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. However, there is a need to research the impact of cultural and geographic factors on student performance in MOOCs, and there is a need to connect this research to existing cultural theoretical frameworks. In this paper we analyze national and cultural differences in students' performance in a large-scale MOOC 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 forum 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. This interest has resulted in considerable evidence for the difference in learner behaviors across cultures, particularly in off-task behaviors[25][21], help-seeking behaviors[21], and collaboration[22][16]. The cultural differences uncovered in these studies suggest that designers of future e-learning platforms could benefit from a better understanding of their target populations and cultures.

Most large-scale MOOCs attract international audiences who invest effort both in taking courses and in promoting the platform more broadly. The course we focus on 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 course content. The materials are typically offered in a single format and language, or with direct translations that use the same structure, pacing, and content.

Prior researchers have shown that country of origin does impact 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 was a significant predictor of their level of content coverage and of the amount of time spent reviewing prior course content. Kizilcec[17] found that a given country's Human Development Index was correlated with the proportion of learners who completed a majority of the assessments. 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 design and deploy more effective, international MOOCs. This understanding can be enriched by relating these differences to the rich body of relevant educational literature such as Hofstede's cultural dimensions theory[13] and Cultural Dimensions of Learning Framework (CDLF). In this paper we report on our analysis of student behaviors in a single large MOOC covering 29,149 registered students drawn from 172 countries and 5 continents. We found clear inter-country and inter-cultural differences in observed student behaviors and in the distribution of user categories. And we found that these differences can be evaluated in the context of existing educational literature and are consistent with prior theoretical frameworks.

2. LITERATURE REVIEW

2.1 Edtech Research with Cultural Awareness

Advances in educational technologies have enabled educators to incorporate technologies at larger scale and collect richer and more diverse educational data. This has in turn motivated substantial increases in interest in the investigation of e-learning behaviors across cultures.

One approach to understanding culture's impact on learning is through field observation. Rodrigo et al.[25] coded students' on- and off-task behaviors in three ITS labs in the U.S. and the Philippines. They found that Filipino students were on-task more of the time compared to U.S. students in all three ITSs, and that the Filipino students gamed some systems more than others. Similarly, Ogan et al.[22] coded on-task behaviors and types of interactions comparing students in Chilean labs. The study found that Chilean students had a higher proportion of on-task interactions observed in U.S. classrooms in prior literature.

Another approach to exploring culture is through educational data mining. Ogan et al.[21] generated student models from ITS logs to predict effective help-seeking from students in three countries: Costa Rica, the Philippines, and the U.S. This study found that the model for U.S. students generalized to Filipino students, but not to Costa Rican students. Saarela and Karkkainen[27] applied a clustering algorithm hierarchically on data from the PISA - a worldwide survey assessing the proficiency of 15-year-old students in reading, mathematics, and science. This work revealed that that students' performance on the PISA clustered by country, suggesting a cultural influence.

While these studies found interesting cross-cultural differences, we have little understanding of why these differences occur, or 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

Large numbers of users learning in highly instrumented systems provide numerous opportunities and potential insights, but MOOCs present unprecedented challenges for educators and researchers: MOOCs have high dropout rates, diverse engagement patterns, and high motivational and demographic diversity among learners. Researchers have therefore sought to better understand MOOC users and their behavior patterns.

One way to understand MOOC students is to build machine learning models through features extracted from clickstream data, such as the frequency and n-gram sequence of activities [29][5]. These machine-learned models are highly accurate but are not necessarily interpretable. Other work has improved understanding of engagement and dropout patterns by detecting subgroups according to engagement with major MOOC activities. Researchers have used hierarchical clustering to discover groups of students, 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]. More specifically, Kizilcec et al.[17] and Ferguson et al.[10] clustered students by engagement factors based upon the number of lectures viewed and assignments submitted. Anderson et al.[1] clustered students by the number of lectures viewed divided by the number of assignments submitted, and Bergner et al.[4] clustered students by the percentage of assessments attempted. These studies highlighted the distinctive behavioral differences between subgroups, and prompted MOOC researchers and platforms to analyze more background information and design corresponding interventions to understand and support different subgroups.

A recent research focus with increasing importance is understanding the diverse backgrounds among MOOC learners, such as their motivation[28][2] and demographic information[19][17][12]. These studies collected background information through voluntary surveys. Nesterko[19] and Deboer[9] found that participation (as indicated by surveys) and certificate attainment rates differed across countries, continents, and genders; they did not, however, delve deeper into student behavior as logged by the learning environment. Wang and Baker[28] found that learners receiving course certificates tended to be more interested in course content, while students not receiving certificates often had the goal of taking MOOCs for a new type of learning experience.

Among studies associating students' backgrounds with learner behaviors, few have addressed geographical information. Guo and Reinecke[12] applied linear regression treating demographic information, such as years of education, as independent variables. They found that country is significantly related to course content coverage and the frequency of reviewing earlier course content, called backjumps. This study attributed this difference to student-teacher ratio, and found that countries with higher student-teacher ratios have higher frequency of backjumps. In other work, Kizilcec[17] separated countries into tiers based on the Human Development Index (HDI), and found that as HDI tier increases, the proportion of course completers increases. However, these studies did not seek theoretical models to interpret the impact of culture on learner behaviors.

To summarize, results from prior MOOC research suggest that understanding participants' backgrounds can be important for providing effective support for MOOC engagement and participation. Geographical location, considered as a group of economical, cultural and educational differences, may play crucial roles in understanding, supporting, and appealing to the increasing MOOC population.

2.3 Theoretical Frameworks for Cross-cultural Data Analyses

As more behavioral differences emerge from cross-cultural data analyses, challenges arise in interpreting and explaining such findings under a theoretical framework.

Previous studies address this challenge by identifying related cultural dimensions and values, and examining their differences across cultures. One commonly used cultural framework is Hofstede's Cultural Dimensions Theory[13]. Hofstede analyzed a set of 117,000 attitude surveys collected by IBM from their international workforce and synthesized 7 general cultural dimensions. These dimensions are: a) power distance; b) collectivism vs. individualism; c) femininity vs. masculinity; d) uncertainty avoidance; e) long/short term orientation; and f) indulgence vs. restraint. The Hofstede[14] numbers for each dimension are calculated from a combination of the large-scale survey, reported by Hofstede et al.[13].

Hofstede's dimensions have been considered as a potential explanations for cross-cultural differences in collaboration[16], help-seeking, and off-task behavior [21][25]. However, these studies have suggested that there are some limitations in how well Hofstede's dimensions may explain the findings, with many key differences in these constructs not corresponding to differences that Hofstede's theory suggests. In particular, collectivism and collaboration/help-seeking strategies do not seem to relate well to the Hofstede dimensions. Thus, we combined the Hofstede dimensions with the Cultural Dimensions of Learning Framework (CDLF), which was specifically developed to understand cross-cultural differences in educational behavior.

The CDLF framework, designed by Parrish et al. in 2010[24], describes 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 analysis and design of e-learning across cultures[23][15]. We are adopting the intersection of the Hofstede dimensions and the CDLF as our theoretical framework to group countries into cultural clusters, and to interpret behavioral differences between cultures. Table 1 provides a brief overview of the shared dimensions as defined by Hofstede and the CDLF.

While these theoretical frameworks may help explain behaviors, it is worth noting that learner behaviors in MOOCs can be affected by many other factors such as personal motivation. For example, Wang and Baker [28] surveyed the motivations of incoming students on a later version of the course we study here and found that the learners receiving course certificates tended to be more interested in course content, while students not receiving certificates often took MOOCs for the sake of receiving a new type of learning experience. Thus, the purpose of our work is to increase understanding of behavioral differences observed in MOOC populations, and the possible roles that nationality and culture may play.

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 in getting the right answer from authoritative sources and from the structured learning activities.

3. DATA

The data in this study are collected from Big Data in Education (BDE), an 8-week long Coursera MOOC by Teachers College of Columbia University [28]. BDE involved video lectures, discussion forums, and 8 weekly assignments. The videos taught students key methods used for analyzing large-scale educational data. The assignments asked students to conduct analyses on provided data (typically genuine data from educational settings) and answer questions about the results. All of the assignments were automatically graded, involving numeric input or multiple-choice questions. Students were allowed 3 to 5 attempts per assignment. Students had to complete each assignment within 2 weeks of its release to receive a grade. The best score out of the multiple attempts was counted. 638 students completed the course and obtained a certificate. Completion was defined as receiving a certificate, which required earning an overall grade average of 70% or above, calculated by averaging the 6 highest grades out of 8 assignments. Depending upon their assignment grades, students could receive a certificate, a certificate with distinction, or no certificate at all.

We analyzed clickstream data containing user IDs, IP addresses, URLs, and timestamps from 29,149 students. Of the students identified in the data, 638 received certificates, and 750 posted on the forums. After classification by behavior types, we found that there were a total of 1,591 students who were actively engaged in the class, while the other 27,588 students were "bystanders" who enrolled but did not do any significant work. We used the most frequent IP address to determine the geographical location of all BDE students. This approach is used in prior work to estimate country[17][9][12]. Figure 1 shows the top 15 countries with the most registrants.

We extracted the following major BDE activities from the URLs in the clickstream data: view lecture (VL), attempt or submit quiz (AQ, SQ), and read or make a post in forum (RP, MP). We took an n-gram approach from previous work[29][5] to generate activity sequences ordered by timestamp. Notice that clickstream data does not contain the information about the actual time spent on an activity. Therefore, we acknowledge that the activities we report in the remainder of the paper simply represent an initial access of the course content, but may not be a reliable indicator of

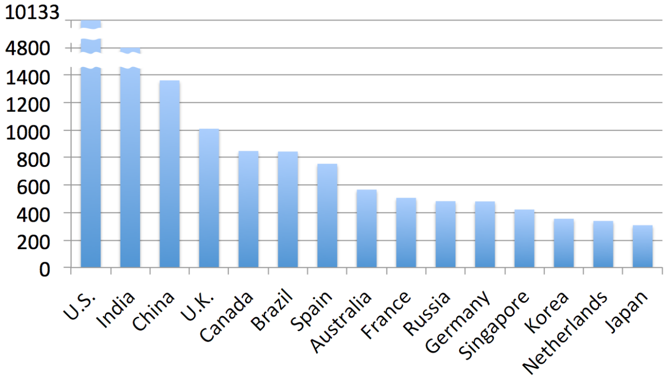


Figure 1: Number of Registrants from the Top 15 Countries with Most Registrants

student engagement.

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

4. METHODS AND RESULTS

We hypothesize that students from different countries or cultures behave differently in the BDE course. To investigate this hypothesis, we examine four research questions: RQ1. (Course Activity Profiles, CAPs) What are the main categories of students, based on the total and relative frequencies of accessing different types of course activities? RQ2. (CAPs by Country) Does the proportion of student categories differ based on country? RQ3. (Quiz Activity Profiles, QAPs) When does each category of student access each type of course activity, relative to 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 use hierarchical clustering to identify five course activity profiles (CAPs) (e.g. students who focused solely on quizzes). For RQ2, we clustered countries by the proportions of each CAP to determine whether students from some countries are more likely to have one CAP rather than another. For RQ3, we segmented the BDE by quizzes and examined when each student CAP category accesses lectures, quizzes, and the forum content to better understand quiz activity profiles (QAPs). For RQ4, we clustered students on cultural dimensions and compared QAPs by culture and student category (CAP). For RQ5, we performed a chi-squared analysis to investigate whether most frequent forum partners were more likely within the same country/culture than cross-country/culture. In each section below, we present the methods and results for each research question in more detail.

4.1 RQ1: Course Activity Profiles

In this section, we present our investigation of RQ1: What are the main student categories, based on the total and relative frequencies of accessing different types of course activities? Researchers have used hierarchical clustering to discover groups of students, 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].

We used hierarchical clustering to classify students by the proportions of activities they engaged in over the entire BDE course. We clustered students by number of lectures, quizzes and forum posts in BDE. We found that clustering the number of lectures viewed and quizzes attempted yielded interpretable CAP clusters of all-rounders (balance both), solvers (more quizzes), viewers (watch lectures), samplers (watch some lectures and do a quiz), and bystanders (do little). In Table 1, we present the CAP clusters whose average silhouette widths (ASWs) were over 0.68, indicating that the clusters are well-chosen classifications [26]. These CAPs closely resemble the types of students found by Anderson et al. when they clustered their MOOC using the ratio of lectures viewed to assignments completed [1], with one difference being that we are using quizzes attempted instead of quizzes submitted.

Table 2: Course Activity Profile clusters in BDE, with size, lectures viewed, quiz attempts, and performance.

			% Certificate	
CAP	**Lectures viewed (max:54)**	**Quizzes Attempted (max:7)**	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%
Sampler (n=574, ASW=0.29): selectively view lectures & quizzes	M:23.18 Sd:6.35	M:1.25 Sd:1.43	0%	0%
Bystander (n=27558, ASW=0.84)	M:1.87 Sd:2.72	M:1.25 Sd:1.43	0%	0%

From Table 2, we see that all-rounders have the highest rate of receiving certificates. In the remainder of the analyses, we focused on the three user categories with a sufficiently high number of activities: viewer, solver and all-rounder.

4.2 RQ2: CAPs by Country

In this section, we present our investigation of RQ2: Does the proportion of student categories differ by country? After identifying meaningful CAP clusters, we compared the countries based on their CAP distribution. We performed hierarchical clustering on countries with more than 15 users from viewer, solver, and all-rounder categories, using the proportions of these three categories. We found that three clusters yielded the highest ASWs, as shown in Figure 2.

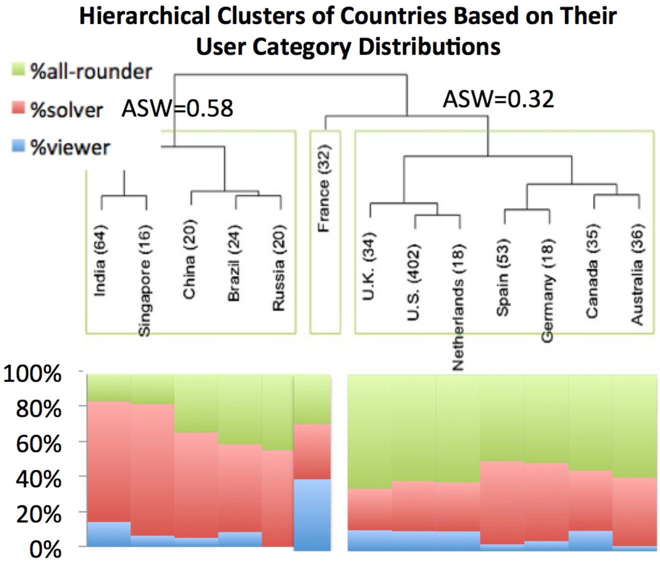


Figure 2: Hierarchical clusters of countries by proportion of user categories. For each country, the proportions of user categories are plotted as stacked bars, and the number of non-bystander registrants is given in parentheses

This clustering grouped solver countries in Cluster 1, which contains all developing countries and Singapore. The all-rounder Cluster 3 contains all developed countries except for Singapore. The proportion of solvers in Cluster 1 is significantly higher than in Cluster 3, $p<0.001$.

4.3 RQ3. Quiz Activity Profiles, QAPs

In this section, we present our investigation of RQ3: When does each category of student access each type of course activity, relative to quiz submissions? After identifying the CAPs and understanding their relative proportion in countries, we proceed to analyze inter-country behavioral differences within CAP. We hypothesize the students from different countries behave differently, given the different Hofstede/CDLF cultural dimensions. Because our clickstream data represent clicks to access course content, we analyzed behavioral differences with regards to course content accessed in three learning phases explained below.

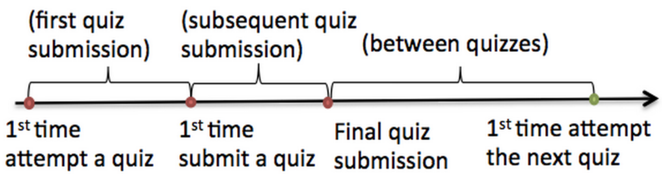


Figure 3: Illustration of the three learning phases

We segmented the activity sequences into three learning phases based upon the quiz attempts. The phases are illustrated in Figure 3. Our goal in doing so was to better understand when students engaged in particular types of learning activities. For each learning phase, we counted the average number of lectures viewed (VL), posts made (MP), and posts read (RP). For the first quiz submission and the subsequent quiz submissions phases, we also counted the average number of times that students attempted and submitted the same quiz (AQ, SQ). Due to the observation that viewers focused solely on viewing videos rather than the other activities, we exclude viewers in the following analyses.

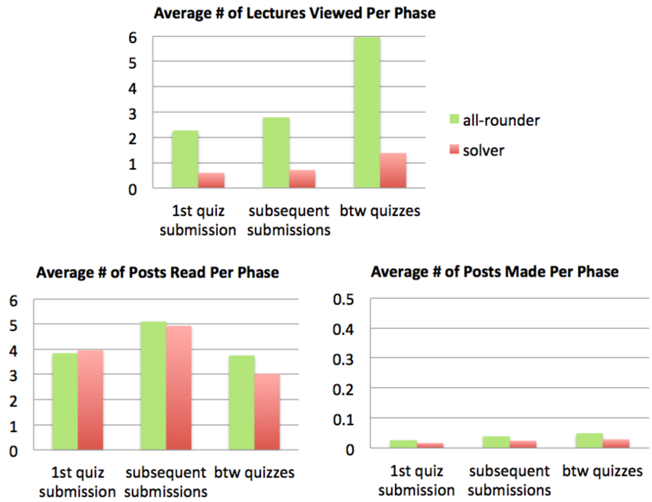


Figure 4: Quiz Activity Profiles for Solvers and All-rounders in Three Learning Phases.

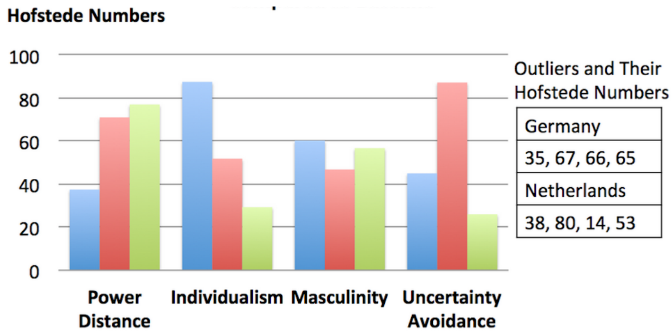
Figure 4 shows the QAP for solvers and all-rounders. Using the Kruskal-Wallis test[20] with Benjamini Hochberg correction[3], we found that both solvers and all-rounders viewed significantly more lectures between quizzes and read more posts during subsequent quiz submissions, compared with other learning phases.

4.4 RQ4. QAPs by Culture & Country

In this section, we present our investigation of RQ4: How do quiz-based activity profiles (QAP) and countries relate to the four overlapping Hofstede/CDLF cultural dimensions?

We applied hierarchical clustering on countries with more than 15 all-rounders, solvers or viewers, based on the four Hofstede dimensions[13] incorporated in CDLF[24]. We found three clusters with ASWs over 0.46. We treated the first cluster as the baseline for comparison since they are the majority population in BDE. We conducted a Kruskal-Wallis test on the QAPs between clusters, for each activity in each learning phase. The results are shown in Figure 4.

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. We found that compared to this baseline cluster 1, solvers in cultural clusters 2 (Russia, Spain, Brazil and France cluster) and 3 (China, India and Singapore cluster) read and made significantly or marginally significantly fewer posts during the multiple learning phases. Moreover, solvers in cultural cluster 3, whose countries are characterized by the highest average



Cluster 1: Australia, Canada, U.S., U.K. (S=0.66)	
All-rounder (n=305)	baseline
Solver (n=151)	baseline
Cluster 2: Russia, Spain, Brazil, France (S=0.46)	
All-rounder(n=54)	No sig diff
Solver (n=58)	***1stSubmission_RP=-1.60** subseqSubmissions_RP=-1.85 subseqSubmissions_MP=0.03
Cluster 3: China, India, Singapore (S=0.48)	
All-rounder (n=21)	1stSubmission_VL=+0.60 subseqSubmissions_SQ=+0.28
Solver (n=70)	1stSubmission_MP=-0.026 subseqSubmissions_MP=-0.03 ***btwQuizzes_RP=-2.25** ***btwQuizzes_VL=-1.04**

Figure 5: Cultural clusters based on Hofstede-CDLF values, and significant (annotated in *) and marginally significant difference in QAPs, as compared to cultural cluster 1 baseline behaviors.

power distance and lowest average individualism, viewed significantly fewer lectures between quizzes. All-rounders in cultural cluster 3 also viewed marginally significantly more lectures during the first quiz submission, and had marginally more submissions per quiz.

Additionally, we found a high degree of overlap between the cultural clusters and the CAP clusters described in section 4.2. The cultural cluster 1 is a subset of the all-rounder CAP cluster, 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 that have higher power distance and lower individualism are more prone to focus on getting evaluated. However, cultural cluster 2 includes students 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 their behaviors.

4.5 RQ5. Forum Best Friends

The previous section showed that different cultures view the role of discussion differently. In this section, we present our investigation of RQ5: Is a student's most frequent forum partner in the same country/culture? We first found students' "best friends" based on forum interactions. Two students have interacted in the forums when one replies to a thread the other has posted in. Following Fire et al. [11] and Brown et al.[6], we constructed a social network graph with student nodes connected by edges weighted by the count of their forum interactions. A student's "best friend" is the adjacent student with the highest-weighted edge for that student's node in the graph. Note that this analysis only considered the 750 students who posted to the forum.

For each of the top 15 countries and the 3 cultural clusters defined in the previous section, we performed a chi-squared test between the proportions of students in and outside the group who have their best friends in the group. The results are shown in Table 3. We found that for all three Hofstede cultural clusters, students are significantly more likely to have best friends from the same culture. We found that for China and Brazil, students are significantly more likely to have best friends in their own countries.

Table 3: Group 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 four dimensions of MOOC behavior by country and culture. We first identified five course activity profiles (CAPs) based upon the number of lectures viewed and quizzes attempted. These were: viewers, solvers, all-rounders, samplers, and bystanders. We found that the all-rounders obtained the most certificates, followed by the solvers. This shows that a balanced ratio of lecture viewing and quiz attempts is a good indicator of students who are working towards a certificate.

Next, we clustered the countries with more than 15 solvers, viewers, or all-rounders based upon the distribution of individual CAPs within them. Interestingly, we found that two of the Hofstede/CLDF clusters align well with the observed student types. The first cluster containing Australia, Canada, the U.S., and the U.K. was dominated by all-rounder CAPs while cultural cluster 3, containing China, India, and Singapore was dominated by solver CAPs. This may reflect differing educational traditions, as Asian countries have historically been more test-centric. It may also reflect differences in the professional culture of the countries; students in cultural cluster 3 may be seeking MOOC certificates for career advancement. Such students may even be studying offline and using the MOOC more as a certification system than as a teaching tool. We then explored quiz activity profiles (QAPs), defined as major activities in different learning phases between and during quiz attempts. We found that regardless of CAP, students viewed most lectures between quizzes and viewed most forum posts during the subsequent quiz attempts. This resembles traditional classroom settings, where students attend lectures before doing homework, and initialize most discussions when they start making progress on the homework.

In the investigation of quiz activity profiles across countries, we built upon the Hofstede framework [13] and the Cultural Dimensions of Learning (CDLF) [24] frameworks. We found that for solvers, cultural clusters 2 and 3, with higher power distances and lower individualisms (cluster 3: Asia cluster; cluster 2: Russia, Spain, Brazil, and France cluster) interact less with forum posts in many learning phases, compared to cultural cluster 1 (U.S., U.K., Canada, and Australia). This result is supported by the CDLF, since the former two culture groups treat the teacher more as the primary unchallenged communicator, while the last culture group values dialogue, discussion and expression of opinions more in the learning process. However, CDLF does not explain other differences in Cluster 3. Because cultural cluster 3 happens to include all Asian countries, we may explain this by noting that the educational culture in most of these countries is test-centric [18][30]. This educational culture may cause Asian students to view quizzes as the primary goal and arrange course activities after seeing the quiz, which leads to more lectures viewed during first quiz submission and less lectures viewed between quizzes. The cultural overemphasis on exams may also lead Asian students to be more concerned with obtaining good scores and thus lead them to focus on re-submitting quizzes rather than moving on to new material. This may explain why cluster 3 is contained within the solver-dominated CAP cluster.

Finally, we analyzed forum best friends. We found that students are more likely to have a "best friend" [6][11] from a country in the same cultural cluster as their own. We also found that Chinese and Brazilian students are more likely to have best friends in their own countries. This may be explained by several factors. First, students from similar cultures may view the role of class discussion similarly, leading them to join threads that fit their shared needs. Secondly, they may be separated from students of other nations due to language barriers and thus be more prone to communicate with students who share the same native language. Thirdly, they may be groups that joined the class together in their home country and are thus working collaboratively offline. Given the small sample sizes for many nations we cannot distinguish among these alternatives.

Given our results, we conclude that students from different countries and cultures do exhibit different learner behaviors in the BDE MOOC. The behavioral differences are explainable by country, Hofstede/CDLF cultural dimensions, and educational cultures. In conclusion, we found that students' behaviors are related to the importance of learning activities within their country or culture. Students who come from a culture that values discussion in learning are more likely to be active in the online forums, and to connect with students who share those values. Students who come from a culture that focuses on quizzes, by contrast, are more likely to focus on improving their individual scores and to organize their other course activities around that. Our findings contribute to the understanding on the role of country and culture in MOOC learner behaviors, and suggest some culturally-influenced behaviors that MOOC designers should consider when designing and improving MOOCs.

5.1 Conclusions & Future Work

The goal of this study was to increase the understanding of behavioral differences exhibited in MOOC populations, and the possible role that country and culture may play. We found interpretable inter-country and intercultural differences in CAP distributions, activity profiles in phases separated by quizzes (QAP), and forum best friends. We interpreted these differences in the context of a hybrid Hofstede-CDLF cultural framework. This paper is one of the first to explore the relationships between MOOC learner behaviors, countries, and cultures. We believe that it highlights both the important research issues in this area and presents novel analyses that can guide future development.

In future work we plan to examine the generality of these findings by analyzing other related MOOCs. Our dataset includes 29,149 accounts identified from the in 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 e-learning platform designers intervene to change culture-related behaviors? For example, should MOOC designers focus on mitigating cultural behaviors, by encouraging students to be broader or communicate across cultural lines? Should they support diverse cultures, by providing language-specific forums and additional tailored tracks? If so, how can we best measure whether such interventions translate into more effective learning and/or positive student experiences? It may also be worthwhile to conduct user-centered research to incorporate the needs and experiences of diverse populations into feature design. This type of research with MOOCs may help us better understand how to support learning for students with diverse cultural, gender, and linguistic characteristics.

6. ACKNOWLEDGEMENTS

The author would like to thank Abhishek Agrawal and Dhyey Shah for segmenting clickstreams and identifying students' geographical locations in BDE. This work was partially supported by NSF grant no. 1418269

7. REFERENCES

[1] A. Anderson, D. Huttenlocher, J. Kleinberg, and J. Leskovec. Engaging with massive online courses. In *23rd ACM Int. conf. on World Wide Web*, pages 687–698, 2015.

[2] M. Barak, A. Watted, and H. Haick. Motivation to learn in massive open online courses: Examining aspects of language and social engagement. *Computers Education*, 94(49-60), 2016.

[3] Y. Benjamini and Y. Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 289-300, 1995.

[4] Y. Bergner, D. Kerr, and D. E. Pritchard. Methodological challenges in the analysis of MOOC data for exploring the relationship between discussion forum views and learning outcomes. In *The 8th Int. conf. on Educational Data Mining*, 2015.

[5] C. Brooks, C. Thompson, and S. Teasley. A time series interaction analysis method for building predictive models of learners using log data. In *In the Fifth Int. conf. on Learning Analytics And Knowledge*, pages 126–135, 2015.

[6] R. Brown, C. Lynch, Y. Wang, M. Eagle, J. Albert, T. Barnes, R. Baker, Y. Bergner, and D. McNamara. Communities of performance & communities of preference. In *the 2nd Int. Workshop on Graph-Based Educational Data Mining.*, 2015.

[7] D. Comer, R. Baker, and Y. Wang. Negativity in massive online open courses: Impacts on learning and teaching and how instructional teams may be able to address it. *Journal of the Center for Excellence in Teaching and Learning*, 10:92–106, 2015.

[8] S. Crossley, D. McNamara, R. Baker, Y. Wang, L. Paquette, T. Barnes, and Y. Bergner. Language to completion: Success in an educational data mining massive open online class. In *The 8th Int. conf. on Educational Data Mining*, 2015.

[9] J. DeBoer, G. S. Stump, D. Seaton, and L. Breslow. Diversity in mooc students' backgrounds and behaviors in relationship to performance in 6.002 x. In *In the Sixth Learning Int. Networks Consortium conf.*., 2013.

[10] R. Ferguson and D. Clow. Examining engagement: analysing learner subpopulations in massive open online courses (MOOCs). In *the Fifth Int. conf. on Learning Analytics And Knowledge ACM*, pages 51–58, 2015.

[11] M. Fire, G. Katz, Y. Elovici, B. Shapira, and L. Rokach. Predicting student exam's scores by analyzing social network data. In *the 7th Int. Workshop on Active Media Technology*, 2012.

[12] P. J. Guo and K. Reinecke. Demographic differences in how students navigate through MOOCs. pages 21–30, 2014.

[13] G. Hofstede and G. J. Hofstede. *Cultures and organizations: Software of the mind (3rd ed.).* McGraw-Hill, New York, USA, 2010.

[14] G. Hofstede, G. J. Hofstede, M. Minkov, and H. Vinken. *Values survey module 2008.* URL: http://www. geerthofstede. nl/media/253/VSM08English. doc, 2008.

[15] A. N. Hunt and S. Tickner. Cultural dimensions of learning in online teacher education courses. *Journal of Open, Flexible and Distance Learning*, 19(2):25–47, 2015.

[16] K. J. Kim and C. J. Bonk. Cross-cultural comparisons of online collaboration. *Journal of Computer-Mediated Communication*, 8(1), 2002.

[17] R. F. Kizilcec, C. Piech, and E. Schneider. Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses. In *the 3rd Int. conf. on learning analytics and knowledge*, pages 170–179, 2013.

[18] F. K. Leung. In search of an East Asian identity in mathematics education. *Educational Studies in Mathematics*, 17(1), 35-51, 2001.

[19] S. O. Nesterko, S. Dotsenko, Q. Han, D. Seaton, J. Reich, I. Chuang, and A. D. Ho. Evaluating the geographic data in MOOCs. In *the 2013 conf. on Neural Information Processing Systems*, 2013.

[20] C. G. Northcutt, A. D. Ho, and I. L. Chuang. Use of ranks in one-criterion variance analysis. *Journal of the American statistical Assoc.*, 47(260):583–621, 1952.

[21] A. Ogan, B. R. Walker, E., M. M. T. Rodrigo, J. C. Soriano, and M. J. Castro. Towards understanding how to assess help-seeking behavior across cultures. *Int. Journal of Artificial Intelligence in Education*, 25(2):229–248, 2015.

[22] A. Ogan, E. Yarzebinski, P. Fernández, and I. Casas. Cognitive tutor use in Chile: Understanding classroom and lab culture. In *the 17th Int. conf. on Artificial Intelligence in Education*, pages 318–327, 2015.

[23] A. C. Ordóñez. *Predicting Int. Critical Success Factors in e-learning: A comparison of four universities from China, Mexico, Spain and USA.* PhD thesis, Universitat Oberta de Catalunya, August 2014.

[24] P. Parrish and J. Linder-VanBerschot. Cultural dimensions of learning: Addressing the challenges of multicultural instruction. *The Int. Review of Research in Open and Distributed Learning*, 11(2), 2010.

[25] M. M. T. Rodrigo, R. S. J. D. Baker, and L. Rossi. Student off-task behavior in computer-based learning in the Philippines: comparison to prior research in the usa. *Teachers College Record*, 115(10):1–27, 2013.

[26] P. J. Rousseeuw. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics*, 20:53–65, 1987.

[27] M. Saarela and T. Kärkkäinen. Do country stereotypes exist in PISA? a clustering approach for large, sparse, and weighted data. In *The 8th Int. conf. on Educational Data Mining*, 2015.

[28] Y. Wang and R. Baker. Content or platform: Why do students complete MOOCs? *MERLOT Journal of Online Learning and Teaching*, 11(1), 17-30, 2015.

[29] M. Wen and C. P. Rosé. Identifying latent study habits by mining learner behavior patterns in massive open online courses. In *the 23rd ACM Int. conf. on conf. on Information and Knowledge Management*, pages 1983–1986, 2014.

[30] J. K. K. Wong. Are the learning styles of Asian int. students culturally or contextually based? *Int. Education Journal*, 4(4), 154-166, 2004.

[31] M. Zhu, Y. Bergner, Y. Zhang, R. Baker, E. Wang, and L. Paquette. Longitudinal engagement, performance, and social connectivity: a MOOC case study using exponential random graph models. In *The 6th Int. conf. on Learning Analytics and Knowledge*, 2016.