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Dropout Patterns and Cultural Context in Online Networked Learning Spaces

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Abstract

Dropout is a major concern in networked learning practices, however, little is known about the issue within the perspective of cultural contexts. On this basis, cultural context and dropout patterns were examined through a mixed-methods approach in which social network analysis and two-way between-group comparisons (culture vs. dropout) were conducted. The sample comprised 179 MOOC learners who were active in a networked extension of the *Introduction to Open Education* MOOC (#openEDMOOC). The dependent variables of interest were centrality metrics, whereas the independent variables were dropout (i.e., yes-no) and cultural contexts (i.e., high-low). The findings of the social network analysis suggested that non-dropout learners hold central positions in the network. Furthermore, learners from high cultural contexts tend to drop out, whereas those from low contexts tend not to drop out.

Keywords: Dropout; cultural context; massive open online courses; MOOCs; online networked learning

Introduction

> *"A mind cannot be independent of culture"* - Lev Vygotsky

Rooting from the idea that knowledge is a common good of humanity, the philosophy of openness has inspired a number of novel practices, among which can be counted Massive Open Online Courses (MOOCs). This practice has provided individuals all around the globe with lifelong learning opportunities, regardless of the barriers of time and space. The first letter of MOOC refers to *massive*, which acknowledges its global capacity and reach; the second letter, *open*, generally means that there is no restriction, barrier or privilege in terms of access to knowledge; and the third and fourth letters refer to *online* and *course,* which connote their conventional meanings. Based on these promising characteristics, MOOCs are perceived to be revolutionary and to open up higher education on a massive scale (El Said, 2017). That said, the literature suggests that MOOCs have low retention (Allione & Stein, 2016) and high dropout rates (Jordan, 2014; 2015), nonetheless, little is known, within a cultural context, as to why learners drop out (El Said, 2017). More specifically, empirical studies pertaining to the relationship of culture and dropping out are understudied, and the critical role of culture on dropout rates is usually ignored. In this respect, the current study explored how, and if, cultural contexts impact learner dropout rates.

Literature review

Dropout and retention/completion rates are two points on a continuum with an inverse correlation. That is, while one increases, the other one decreases. Ideally, educators aim for high retention and low dropout rates, being an indicator of a program's success. Similarly, high dropout rates partly imply a failure to engage learners. While this is the case in conventional educational contexts, high dropout rates in MOOCs is a highly criticized issue (Jordan, 2014). As MOOCs are open and flexible

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in many ways, high dropout rates can be tolerated to a certain extent in such an open and flexible learning ecology, although it also interferes with MOOCs' transformative potential (Yang, Sinha, Adamson & Rosé, 2013).

Though research into dropout rates is not a new concept (Tinto, 1975), online networked learning spaces in general and MOOCs in particular are a topic of heated debate when dropout rates are compared with rates in conventional higher education courses. Due to differences in regard to enrollment numbers and the flexibility of the two contexts, comparing dropout rates may not be appropriate (Eriksson, Adawi & Stöhr, 2017; Jordan, 2014). One of the most comprehensive studies on learner dropout was carried out by Jordan (2014), who reported that completion rates in MOOCs are around 10% whereas dropout rates are as high as 90%. In a follow-up study by Jordan (2015), it was found that MOOCs with longer durations have lower completion rates. It was also observed that when compared to earlier MOOCs, contemporary MOOCs (i.e., 2014 onwards) and MOOCs with auto-grading systems have higher completion and lower dropout rates.

Other studies on completion and dropout have focused on learner motivation (Rothkrantz, 2016), learner types (Kizilcec, Piech & Schneider, 2013), behavioral patterns (Onah, Sinclair & Boyatt, 2014), social factors (Yang et al., 2013), learner demographics (Allione & Stein, 2016) and socio-psychological perspectives (Henderikx, Kreijns & Kalz, 2017). In order to predict, detect and intervene in dropout patterns, contemporary researchers resorted to machine learning, data mining and learning analytics (Kloft, Stiehler, Zheng & Pinkwart, 2014). For instance, these methods have been used to build a dropout prediction model (Xing, Chen, Stein & Marcinkowski, 2016), to identify and classify at-risk dropout learners (Vitiello et al., 2017) and to examine learner behavior patterns (Hong, Wei & Yang, 2017). In short, existing literature demonstrates an increasing interest in and awareness of dropout rates which have been analyzed also through cutting-edge analytical solutions. The cultural context, which is a critical factor for social learning, has, however, been somewhat ignored.

Culture can be defined as a system that is developed collectively by members of a society. It reflects how individuals live and interpret the world around them (Powell, 1997). Even though it is of crucial importance, such a critical factor as a social construct (Boyacigiller, Kleinberg, Phillips & Sackmann, 2004) has not been considered adequately while designing MOOCs (Nkuyubwatsi, 2014; Stager, 2015). It is known that culture influences how one processes information (Matsumoto, 1996), and teaches and learns (Hofstede, 1986). Furthermore, cultural contexts surrounding learners are associated with their engagement and success (Skrypnyk, Hennis & Vries, 2014; Wang, 2007), and reported that culture and learning styles have an interrelated interaction which can be used to predict academic performances (Strang, 2010). Prior research indicates that learners from different cultural contexts can behave differently in their educational task behaviors, help-seeking (Ogan et al., 2015) and collaboration processes (Kim & Bonk, 2002). It is also argued that cultural translation, which refers to proper contextualization as a means of avoiding misunderstandings, should be enabled when participation is culturally diverse (Nkuyubwatsi, 2014). In line with these arguments, considering that learning processes are socially and culturally mediated (Groulx & Silva, 2010), culturally relevant learning processes are considered to be critical for academic success (Adams, Rodriguez & Zimmer, 2018). Taskeen claims (2019, para. 10) that "MOOCs [for instance], if designed inclusively, have the potential and ability to create reciprocal channels between truly diverse global participants, where a plurality of voices can be heard and true diversity of global knowledge can be achieved." Accordingly, instructional designers need to consider cultural inclusion (Marrone, Mantai & Luzia, 2013) and diversity as a critical factor in increasing learner participation and preventing learner dropout (Tapanes, Smith & White, 2009). The aforementioned literature and accompanying inferences demonstrate the need for further research and justify the current research rationale to investigate dropout with regard to cultural contexts.

Theoretical framework

Hall (1998) noted that communication is one of the core components of any culture, and differences in communication styles can be an indicator of cultural differences, which is a view that is still held today (e.g., Keller, Ucar & Kumtepe, 2018). Hall (1976) proposed high context cultures (HCC) and low context cultures (LCC), resorting to communication styles of societies (Figure 1).

HIGH CONTEXT CULTURES

- Indirect and implicit messages
- Polychronic
- High use of non-verbal communication
- Low reliance on written communication
- Use intuition and feelings to make decisions
- Long-term relationships
- Relationships are more important than schedules
- Strong distinction between in-group and out-group

LOW CONTEXT CULTURES

- Direct, simple and clear messages
- Monochronic
- Low use of non-verbal communication
- High reliance on written communication
- Rely on facts and evidence for decisions
- Short-term relationships
- Schedules are more important than relationships
- Flexible and open

Figure 1: Characteristics of Hall's HCC versus LCC

In HCCs, communication is implicit and based on nonverbal clues, and the message can be understood if the receiver has background information. In LCCs, communication is explicit, and the message is loaded with the information that makes it easy to be understood. In HCCs, interaction is based on nonverbal cues such as tone, gesture and facial expressions, while nonverbal cues are not important in LCCs, as the intended message is spelled out explicitly. In HCCs, the building of relationships and the formation of communities are slow, but last longer. In LCCs, building relationships and community formation begin quickly but last shorter. In HCCs, the boundaries of communities are strong and visible, whereas those boundaries are more flexible in LCCs, meaning that it is easier to become part of a community in LCCs. In contrast, individuals in HCCs can face difficulty in entering, being included and expressing themselves in an unknown community.

Purpose of the Research

The purpose of this embedded mixed-method study is to investigate the cultural context and dropout patterns. The first phase of the research made a qualitative and quantitative exploration of the network data of MOOC learners, and the quantitative information garnered in the first phase was then used in the second phase to assess the contribution of cultural context and dropout patterns to centrality metrics in online networked spaces. Thus, the current research team generated the following research questions:

- How does network formation emerge based on the cultural contexts of dropout and non-dropout learners?
- How do centrality metrics vary with regard to cultural contexts of dropout and non-dropout learners?

Method

Research design

An embedded mixed-design approach was adopted in which the secondary form data were analyzed to support and ameliorate the inferences stemming from the primary form (Creswell, 2012).

The primary form data were retrieved from #OpenEDMOOC and processed through social network analysis (SNA). The secondary form of data revealed after the SNA was processed further through a correlational approach that involved parametric analyses. More specifically, social network analysis (SNA) (Hansen, Shneiderman & Smith, 2010) was utilized to provide quantitative network metrics and qualitative sociograms for the mapping and visualization of network structures. Subsequently, a correlational approach with parametric analyses (Field, 2009) was implemented to augment the primary inferences and to test statistically the association between cultural context and dropout patterns.

Research context

The data were garnered from the *Introduction to Open Education* MOOC (henceforth, #OpenEDMOOC), which was facilitated by David Wiley and George Siemens on edX platform during the six weeks, and from distributed online networked spaces, such as blogging and microblogging platforms, between October 2 and November 12, 2017. The MOOC covered topics such as openness in education, OERs and copyright issues. There were no prerequisites for participation, and learners could participate through both the edX platform or through Twitter by using the #openEDMOOC hashtag. The data were collected from learners who were active on Twitter.

Sampling

The sample consisted of 179 learners who registered for #OpenEDMOOC and participated in learning activities in open online networked spaces (i.e., Twitter) rather than on closed edX platform. As the data were crawled from online networks, the demographic data of the sample include the learners' origin countries (Figure 2), time zones, social capitals (e.g., number of followers, people followed, number of created threads) and bios in Twitter profiles.

Data collection and analysis

Data were crawled from online networks using NodeXL software. The network data were analyzed based on quantitative node (local) and network (global) metrics along with qualitative sociograms. In the SNA, node metrics represent the learners while edges represent any relationships across learners (Hansen, Shneiderman & Smith, 2010). While analyzing node metrics, in-degree, out-degree, and betweenness centrality values were calculated (When the graph is directed, degree metrics can be in-degree [points inward] or out-degree [points outward]; betweenness centrality is a measure of a node's bridging score, that is, centrality in the network which is equal to the number of shortest paths from all other nodes to all others that pass through that node). Nodes' cultural contexts are based upon Hall's (1998) HCC and LCC classification that were assigned according to learners' country of origin. To analyze network metrics, total numbers of the nodes (i.e., learners) and edges (i.e., interactions among the learners), graph density (i.e., interaction), and geodesic distance values were calculated for each week (Graph density is a metric that measures the sum of edges divided by the total number of possible edges and demonstrates the level of interconnectedness of the nodes; Geodesic Distance is the length of the shortest path between vertices). Sociograms were calculated through Harel-Koren Fast Multiscale layout algorithm (Harel & Koren, 2001). Following that, descriptive statistics and two-way between-groups analysis of variance (ANOVA) were used to assess the effects of cultural context and dropout patterns on node metrics addressed in the current work using IBM SPSS Statistics 24.

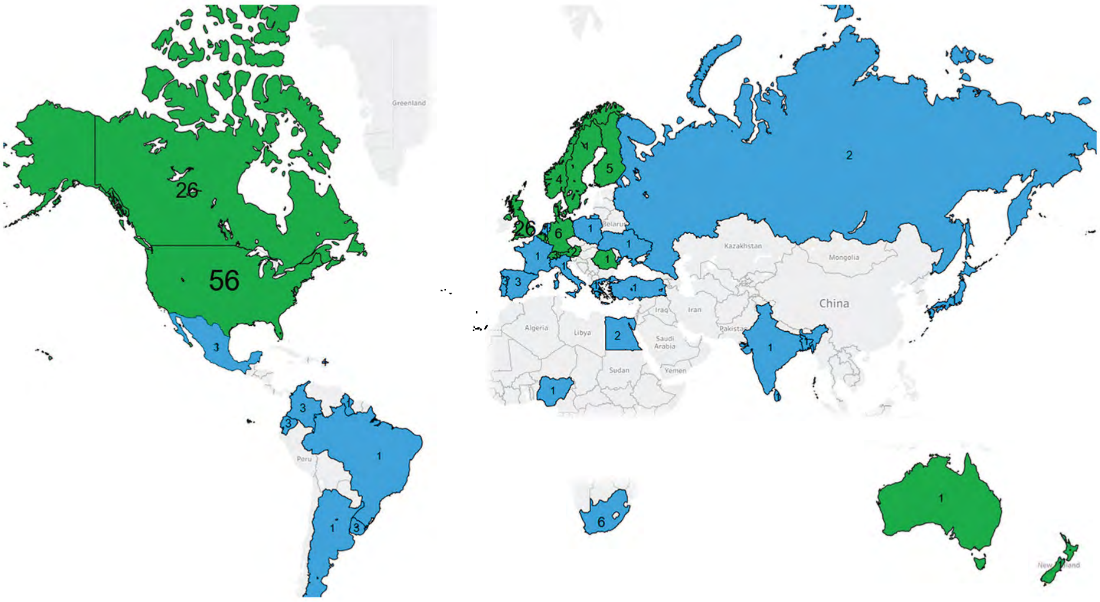

Figure 2: Countrywide distribution of learners (Blue for HCC; green for LCC).

Strengths and limitations

Along with the significance of the topic, the relative strength of the current work lies in the methodology of data collection and analysis. More specifically, rather than being based on self-reports, the cultural context and the dropout pattern status were identified through learners' actual network data. However, the study has some limitations, in that the network data is sourced only from those who used the #openEDMOOC hashtag on Twitter, and thus excludes those who preferred to be active on the edX platform. Furthermore, the cultural contexts of the learners were identified according to their country of origin, where Hall's (1998) high and low culture framework was used as a theoretical lens.

Ethical Issues

This research applied the guidelines set out in *Ethical Decision-Making and Internet Research Report* (AoIR, 2012). The #openEDMOOC facilitators were informed and permission to use the data was granted. The data were collected from public domains. In the event of any personal data being available, they were removed from the data to ensure complete anonymity.

Findings

First strand: Social Network Analysis (SNA)

The #openEDMOOC data were collected during the course, which lasted for six weeks. To identify dropouts, the unique identifiers of each node in the first week, when none of the learners were identified as dropouts, were compared with the final week. The network data per week (see Figure 3) demonstrated that total number of the nodes and edges decreased towards the final week. Even though there was a decrease in the number of nodes and edges, geodesic distance, which indicates the total number of the steps to reach another node, was steady. Interestingly, in contrast to the decrease in the number of nodes and edges, there was an increase in the graph density value, which is an indicator of interaction in the network. This means that throughout the weeks, the learners on the periphery of the network dropped out, while the core community interacted with each other more, increasing the overall graph density. In line with the research purposes, only those explicitly active (i.e., nodes with 1+ out-degree; *n*=179) were included in the analysis. In brief, the completion rate for active nodes was 22.48% while dropout rate was 77.52%.

Metrics	W1	W2	W3	W4	W5	W6
Total Number of Nodes	199	162	110	74	82	49
Total Number of Active Nodes	179	125	75	53	55	38
Total Number of Edges	533	588	308	166	167	98
Maximum Geodesic Distance	6	6	7	6	7	5
Average Geodesic Distance	2,8542	2,9652	3,3039	3,1310	3,2270	2,4971
Graph Density	0,0089	0,0152	0,0169	0,0165	0,0155	0,0251

Figure 3: Dashboard for weekly network metrics.

The overall examination of the #openEDMOOC network was followed by an examination of the first week network. The first week was used as a base as it included all nodes, which further enabled the researchers to mark learners according to their cultural contexts and dropout status. The network data were processed through the Harel-Koren Fast Multiscale layout algorithm (Harel & Koren, 2001), which is a force-directed approach for multi-scale representations.

The node sizes and layout orders are based on the #openEDMOOC learners' *betweenness centrality* (Newman, 2005), which refers to the learners' bridging score and can be defined as the number of shortest paths from all nodes to others that pass through that node (Hansen et al., 2010). In Figure 4, the node shapes are based on their cultural contexts (i.e., square for HCC and disk for LCCs). The node colors denote dropout status (i.e., navy blue for dropouts and green for non-dropouts); the edge colors denote dropout status (i.e., green for dropouts and grey for non-dropouts). The edge widths and opacities are based on edge weight values, which indicate the strength of the relationships among the nodes (Hansen et al., 2010). The sociogram revealed that while non-dropouts hold central positions, dropouts hold peripheral positions (Figure 4). That is, those tightly connected to the learning network were less likely to drop out. It was also observed that all isolated nodes (i.e., nodes that didn't build any connections with other nodes, *n*=14), were dropouts.

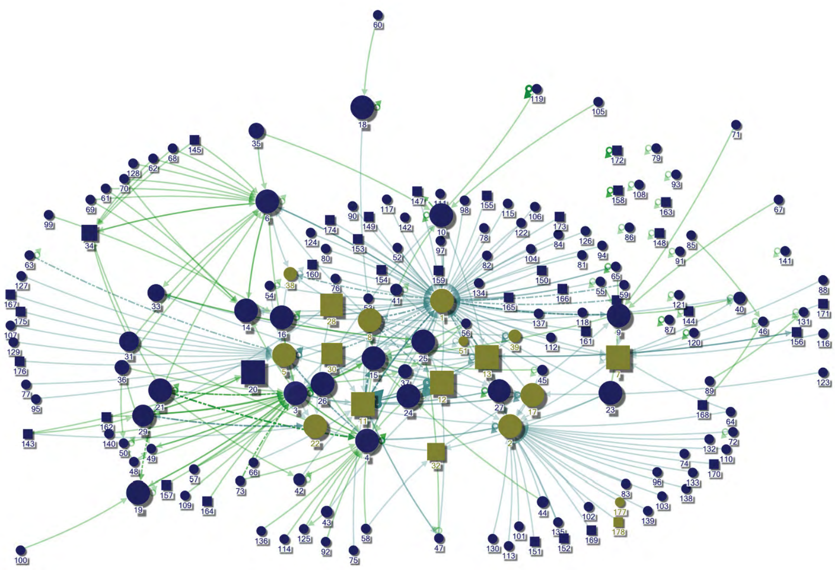

Figure 4: Non-clustered, directed sociogram of #openEDMOOC.

When #openEDMOOC clustered by dropout/non-dropout pattern through Clauset-Newman-Moore cluster algorithm (Clauset, Newman & Moore, 2004), network metrics revealed intriguing findings (Figure 5). Accordingly, dropouts demonstrated a greater average geodesic distance than non-dropouts. In line with this finding, graph density was examined, and it was found that the network interaction was relatively low when compared to non-dropouts. That is, dropouts were loosely connected to the network and their engagement was low, while non-dropouts were tightly connected, and their engagement was considerably high.

	Nodes	Total Edges	Maximum Geodesic Distance (MGD)	Average Geodesic Distance (AGD)	Graph Density (GD)
Dropouts	161	178	7	3,339	0,004
Non-dropouts	18	122	4	1,889	0,111

Figure 5: Dashboard for cross tabulated network metrics.

Second strand: Two-way ANOVA

The in-degree, out-degree and betweenness centrality values were calculated to address node metrics. Betweenness centrality (i.e., bridging score) correlated significantly with both the in-degree (r=0.53; p<0.001) and out-degree (r=0.58; p<0.001) values. Besides, the in-degree and out-degree values were correlated (r=0.53; p<0.001). In this respect, betweenness centrality was considered to be the dependent variable in subsequent parametric analyses. Descriptive statistics pertaining to the betweenness centrality values in terms of both cultural context and dropout condition are provided in Table 1.

Table 1: Descriptive statistics pertaining to betweenness centrality values

Cultural context	Dropout	Mean	SD	n
Low context	No	3137.00	5823.94	11
	Yes	162.36	730.66	124
	Total	404.74	1920.53	135
High context	No	560.15	596.35	7
	Yes	11.57	57.74	37
	Total	98.85	305.96	44
Total	No	2134.89	4663.51	18
	Yes	127.71	644.36	161
	Total	329.55	1678.32	179

It appeared that the means varied across cultural contexts and dropout conditions in favor of LCC learners and those who did not drop out. A two-way between-groups ANOVA was conducted to identify the individual and combined contributions of cultural contexts and dropout conditions to the betweenness centrality values. As summarized in Table 2, the statistical power pertaining to the current sample was satisfactory for the analysis (i.e., >0.80).

Table 2: Two-way ANOVA summary for betweenness centrality means across cultural contexts (low-high) and dropout conditions (yes-no)

Source	SS	df	MS	F	Sig.	Partial Eta²	Observed Power
Cultural context (Low-High)	27672725.15	1	27672725.15	11.896	0.001	0.064	0.929
Dropout Condition (Yes-No)	46169619.77	1	46169619.77	19.847	0.000	0.102	0.993
Cultural context * Dropout condition	21891910.22	1	21891910.22	9.411	0.003	0.051	0.862
Error	407101470.58	175	2326294.12				
Total	520820108.71	179					

The ANOVA results revealed that the betweenness centrality mean pertaining to LCC learners was statistically higher than that of HCC learners with a medium effect size ($F_{1,175}$=11.896; *p*<0.001; *partial* eta^2=0.064). In addition, the betweenness centrality mean of the learners who did not drop out was higher than that of the dropouts, with a medium effect size ($F_{1,175}$=19.847; *p*<0.001; *partial* eta^2=0.102). Finally, the interaction effect of the cultural context in the dropout condition was statistically significant with a small effect size ($F_{1,175}$=9.411; *p*<0.003; *partial* eta^2=0.051). That is, the difference between HCC and LCC learners varied across dropout conditions significantly. This pattern is illustrated in Figure 6.

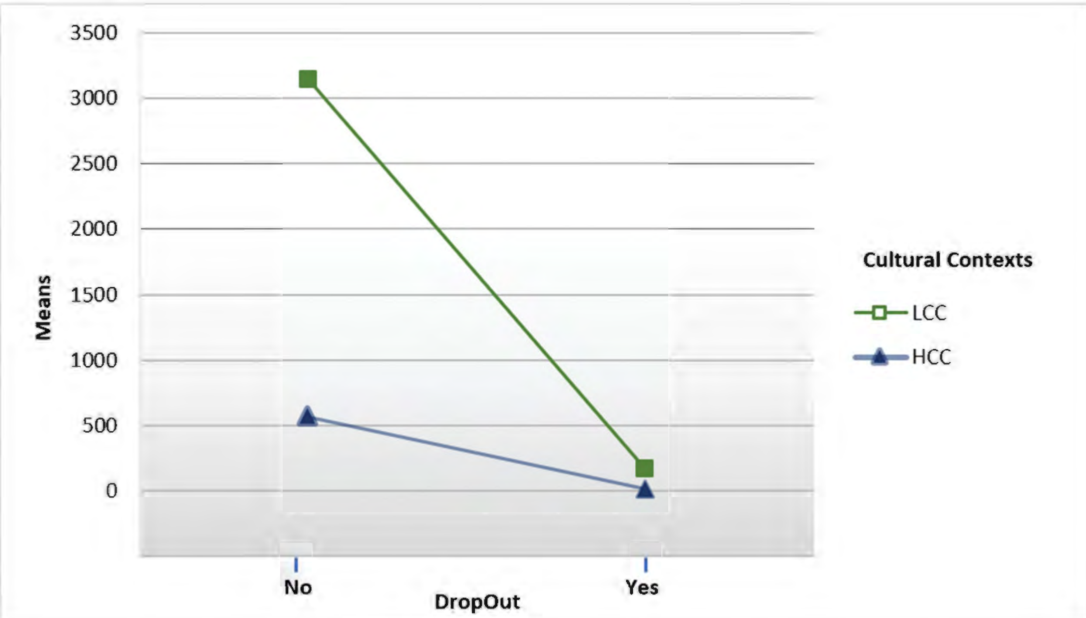

Figure 6: Illustration of the interaction effect of dropout by cultural context pattern.

Simple main effect analyses confirmed that learners who did not drop out had a higher betweenness centrality mean than the dropouts in both cultural contexts (p<0.001), and the effect size values were high (i.e., eta squared = 0.18 and 0.44 respectively). Besides, the betweenness centrality means of the dropouts were similar between the HCC and LCC learners (eta^2= 0.01), but somewhat different between the HCC and LCC learners who did not drop out (eta^2 = 0.077). More specifically, those who did not drop out had a tendency to demonstrate higher betweenness centrality means if they were from a low cultural context.

Discussion

The findings of the study revealed some intriguing issues. First of all, as the weeks progressed, the number of active nodes decreased (from 179 to 38) while the degree of the graph density increased (from 0.0089 to 0.0251) (see Figure 3). The density of any network implies interaction and can be defined as ratio of the total number of the edges if all nodes are connected to each other. In this regard, the "M" letter of MOOC (i.e., massive), referring to the number of the enrollments, is worth discussing. More specifically, instructors may prefer small private online courses (SPOCs) for better social interaction opportunities and less dropout rates (Baggaley, 2014), and so instructional designers need to develop better strategies to support the universal ideals of massive and open learning.

The pattern pertaining to dropouts and non-dropouts along with HCCs and LCCs was further investigated through the average geodesic distance (i.e., AGD), which reflects the shortest paths between two nodes in any network (Figure 5). The findings indicated that AGD was considerably better for non-dropouts (AGD: 1.889) than for dropouts (AGD: 3.339). The Milgram Experiment (MIlgram, 1967) has shown previously that, ideally, all nodes can reach each other in six steps, even in very large networks. In other words, the lower the AGD, the better the network formation is available to connect and interact in the network structure. Considering value as a threshold for AGD, learners from LCCs build closer connections than HCCs, which results in a stronger engagement with the network. The graph density values support the results of AGD (Figure 5). Accordingly, the graph density favors LCCs (0.011) over HCCs (0.005); and non-dropouts (0.111) over dropouts (0.004). This supports the ANOVA results depicted in Figure 6. Accordingly, learners from LCCs build better connections that require fewer steps to interact, and this serves as a social glue, encouraging the student to stick to the learning network and not be a dropout. The importance of this finding is twofold. First, interaction is a vital ingredient in online learning spaces for meaningful learning experiences (Moore, 1989) and lower dropout and higher retention rates; and second, considering that culture is one of the indicators, strategies to lessen transactional distance (Moore, 1993), can be helpful in preventing high dropout rates.

SNA findings have further demonstrated that isolated learners, referred to as lurkers (Sun, Rau & Ma, 2014), have a tendency to drop out. As illustrated in the sociogram (Figure 4), all isolated nodes (n=14) appear to be dropouts, and so it can be suggested that course facilitators need to adopt new roles to welcome, embrace and pull these types of learners from the peripherals to the core network. The network structure in Figure 4 shows that the more central positions the learners occupy, the less likely they are to drop out. This finding also indicates the significance of social learning and community formation processes for the provision of social interaction.

The betweenness centrality values of LCCs (m=404.74) seem to be more salient than those of HCCs (m=98.85) (Table 1). The betweenness centrality outputs of cultural contexts imply that learners from LCCs hold more central positions and have the ability to bridge other nodes or clusters, which emerge as a catalyst for a tightly-connected network formation. Furthermore, the betweenness centrality for non-dropouts in any cultural context (BC: 3137.00 in LCCs; BC: 560.15 in HCCs) outweighs that of dropouts (BC: 162.36 in LCCs; BC: 11.57 in HCCs). The SNA findings and ANOVA results support the idea that betweenness centrality can be used as a predictor of dropout, both in HCCs and LCCs. The findings of this study further corroborate the assumptions of Bayer, Bydzovská, Géryk, Obsivac and Popelinsky (2012), who maintain that SNA can be used to predict dropouts. This finding further confirms Liu et al. (2016), who state that a students' country of origin and the cultural context they belong to can be an indicator of their performance and behaviors. In addition, the findings support the assumptions of Yang et al. (2013) who claim that betweenness centrality is highly related to dropout rates. The findings of the present study also suggest that cultural contexts may define learners' cultural distances to predict learners' interaction and dropout status, which is in line with the findings of existing literature. That is, culture predicts every aspect of our lives (Hofstede, 1986), and cultural distance (Shenkar, 2001) has an effect on how we learn and behave in learning spaces (Alabdullaziz, 2015; Skrypnyk et al., 2014; Stager, 2015; Tapanes et al., 2009).

According to Hall (1998), learners from HCCs tend to be dropouts. Their characteristics involve indirect and implicit messages, frequent non-verbal communication, and intuitively and emotionally driven decisions. On the other hand, learners from LCCs tend not to be dropouts, and their characteristics involve direct and clear messages, less frequent non-verbal messages, and decisions that are taken on the basis of facts and evidence. In the original theoretical framework of Hall (1998), learners from HCCs seem to prefer long-term relationships, while learners from LCCs can survive with short-term relationships. Considering the lengths of MOOCs, this can be a crucial factor explaining dropout and retention. For learners in HCCs, there is a distinction between the in-group and out-group, while in LCCs, this distinction is more flexible and open. In this regard, the learners' perceived sense of community can be another factor affecting dropout status. Though synchronous and asynchronous communication opportunities are available in online networked spaces, most of the communication is text-based, since learners are globally distributed in time and space. On the other hand, the low reliance on text-based communication in HCCs can explain less connection to the network and low betweenness centrality. In contrast, the high reliance on text-based communication in LCCs can explain the high connection to the network and high betweenness centrality.

Conclusion and theoretical/practical implications

Online networked learning spaces are global and distributed, and accommodate culturally-diverse learners. The fundamental role of culture in interpreting behavioral communication patterns cannot be ignored, as these contexts are subject to cultural influences. Based on these thoughts, the present study examines the dropout patterns of learners in online networked spaces through the lenses of high and low cultural contexts. The research findings revealed that cultural contexts affected learners' dropout patterns.

As learning spaces have become more online and network-based, there is a need for further research focusing on cultural issues in these spaces. Other theoretical lenses, such as GLOBE Societal Clusters (House, Hanges, Javidan, Dorfman & Gupta, 2004) and Hofstede's National Cultural Dimensions (NCD) (Hofstede, 1986) can help enrich our understanding on how culture affects communication, interaction and dropout patterns.

The present study has several pedagogical and practical implications. For instance, Universal Instructional Design (UID) provides core principles that embrace learners from diverse backgrounds and provide equality and accessibility (Scott, McGuire & Shaw, 2003). In line with the inferences of this approach, instructors can design online learning spaces in such a way that learners from different cultural backgrounds are welcomed. To achieve this, vital components of the culture, such as language, symbols, norms, beliefs, and values, can be considered during instructional design.

Considering the global nature of MOOCs and other similar online networked learning practices that are global, multiple entry points can be provided for a culturally-diverse learner population. Universal learning processes can be designed to welcome any learners from different cultural contexts. In addition, learners can be provided with opportunities to customize their learning processes, which can lower barriers stemming from cultural differences, and ease the integration of learners into the learning process. Innovative approaches of learning analytics can also be used to identify and analyze learners from different cultural contexts so as to provide communication opportunities that fit their preferences. Additionally, direct communication after the identification of learners on the peripherals of the networks can be helpful in pulling them to the central network and building stronger connections to prevent dropout.

The findings of this study are based upon learners' actual behaviors in online networks and are derived from objective and quantitative data. Nonetheless, culture is a significant component of social structures, both in online and offline spaces, and so qualitative in-depth studies that involve both internal and external motives may ensure a broader understanding of culture and dropout patterns.

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