to value diverse opinions in learning, and to be motivated by personal gain.
Masculinity: the degree to which a culture is motivated by competition (instead of life quality)	More masculine cultures are associated with increased levels of competition and a heavier pursuit of recognition.
Uncertainty Avoidance: The extent to which a culture feels threatened by ambiguous or unknown situations and tries to avoid these	Students who avoid uncertainty tend to focus more on getting the right answer from authoritative sources and from the structured learning activities.

attempts to complete each assignment with the best score being counted. Students were required to complete their assignments within 2 weeks of it being released. In order to obtain a certificate students were required to obtain an average grade of $\geq 70\%$ over all 8 assignments. High performing students could receive a certificate with distinction. 638 students completed the course and obtained a certificate.

Data from this course has been previously used to study motivation [28], negativity [7], student communities [6], the relationship between linguistic quality of forum posts and completion [8], as well as longitudinal behavior patterns [31].

For the purposes of our analysis we analyzed clickstream data containing user IDs, IP addresses, URLs and timestamps for 29,149 students. This data included all 638 students who received a certificate as well as 750 who posted on the forum. After classifying students by behavior type we found that a total of 1,591 students were actively engaged with the course while the remaining 27,588 were 'bystanders' who enrolled but did not do any significant work. We assigned users to regions based upon their most frequent IP address as has been done in prior work [17, 9, 12]. The top 15 countries by registration are shown in Figure 1.

We then analyzed the URLs located in the clickstream data to identify the following major activities: view lecture (VL), attempt or submit quiz (AQ, SQ), and read or make a post in forum (RP, MP). We then generated activity sequences from this data using an n-gram approach consistent with prior research [29, 5]. Note that this data does not contain information about how long the student spent viewing a URL. The data only records individual mouseclicks. Therefore it functions as a record of student access but not
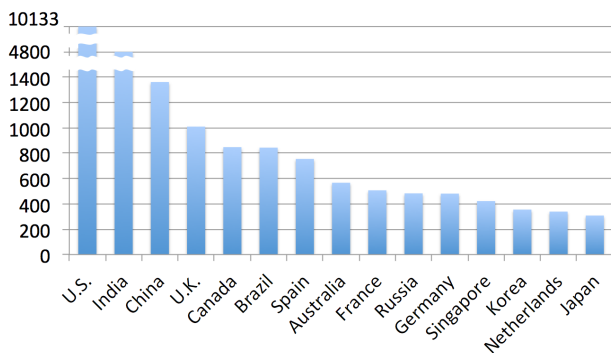
Figure 1: Number of Registrants from the Top 15 Countries with Most Registrants

a reliable indicator of engagement.

4. METHODS AND RESULTS

We hypothesize that students from different countries or cultures will behave differently in the course. We chose to examine four research questions: *RQ1. (Course Activity Profiles, CAPs)* What are the primary categories of students based upon the frequency (both total and relative) with which they accessed different course activities? *RQ2. (CAPs by Country)* Does the proportion of student categories differ by country? *RQ3. (Quiz Activity Profiles, QAPs)* When do students in each category access the different types of course activities and how is that correlated with quiz submissions? *RQ4. (QAPs by Culture & Country)* How do quiz-based activity profiles and countries relate to the four overlapping Hofstede/CDLF cultural dimensions of: power distance, individualism, masculinity, and uncertainty avoidance? *RQ5. (Forum best friends)* Is a student's most frequent forum partner in the same country/culture?

For RQ1, we used hierarchical clustering to identify five course activity profiles (CAPs) (e.g. students who focused solely on quizzes). For RQ2, we clustered countries by the proportion of students who fit each CAP in order to determine whether or not students from a given country are more likely to fit one CAP over another. For RQ3, we partitioned the course data by quizzes and examined whether or when students in each CAP accessed the lectures, quizzes, and forum content. This led to the development of Quiz Activity Profiles (QAPs). For RQ4, we then clustered students based upon their cultural dimensions and compared the QAPs by culture and student category (CAP). For RQ5, we performed a χ^2 analysis to investigate whether the students' most frequent interlocutor on the forums were more likely to be drawn from the same country/culture. In each section below, we will present the methods and results for each of these questions in greater detail.

4.1 RQ1: Course Activity Profiles, CAPs

What are the primary categories of students based upon the frequency (both total and relative) with which they accessed different course activities? Prior researchers have used hierarchical clustering to discover meaningful subgroups such as: users who viewed many lectures but rarely attempted

quizzes and users who balanced the number of lectures viewed and quizzes attempted [17, 10, 4, 1].

In this work we applied hierarchical clustering to classify students based upon the proportion of activities that they engaged in over the course. These included: lectures accessed, quizzes attempted, and form posts made or accessed. We found that clustering students by the the number of lectures that they accessed and quizzes attempted yielded five interpretable clusters which we designated solvers (generally take more quizzes), viewers (generally watch more lectures), all-rounders (balance both), samplers (watch some lectures and do a quiz), and bystanders (do very little). Table 2 shows the CAP clusters with average silhouette widths (ASWs) in excess of 0.68, which indicates that they are well-chosen classifications [26]. These CAPs closely resemble the student types described by Anderson et al. [1] who clustered MOOC students based upon the ratio of lectures viewed to assignments completed. In this case we used attempts in place of submissions.

Table 2: Course Activity Profile Clusters: size, #lectures viewed, #quiz attempts, and performance.

CAP	Lectures viewed (max:54)	Quizzes Attempted (max:7)	% Certificate	
			Distinct	Normal
Viewer (n=107, ASW=0.72):mainly view lectures	M:49.57 SD:2.95	M:0.55 SD:0.96	0%	0%
Solver (n=388, ASW=0.72):mainly attempt quizzes	M:5.30 Sd:7.15	M:7.67 Sd:0.77	41.10%	0.07%
All-rounder (n=519, ASW=0.68):balance lectures & quizzes	M:45.23 Sd:8.3	M:7.58 Sd:0.89	79.19%	8.29%
Bystander (n=27558, ASW=0.84):do little	M:1.87 Sd:2.72	M:1.25 Sd:1.43	0%	0%

As Table 2 shows, the all-rounders have the highest rate of certificate completion. For the rest of our analysis we will focus on three categories: viewer, solver, and all-rounder.

4.2 RQ2: CAPs by Country

Does the proportion of student categories differ by country?

After identifying the meaningful CAP clusters, we compared countries based upon the proportion of CAPs observed. We again applied hierarchical clustering on countries with more than 15 users from the viewer, solver, and all-rounder students. In this case we found that three clusters yielded the highest ASW values. These clusters are shown in Figure 2.

This clustering grouped countries with a high proportion of solvers in Cluster1. This includes developing countries, Russia, and Singapore. The proportion of solvers present in Cluster 1 is significantly higher than that of cluster 3:

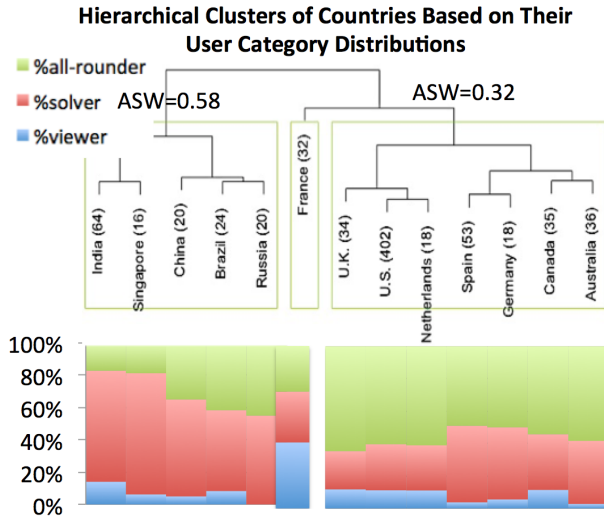**Hierarchical Clusters of Countries Based on Their User Category Distributions**

Figure 2: Hierarchical clusters of countries by proportion of user categories. For each country, the proportion of user categories is plotted as stacked bar, and the sample size is given in parentheses

$\chi^2(1, N = 740) = 34.95, p < 0.001.$

4.3 RQ3. Quiz Activity Profiles, QAPs

When do students in each category access the different types of course activities and how is that correlated with quiz submissions?

After identifying the CAPs and examining their relative proportion within countries, we proceeded to analyze the inter-country behavioral differences within each CAP. It is our hypothesis that students from different countries will behave differently given the different Hofstede/CDLF dimensions. In order to assess this hypothesis we analyzed the behavioral differences among users with regards to the course content accessed in the three learning phases described below.
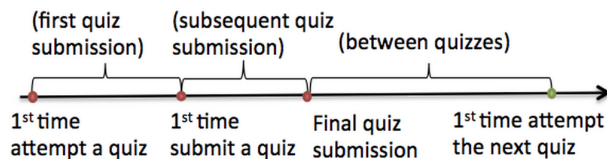

Figure 3: Illustration of the three learning phases

In order to better understand when students engaged in different learning activities we segmented the activity sequences into three phases based upon the quiz attempts. These phases are shown in Figure 3. For each phase we counted average number of lectures viewed (VL), forum posts made (MP), and posts read (RP). For the first quiz submission, and for the subsequent submission phases, we also counted the average number of times that a student attempted and submitted the same quiz (AQ, SQ). We excluded viewers from this analysis as they made little to no attempts at the quizzes.

The relative QAP values for solvers and all-rounders in this analysis are shown in Figure 4. We then conducted a series of pairwise Kruskal-Wallis tests [20] with Benjamini-Hochberg correction [3] comparing the performance by group and learning phase to a baseline of the course average. We found that the solvers and all-rounders viewed significantly more lectures between the quizzes and read more posts during subsequent quiz submissions than in the other learning phases.
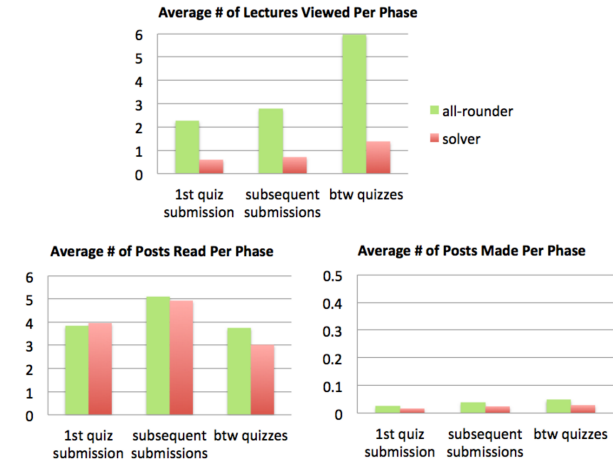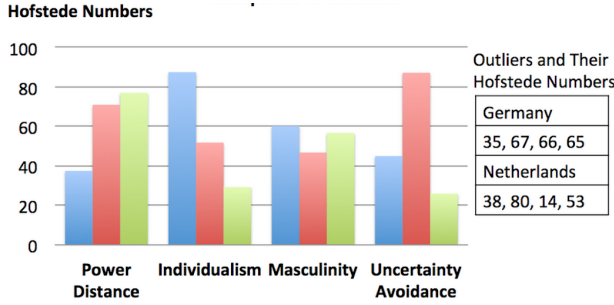

Figure 4: Quiz Activity Profiles for Solvers and All-rounders in Three Learning Phases.

4.4 RQ4. QAPs by Culture

How do quiz-based activity profiles and countries relate to the four overlapping Hofstede/CDLF cultural dimensions of: power distance, individualism, masculinity, and uncertainty avoidance?

We applied hierarchical clustering on countries with morethan 15 all-rounders, solvers or viewers, based on the fourHofstede dimensions [13] incorporated in CDLF [24]. We foundthree clusters with ASWs over 0.46. We treated the firstcluster as the baseline for comparison since it contains themajority population in BDE. We conducted a Kruskal-Wallistest on the QAPs between clusters, for each course activityin each learning phase. The results are shown in Figure 5.

Countries in cultural cluster 1 (Australia, Canada, the U.S. and U.K. cluster) have the lowest average power distance and the highest average individualism. In our analysis we found that solvers in clusters 2 (Russia, Spain, Brazil, & France) and 3 (China, India, & Singapore) read and made fewer posts during multiple learning phases. These differences were significant or marginally-significant. Moreover, solvers in cluster 3, whose countries are characterized by the highest average power distance and lowest average individualism, viewed significantly fewer lectures between the quizzes. All-rounders in cluster 3 also viewed significantly fewer lectures during the first quiz submission and made more submissions per quiz, this difference was marginally significant.

Figure 5: Cultural clusters based on Hofstede-CDLF values with statistically-significant values ($p \leq 0.05$ bolded) and marginally significant ($p \leq 0.1$) QAP differences as compared to baseline behaviors.

We found a high degree of overlap between the cultural clusters and the CAP clusters described in section 4.2. Cultural cluster 1 is a subset of the all-rounder CAP cluster, by country, and cultural cluster 3 is a subset of the solver CAP cluster. These results suggest that students from countries with higher individualism and lower power distance are twice as likely to be all-rounders, while students from countries with higher power distance and lower individualism are more prone to focus on evaluations. However, cultural cluster 2 includes students that were evenly split between solvers and all-rounders. These findings suggest that the cultural dimensions are directly connected to some aspects of the students' observed behaviors, but other personal motivations may also dominate student behaviors.

4.5 RQ5. Forum "Best Friend"

Is a student's most frequent forum partner in the same country/culture?

For this analysis we identified each students' "best friend" based upon their forum interactions. In a prior study, we tested whether we can predict students' performance in the course based upon their implicit social relationships in the forum [11]. In this case we constructed a similar relationship graph for the 750 forum users based upon that work and the work of Fire et al. [6]. Edges in the graph were weighted based upon the number of times that a user had replied to a

thread that the other used had posted in. We then defined a students' "best friend" as the individual with the highest-weighted edge between them.

Then, for each of the top 15 countries and the 3 cultural clusters defined in the prior section we performed a χ^2 test with the proportion of "best friends" within the cluster as the dependent variable. Our goal was to test whether or not the cluster was a significant predictor of the proportion of individuals with "best friends" in their cluster. The results are shown in Table 3. We found that for all three cultural clusters, the students are significantly more likely to have a best friend within their own country.

Table 3: Groups whose "best friends" are significantly more likely to be from the same group

Clusters & Countries	% IN this group with best friends in this group	% NOT IN this group with best friends in this group	p
Cluster1(n=381): Australia, Canada,U.S.,U.K.	64.04%	54.09%	0.0065
Cluster2(n=83): Russia, Spain, Brazil, France	36.60%	5.93%	<0.001
Cluster3(n=91): China, India, Singapore	19.78%	10.13%	0.0066
China (n=19)	26.32%	1.99%	<0.001
Brazil (n=38)	63.16%	1.31%	<0.001

5. DISCUSSION

In this study, we conducted an exploratory analysis on three dimensions of MOOC behavior by country and culture. We first identified five Course Activity Profiles (CAPs) based on the number of lecture views and quiz attempts: viewers, solvers, all-rounders, samplers, and bystanders. We found that the all-rounder students were most likely to obtain a certificate of completion, followed by the solvers. This indicates that the behavior profiles exhibited by these groups are a good indicator of students who are working toward certification.

We then studied the distribution of CAPs over countries. To that end we clustered countries with 15 or more students in the solver, viewer, or all-rounder categories based upon their CAP distributions. Interestingly we found that the developing countries in our dataset all contained a substantially higher proportion of solvers than other countries. We then clustered the same set of countries using the Hofstede/CDLF cultural frameworks [13, 24]. We found that the resulting cultural clusters also aligned with the observed student types. Our first cultural cluster, which included Australia, Canada, the U.S., and the U.K., was dominated by all-rounders while our third cluster, which included China, India, and Singapore, was dominated by solvers. This distinction may reflect differing educational traditions, as Asian countries are historically more test-centric [18, 30]. It may also reflect differences in the professional environments of the countries as certificates may be more valuable for ca-

reer advancement in Asian nations. Indeed, it may be the case that the solvers are studying offline and are using the MOOC as a certification system.

Following that we focused on the students' quiz-centric behavior. We defined the Quiz Activity Profiles (QAPs) based upon the students' major activities between quizzes and before subsequent quiz attempts. We found that, regardless of the student's CAP, they typically viewed lectures between quizzes, and then turned to forum posts after their initial submission and before any resubmission. This resembles some traditional classroom settings where students attend lectures before doing homework and then only turn to the office hours or peers after they face some difficulty.

When clustering the countries by cultural dimensions we also found that two of our clusters were dominated by countries with higher power distances and lower individualism (cluster 2: Russia, Spain, Brazil, and France; cluster 3: China, India, & Singapore). Students in these clusters were less likely to interact on the forum in most of the learning phases than the students in cluster 1 which was dominated by countries with low power distance and high individualism. This finding is consistent with other work on the CDLF which found that students in countries with high power distance tend to treat the teacher as the unchallenged communicator versus students in countries with low power distance who place a higher value on dialogue and discussion in the learning process. This framework, however, does not explain the other observed variations in cultural cluster 3, notably their apparent focus on work between quiz attempts. We believe that the explanation may lie in the educational culture of this cluster. As noted above this cluster consists entirely of Asian nations which are historically test-driven. We believe that this educational culture may cause the students to view quizzes as the primary goal, leading them to focus their efforts on viewing lectures and forums after they have seen the quiz. Moreover, this cultural emphasis on exams may be the primary reason that Asian students were more prone to re-submit quizzes rather than moving on to new material.

Finally, we analyzed students' "best friend" on the forums. We found that students are more likely to have a "best friend" [6, 11] from countries in the same cultural cluster as their own. Chinese and Brazilian students, in particular, are more likely to have "best friend" from their own country. This close connection may be explained by several factors. First, students from the same country may have the same motivations and overall view of the course which would lead them to join forums that fit their shared needs. Second, students may face difficulties in communicating with individuals from other nations due to language barriers, thus making them more connected to their neighbors. And third, the observed relationships in the forums may reflect real offline relationships among students who joined the class together and are collaborating offline. In the absence of additional data we cannot distinguish among these alternatives.

Ultimately we conclude that students from different countries and cultures do exhibit different learner behaviors on the BDE MOOC. These differences may be explained by country, cultural dimensions, and educational differences. We believe that the students' observed behaviors are driven in part by their own goals and their unique cultural background. Students who come from countries that value discussion are more prone to interact on the forums. Students who come from countries that are test-centric are more prone to focus on improving their quiz scores and will structure their efforts around that. These findings contribute to our understanding of the role that culture and country play in MOOC learner behaviors. They also suggest some culturally-influenced behaviors that MOOC designers should consider when designing their materials.

5.1 Conclusions & Future Work

Our goal in this study was to increase general understanding of behavioral differences in MOOC populations, and the possible role that country and culture may play. We found interpretable inter-country and intercultural differences in students' observed activities, both across the whole course and when segmented by quizzes. We also found that forum users were most strongly connected to individuals from their own country or from culturally-related countries. We analyzed these findings in the context of a hybrid Hofstede/CDLF cultural framework and found that our observed clusters were consistent with the theoretical literature.

This paper is one of the first to explore the relationship between observed behaviors and learners' country or culture. In future work we plan to examine the generality of these findings by analyzing other related MOOCs. Our present dataset includes 29,149 accounts identified from the clickstream data, only 1,591 of which were non-bystanders, and only 750 of whom participated in the forum. While this is consistent with other MOOCs, it is also somewhat skewed and contains relatively small samples for many countries.

As we build a better understanding of the interactions between culture, behavior, and MOOC performance, new questions arise for MOOC designers. Should elearning platform designers intervene to change cultural behaviors? For example, should they encourage students to use forums more or to communicate across cultural lines? Or should they consider supporting many separate groups by providing language specific forums and tailored tracks? If so, how can we assess the impact of such interventions? It may be worthwhile to conduct more user-centered research so that we can better understand the unique needs of diverse populations. This type of work may help us to better understand *how* to address the diverse needs of such unprecedented student populations.

6. ACKNOWLEDGEMENTS

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