Impact of cultural diversity on students' learning behavioral patterns in open and online courses: A lag sequential analysis approach

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ABSTRACT: Online and open learning has recently been made prevalent in many regions in order to mitigate educational inequality and to enhance students' learning experiences and outcomes. Previous studies showed that students perform differently in the learning process, where cultural differences matter. However, little is known about how cultural differences affect students' learning behavioral patterns. This study applies a lag sequential analysis approach to understand the behavioral patterns in an online six-week course of 262 students from three cultures, namely Confucian (for Chinese students), Arab (for Tunisian students), and Serbian (for Serbian students). This study then discusses the different learning behavior patterns based on the theoretical framework of Hofstede's National Cultural Dimensions (NCD). The obtained results highlighted that students from each culture behave differently due to several interconnecting factors, such as educational traditions. The results also showed that some of the learning behaviors were not in line with their students' cultures based on NCD, calling for further investigation in this regard. Finally, the results pointed out that culture is a complex dimension, and further investigation is needed to understand the other dimensions that may affect online and open learning behaviors.

Keywords: Cross-cultural online learning, Hofstede cultural dimensions, Open education, MOOCs, Lag sequential analysis

1. Introduction

With the rapid adoption of open education worldwide, several universities have started providing Massive Open Online Courses (MOOCs) for students. This tendency was further increased especially during the COVID-19, where several universities shifted to MOOCs to maintain learning. Unlike traditional online courses, MOOCs can accommodate hundreds of students online from different regions/locations (Stracke, Downes, Conole, Burgos, & Nascimbeni, 2019). For instance, Liu et al. (2016) discussed a MOOC that has attracted students from over 172 countries in five continents.

Bozkurt and Aydın (2018) mentioned that each country has its own pattern of learning behaviors that fulfils the specific criteria of that country. Consequently, a strong relationship is developed between learning behavioral patterns and culture (Yamazaki, 2005). Pratt (1991) and Joy and Kold (2009) mentioned that culture can affect the way students behave and learn. Culture can be interpreted differently in the literature, and it has a broad meaning. Therefore, culture is defined in this study as "the set of attitudes, values, beliefs, and behaviors shared by a group of people, but different for each individual, communicated from one generation to the next" and it affects the way we receive information and process it (Matsumoto, 1996, p. 16). Bates (2001) stated that culture could affect both the teaching and learning processes. In line with this, Che, Luo, Wang and Meinel (2016) also stated that participation in educational processes could also be affected by culture.

Understanding and considering a student's culture in online learning may result in better design for learning. For instance, it is possible to use cultural diversity to promote collaborative learning and social interaction within a given course. Additionally, the non-considerations of cultural diversity might lead to miscommunication between students, which can affect their relatedness to a given course. While several studies discussed culture in online learning, they focused on single learning actions/behaviors (e.g., accessing course, time reading a given learning material, etc.). However, Shang, Xiao and Zhang (2020) mentioned that these single behaviors cannot reflect the students' cognitive engagement and learning behavior characteristics in detail. Therefore, this study analyzes the students' transition behaviors in an online course to understand how culture affected their behavioral patterns. Specifically, this study relies on lag sequential analysis approach to analyze students' learning behaviors. It also refers to Hofstede's National Cultural Dimensions to discuss these learning behaviors.

The reminder of this paper is as follows: Section 2 presents related work about culture and learning analytics, as well as motivates the need for this study. Section 3 presents the method of this study. Section 4 presents and discusses the obtained findings. Finally, Section 6 summarizes this study with the lessons learned, and discusses limitations and future directions.

2. Related work

2.1 Impact of culture on learning

Several research studies have showed that the students' geographical regions could affect their online learning behaviors. This can be due to the culture and habits of that specific region. Vatrapi (2008) argued that culture greatly influences social behavior, communication, cognitive processes, and pedagogical technologies, where all of them are key components in online education. Therefore, culture should be considered as a key element when designing online education in terms of how students learn and what perceive as important to learn (Gómez-Rey, Barbera, & Fernández-Navarro, 2016). Understanding the set of cultural and learning/teaching features will help the educational community to provide better quality yet also culturally sensitive instruction.

Guo and Reinecke (2014) highlighted that a student's country of origin can significantly affect how this student navigates in a Massive Open Online Course (MOOC), including the time that they will spend to read a specific learning material and to re-visit again while learning. Kizilcec, Piech, and Schneider (2013) suggested that students' completion of assignments is correlated with their home countries' level on the Human Development Index. Rodrigo, Baker, and Rossi (2013) used three Intelligent Tutoring Systems (ITSs) to investigate how students from different regions behave while learning. They found that Filipino students spent more time on-task in all the three ITSs than U.S. students. They also reported that the Filipino students gamed the ITS more than the U.S. students. Similarly, Ogan, Yarzebinski, Fernández, and Casas (2015) coded the on-task behaviors and interaction of students in Chile. The result showed that, compared to U.S. students, the Chilean students had a higher portion of on-task interactions. Nesterko et al. (2013) found that non-American students were more prone to complete a MOOC and to seek certification than their U.S. counter-parts. 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.

Specifically, the participants of this study were from three different cultures (see Method section), namely Confucian (for Chinese students), Arab (for Tunisian students), and Serbian (for Serbian students). In Confucian-heritage culture classrooms, Chinese students are influenced by Chinese belief systems, particularly Confucian values. This cultural value focuses on academic achievement, diligence in academic pursuits, and the belief that all children, regardless of their innate ability, can do well through the exertion of effort (Rao & Chan, 2009). Chinese students value certificates in the learning process, giving them a sense of achievement (Liu et al., 2016). Several studies pointed out that the Confucian-heritage culture is more assessment-driven with less emphasis in critical thinking and more deference to authority. Affected by this culture, students may fear exhibiting different opinions to the instructor (Leung, 2001; Sit, 2013, Wong, 2004). Zhang (2013) found that Chinese students demonstrated strong power distance in online settings, and perceived learning as more instructor-centered. When meeting challenges and difficulties, Chinese students tend to seek help from their peers rather than interacting with their instructors.

Arab culture is known for its high uncertainty avoidance, where people feel more threatened by uncertain or unknown situations (Hofstede, 1991). Influenced by this cultural feature, it is seen that most Arab students perceived distance education very differently from students from the western world. Al-Harthi (2005) found that many students from the Arab countries were anxious and resistant to take distance courses, as, unlike traditional classrooms, it contains several uncertain learning scenarios. Additionally, one feature related to the Arab culture is a woman's constant concern of society's perception of her family or family name and honor (Al-Harthi, 2005). Therefore, interacting with men, even in classrooms, has always been restricted in some Arab countries (Al-Harthi, 2005). This made distance education, on the other hand, a good opportunity for female students to learn without the social pressure and through interactions online (Al-Harthi, 2005). Furthermore, since the Arab culture scores well on the femininity index (Hofstede, 1991), Arab students might not want to show that they are too eager to learn, resulting in limited interactions in distance education (Al-Harthi, 2005).

As a "young democracy country," the Serbian culture has been influenced by the communist regime and western cultural values. As legacies from its communist history, which emphasized equality and safety, there are high uncertainty avoidance values in Serbian culture, which means that members of the culture feel threatened by ambiguous or unknown situations (Podrug, Filipović, & Stančić, 2014). This cultural feature made Serbian teachers reluctant to adopt distance education since they raised concerns about online fraud and cheating (Perčić, & Vukadinović, 2019). Similarly, Serbian students, at all higher education study levels (undergraduate studies and postgraduate-master studies), were more willing to use traditional textbooks rather than distance learning systems (Perčić, & Vukadinović, 2019). The Serbian culture has high power distance which means that people accept hierarchical order, so students in Serbia are likely to ask instructors or people who have a place for help rather than accepting the less powerful members of institutions and organizations (Hofstede, 1991).

2.2 Learning analytics and lag sequential approach

The widespread use of online learning and MOOCs have generated increasingly large set of learning interaction data that could be analyzed to enhance the learning process. However, the way of analyzing these data for optimizing the learning process has been a challenge in the fields of Learning Analytics (LA) and educational data mining (EDM) (Ferguson, 2012). In LA/EDM, different analytics approaches can be applied to achieve several objectives, namely, prediction, clustering, relationship mining, distillation of data for human judgment, and discovery with models (Baker & Yacef, 2009). Lag Sequential Analysis (LSA) is one particular approach that is situated within the technical domain of discovery with models, and the application area of modelling user knowledge and experience. Much emphasis has been placed on the integration of LSA within the temporality perspective of learning analytics, since it is previously under examined that the temporal nature of learning, which is hidden within high-resolution temporal data, is placed in the central of learning analytics (Knight, Wise, & Chen, 2017).

LSA was proposed by Sackett (1978), and it aims to conduct in-depth investigation on learning behaviours or event chains that occur at frequencies greater than chance. In education specifically, LSA takes transitional relationships into consideration to identify temporal differences in learning behaviours (Chen, Resendes, Chai, & Hong, 2017). For instance, LSA was used to extract common patterns between students that can support teachers to provide personalized feedback when needed (Hou, 2012; Hwang & Chen, 2017; Yin et al., 2017). Hou, Sung, and Chang (2009) used LSA to explore the discussion patterns of teachers during problem-solving tasks. Moreover, LSA was applied to investigate the learning behaviors of high achievement or low achievement students, and confirming the relationship between students' interaction transitions and learning outcomes (Cheng, Wang, Cheng, & Chen, 2019; Zhang, Gao, Holmes, Mavrikis, & Ma, 2019).

2.3 Research gap and study objectives

Several studies have discussed the impact of cultural differences on learning behaviors. However, most of these studies used simple self-report instruments (e.g., Gómez-Rey, Barbera, & Fernández-Navarro, 2016). Those studies, on the other hand, which analyzed students' learning data, mostly focused on single behaviors. Shang, Xiao and Zhang (2020) mentioned that these single behaviors cannot reflect the students' cognitive engagement and learning behaviors characteristics in details. Yang. Wang and Li (2016) mentioned that investigating the behavior transformation sequence can deeply explain how students engaged in a given a course and their cognitive behaviors. Therefore, this study used LSA to analyze the students' behavioral patterns, and understand how the culture impacted the students' engagement within the online course. Therefore, the first objective of this study is to *discuss the similarities and differences in learning behavior sequences between students from different cultures.*

Furthermore, Liu et al. (2016) mentioned that limited research has discussed the obtained investigation findings from a theoretical cultural framework. Specifically, to the best of our knowledge, no study has discussed the students' behavior sequences in online courses based on theoretical cultural framework. Therefore, the second objective of this study is to *use Hofstede's National Cultural Dimensions (NCD) to discuss the similarities and differences students' sequence behaviors from each region (Hofstede, 1983).* NCD is the most widely accepted in cross-cultural educational studies (Viberg & Grönlund, 2013; Nistor et al., 2013).

NCD is considered as one of the reliable cultural frameworks in the literature, as it was the result of a seven-year study of investigating the cultural values of the IBM staff working in 72 countries in 1960s and 1970s (Triki, Bay, Cook, & Law, 2012; Yang, 2019). NCD was considered as the most influential cultural framework as since its publication, hundreds of studies started using it to investigate cross cultural challenges in different fields, including education (Triki, Bay, Cook, & Law, 2012; Yang, 2019). While several research studies are still considering the old 4D/5D model (Marambe, Vermunt, & Boshuizen, 2012; Viberg & Grönlund, 2013; Nistor, Göğüş, & Lerche, 2013; Gómez-Rey et al., 2016), this study used the updated NCD with the following six dimensions:

- Power distance index (PDI). This dimension refers to the extent to which a society accept and expect that power is unequally distributed between members. It means that inequality is endorsed by both followers and leaders of a society. In cultures with high PDI, education is usually teacher centered and teacher defined, and the authority is respected and feared (Hofstede, 2011).
- Individualism vs. collectivism (IDV). This dimension implies the degree to which

people in a society are integrated into groups. In societies with low IDV, students show great dependence on social relationships (Gómez-Rey et al., 2016). In societies with high IDV, knowledge management can be better facilitated through teamwork (Moss et al., 2007).

- Masculinity vs. femininity (MAS). It refers to the distribution of values between genders. Countries with high MAS encourage competition and people of these countries are more assertive and competitive. This dimension gives details on how an education system can focus on cooperation and security or recognition and advancement (Cambridge, 2012).
- Uncertainty avoidance index (UAI). This index deals with a society's tolerance for ambiguity. It indicates to what extent members in a culture feel either uncomfortable or comfortable in unstructured situations (Hofstede, 2011). Students from cultures with high UAI tend to be more comfortable in a structured curriculum with clear instructions and try to minimize such uncomfortableness brought by unknown.
- Long term orientation vs. short term orientation (LTO). This dimension is related to the choices that people want to focus on. According to Hofstede, people in cultures with long-term orientation believe most important events will occur in the future, whereas people with short-term orientation focus on the present. This dimension sheds light on how educational aspiration and motivation differs in different cultures.
- Indulgence vs. restraint (IND). Indulgence stands for a society that allows relatively free gratification of basic and natural human desires related to enjoying life and having fun (Hofstede, 2011). Indulgence index indicates to what extent a culture allows the freedom of speech. In cultures with high indulgence score, a relaxed structure governs the relationship between students and teachers (Gómez-Rey et al., 2016).

Figure 1 shows the scores of the six Hofstede's National Cultural Dimensions (described above) for Tunisian, Serbian and Chinese nationalities. Students from these nationalities joined the online course in this study (see Method section). It should be noted that these scores are obtained by using the Hofstede's online tool (https://www.hofstede-insights.com/product/compare-countries/). This tool is used in several studies to investigate the cultural scores of the six Hofstede's National Cultural Dimensions for a given country (e.g., Bozkurt & Aydın, 2018). It should be noted that the dimension scores related to LTO and IND for Tunisia were missing using this tool. Therefore, these scores were obtained based on these two references (Messner, 2020; Triki, Bay, Cook, & Law, 2012). Specifically, Triki et al. (2012) found that LTO score for Tunisia is 26, while Messener (2020) found that IND score for Tunisia is 34.

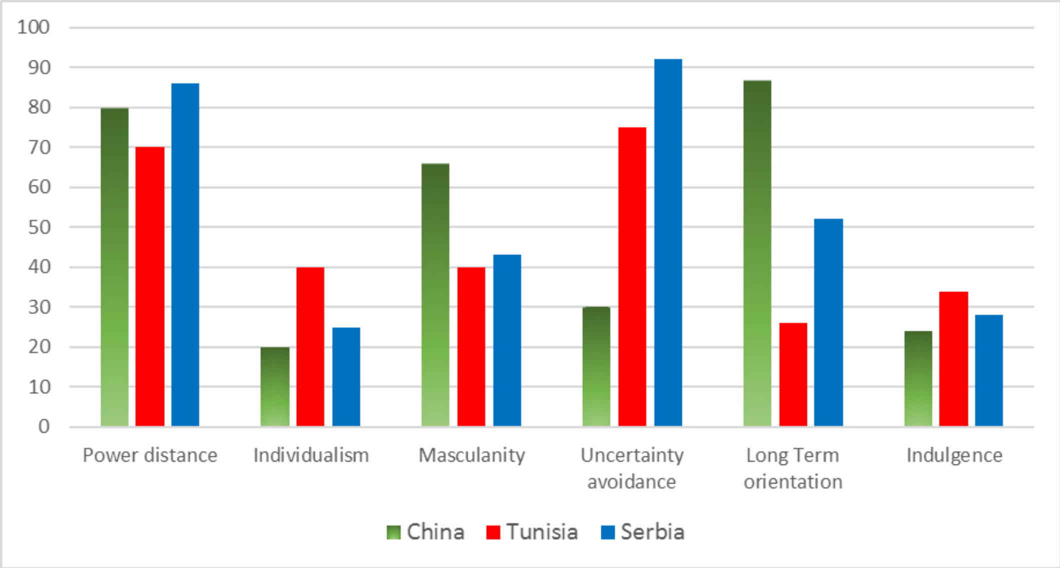

Figure 1. Scores of the six Hofstede's National Cultural Dimensions for China, Tunisia and Serbia

3. Method

3.1.Study context: Course design

A Global Competition on Design for Future Education was launched and hosted last year by [this information was deleted for the blind review process] to cultivate young talents, promote the concept of "future education design" and the development of future educational models. The competition was open for both undergraduate and graduate students worldwide. In this context, a "Design and Learning" course for six-weeks was launched on Moodle in August 2019 for those enrolled in the competition. Formal (e.g., University' international office department) and informal (e.g., social networks) channels were used to advertise for the course and competition worldwide. The course was mandatory for the competition, which means that students cannot join the competition if they do not finish this course. Nonetheless, the students had the chance to freely dropout of the course whenever they want. It was also made clear for all the students that taking this course or not does not have an impact on their university grades or credits.

This course was prepared by the competition's host university for novice students learning about educational technology. It aimed to familiarize the participants with education, educational technology and design theories and concepts. The students were requested to fill their profile on Moodle when they registered for the course. The profile information aims to help students learn about their peers from their profiles. It covers full name, country, university, background and a short biography (couple of lines) about each student, like their passion and competencies. For each course module (one week), the students had to go through different learning materials (videos, PDF, etc.) and upload different written assignments about several questions/tasks asked by the teachers. For each completed module, students earned a course badge. The students had also the option to view their course report that includes the number of completed assignments/modules, course progress bar, and the received grades.

The students had the possibility to freely use the course forum to post their questions and to communicate with their peers (i.e., not mandatory task). The teachers were more as facilitators by encouraging participants and helping them online by joining their forum discussions, when needed. Additionally, at the beginning of the course, students were strongly encouraged to use the communication channels within the course to communicate with their peers (i.e., get to know each other, as well as their skills), as they need to build teams by the end of the course to enter the competition.

The online course system was run on the Modular object-oriented dynamic learning environment (Moodle), a free and open-source Learning Management System (LMS). As shown in Figure 2 (a) and (b), the students had to go through different learning materials (e.g., video lectures and PDF resources) each week with a final assignment to finish (see Figure 2 (c)). The students could go to the “Design and Learning Forum” (see Figure 2 (a)) to interact with their peers or ask questions. Finally, the students had the possibility to see the list of their peers, as well as generated reports related to the collected badges, competencies and grades (see Figure 2 (a)).

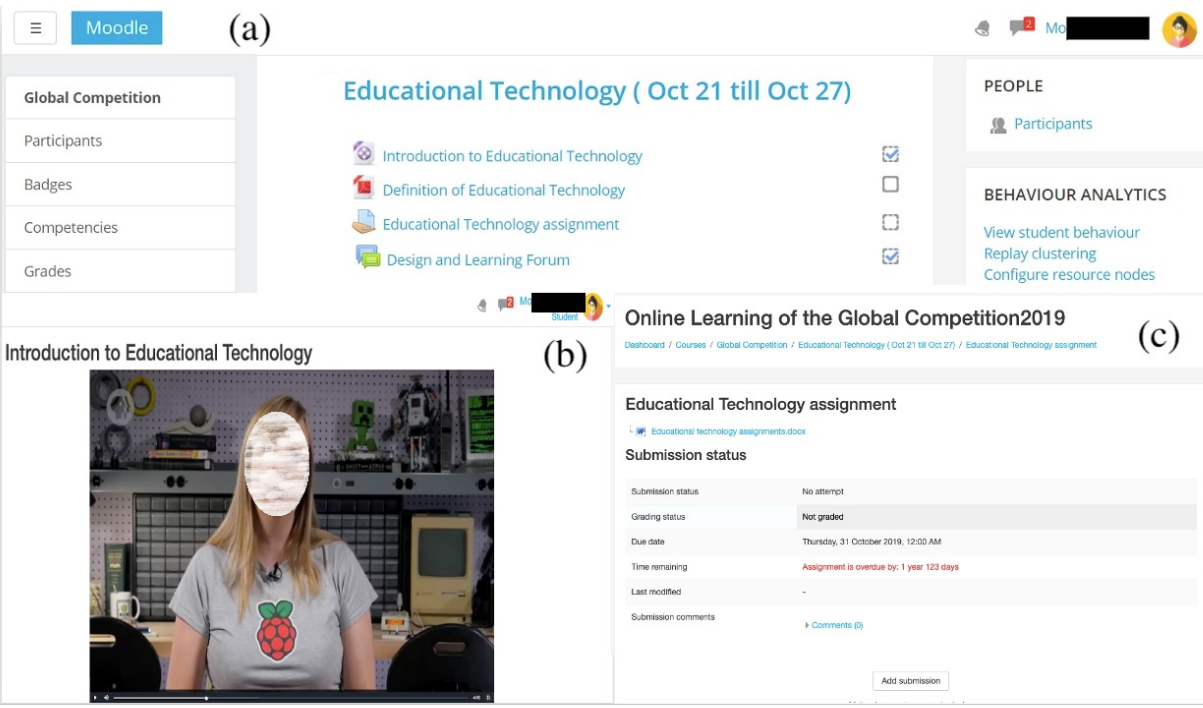

Figure 2. The Moodle system: (a) learning resources of the course, (b) an example of a video lecture and (c) example of an assignment submission form.

Since the course was offered in August, which was during summer holidays for several universities, only students from three countries, namely Tunisia (Africa), China (Asia) and Serbia (Europe), participated in the course. Despite that the course was open, it still cannot be fully considered as MOOC due to the limited number of students and countries joining in. However, this course can constitute a case study to analyze the impact of cultural differences on online learning behaviors, as these countries have different cultures.

3.2.Participants

Two-hundred and sixty-two students voluntarily participated in this competition after their universities (contacted by the host University' international office department) shared the call for participation in this competition, where all of them were enrolled in the "Design and Learning" course. These students were from three different countries, namely Tunisia (Africa), China (Asia) and Serbia (Europe). Table 1 presents the regional distribution of the students.

Table 1. Regional distribution of students

Gender	Tunisian	Chinese	Serbian	Total
Male	45	35	9	89
Female	71	81	21	173
Total	116	116	30	262

3.3.Data coding and analysis

Students' learning behaviors were automatically captured and stored by Moodle online. Specifically, after data cleaning, this study collected 1475869 log data from the 262 students (described above). These log data describe seventeen online learning behaviors. For coding reliability purposes, the collected log data were independently coded by two expert coders (Lipsey & Wilson 2001), as shown in Table 2. After that, the two coders examined the inconsistent coding results. Inter-rater reliability was 79% before consensus was reached. It was then increased to reach 100% after regular meetings and discussions between the coders to solve coding disagreements. To identify the learning behavior patterns from each country, LSA was applied using GSEQ version 5.1. The z-score value of each connection between each sequence was calculated to determine if that connection reached the statistical significance. A z-score greater than 1.96 indicates that a specific sequence has reached the level of significance ($p<0.05$). This indicates that the occurrence of that behavioral transformation sequence is significant (Bakeman & Quera, 1995). The transitional probabilities, which is the conditional probability of a transition type (Cheng, Liu, Sun, Liu, & Yang, 2017), were calculated using GSEQ version 5.1. Kruskal Wallis H test with post-hoc analysis was conducted to further investigate the significance difference between the students' behaviors and behavioral patterns within the three cultures.

Table 2. Coding of the 17 learning behaviors

Course activity category	Learning activity	Code
Course module activity	course module searched	A
	course module viewed	B
	course module completion	C

	submission form viewed	D
Assignment submission	submission upload	E
	submission updated	F
	comment created	G
	discussion created	H
Discussion	discussion subscription created	I
	discussion viewed	J
	comment deleted	K
	the list of peers is viewed	L
Peers	peers' profile is viewed	M
	peers' course report is viewed	N
	Collected badge is viewed	O
Achievement result view	Personal course report is viewed	P
	grade report viewed	Q

4. Results and discussions

4.1.Impact of culture on the frequency of online learning behaviors

The frequency of each (single) learning behavior was measured and presented in Figure 3. It is seen that the students from the three cultures had almost the same frequency of some learning behaviors, such as B and C. They also behaved differently when it comes to other behaviors such as L.

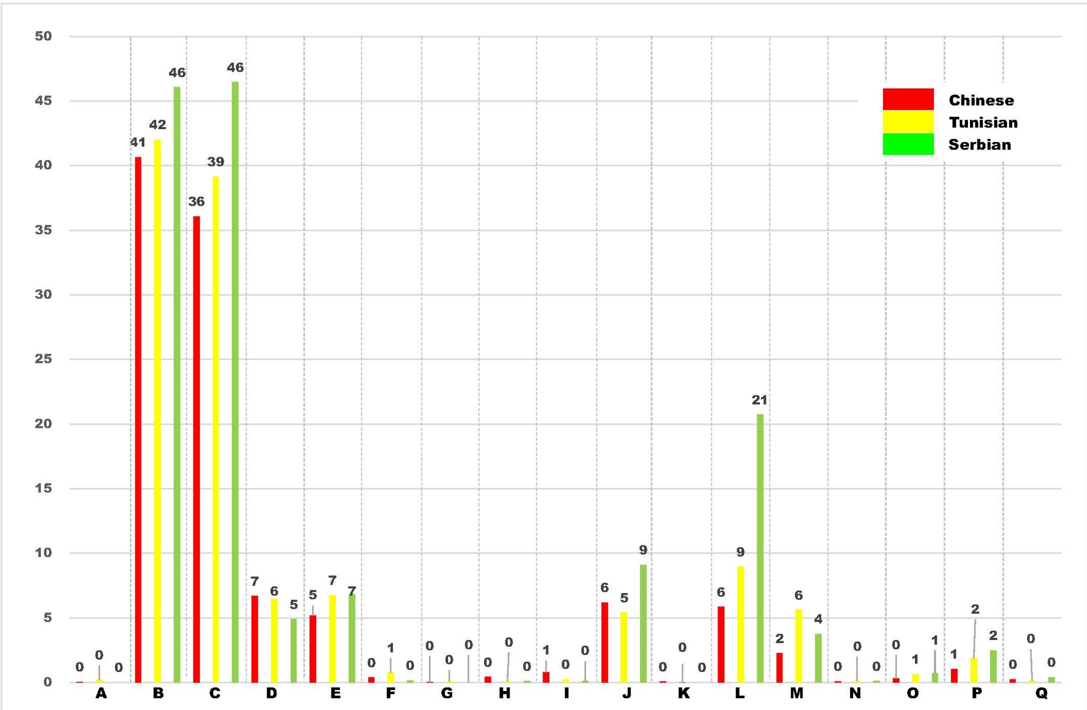

Figure 3. Frequency distribution of the 17 behaviors among the three cultures

To further investigate the significance difference between the frequency of the online behaviors within the three cultures, Kruskal Wallis H test with post-hoc analysis was conducted. As shown in Table 3, out of the seventeen behaviors, only five behaviors were significantly different among the three cultures, namely updating assignment (F), creating discussions (H), subscribing to discussions (I), viewing the list of peers (L) and viewing the profile of peers (M). Post hoc analysis was then conducted for these five behaviors to understand the obtained significant difference. For behavior F, it is found that there is a significant difference only between Serbian and Arab cultures ($t = 2.936$, $p = .01$). For behavior H, it is found that there is a significant difference only between Confucian and Arab cultures ($t = 3.00$, $p = .00$). For behavior I, it is found that there is a significant difference between both Confucian and Arab cultures ($t = 2.42$, $p = .04$), and Confucian and Serbian cultures ($t = 3.35$, $p = .02$). For behavior L, it is found that there is a significant difference between both Serbian and Arab cultures ($t = -2.59$, $p = .02$), and Serbian and Confucian cultures ($t = -3.65$, $p = .00$). Finally, for behavior M, it is found that there is a significant difference between both Confucian and Arab cultures ($t = -6.35$, $p = .00$), and Confucian and Serbian cultures ($t = -2.60$, $p = .02$).

Based on the findings above, it is found that culture can impact the frequency of specific learning behaviors which are under three categories (see Table 2), namely: Assignment submission, Discussion and Peers. To have deeper understanding of the behavior differences, behavioral patterns were further analyzed using LSA.

Table 3. Results of the Kruskal Wallis H test for the 17 learning behaviors

Behavior	Culture	Mean Rank	Chi-Square	df	Sig
A	Con	128.85	4.24	2	1.12
	Ara	134.6			
	Ser	125.5			
B	Con	125.06	2.33	2	.31
	Ara	132.5			
	Ser	148.25			
C	Con	125.42	2.52	2	.28
	Ara	131.7			
	Ser	149.88			
D	Con	129.87	.86	2	.64
	Ara	134.79			
	Ser	120.85			
E	Con	121.33	3.79	2	.15
	Ara	137.58			
	Ser	143.15			
F	Con	126.22	10.07	2	**.00***
	Ara	141.95			
	Ser	107.52			
G	Con	132.47	1.49	2	.47
	Ara	130.30			
	Ser	128			
H	Con	140.31	9.42	2	**.00***
	Ara	122.85			
	Ser	126.25			
I	Con	143.94	13.31	2	**.00***
	Ara	121.24			
	Ser	118.40			
J	Con	137.67	5.33	2	.7
	Ara	119.91			
	Ser	147.73			
K	Con	133.01	2.72	2	.25
	Ara	129.62			
	Ser	128.50			
L	Con	118.38	13.57	2	**.00***
	Ara	133.43			
	Ser	170.47			
M	Con	99.95	40.76	2	**.00***
	Ara	160.36			
	Ser	138.52			
N	Con	129.99	.59	2	.74

	Ara	131.21			
	Ser	134.10			
O	Con	126.30	1.63	2	.44
	Ara	133.96			
	Ser	137.83			
P	Con	125.7	1.97	2	.37
	Ara	133.53			
	Ser	141.78			
Q	Con	134.95	1.98	2	.37
	Ara	127.23			
	Ser	130.15			

Confucian (Conc), Arab (Ara) and Serbian (Ser)

Statistical significances are boldfaced and reported as $*p < .01$.

4.2. Impact of culture on the online learning behavioral patterns

Sequential analysis of students' (Chinese, Tunisian and Serbian) behaviors was applied and the results are presented in Table A1, A2, and A3 (see Appendix A) for Tunisian, Serbian and Chinese students, respectively. These tables show the z-score in which students of the respective nationality go from one kind of learning activity (in each row) to another (in each column). Based on these tables, a behavior transition diagram was drawn for each nationality, as shown in Figures 4, 5 and 6, showing those sequences which reached a significant effect. The significant sequence is the sequence with z-score of more than 1.96 (Bakeman & Quera, 1995). Each transition (in Figures 4, 5 and 6) has both significance and probability values represented on each line as follow: *Significance (Probability)*. The effect size was highlighted based on the probability of each transition (Jeong, 2007), where the thicker the lines, the higher the probability of each transition.

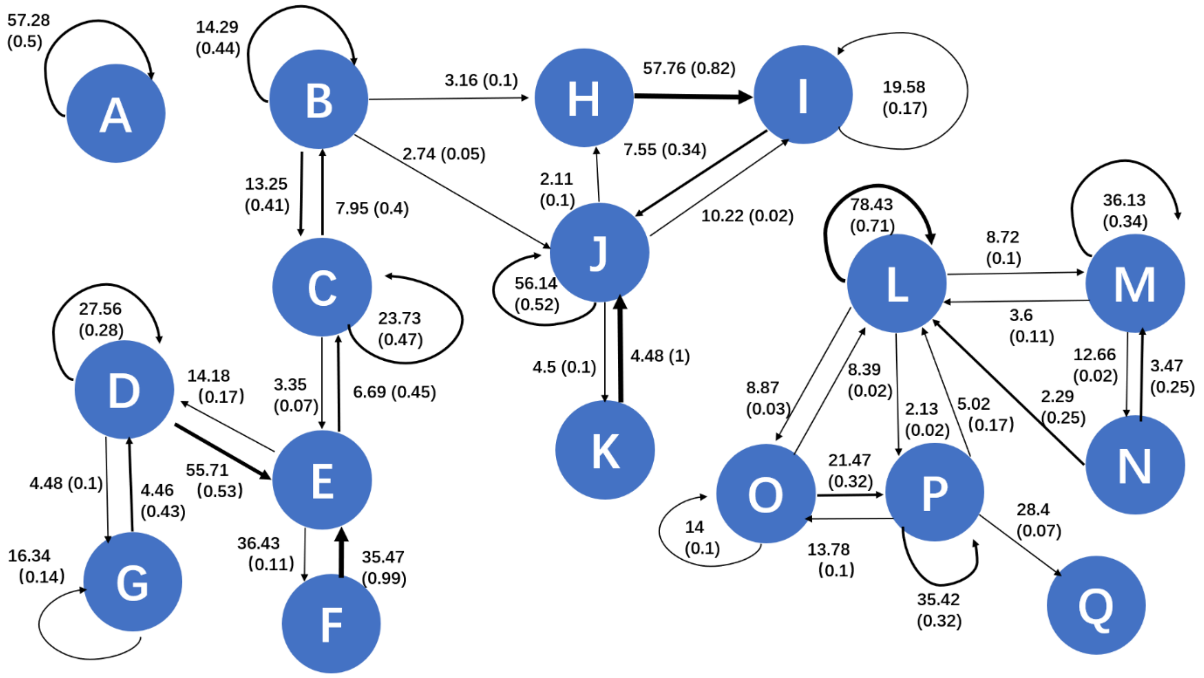

Figure 4. Behavior transition diagram of Tunisian students

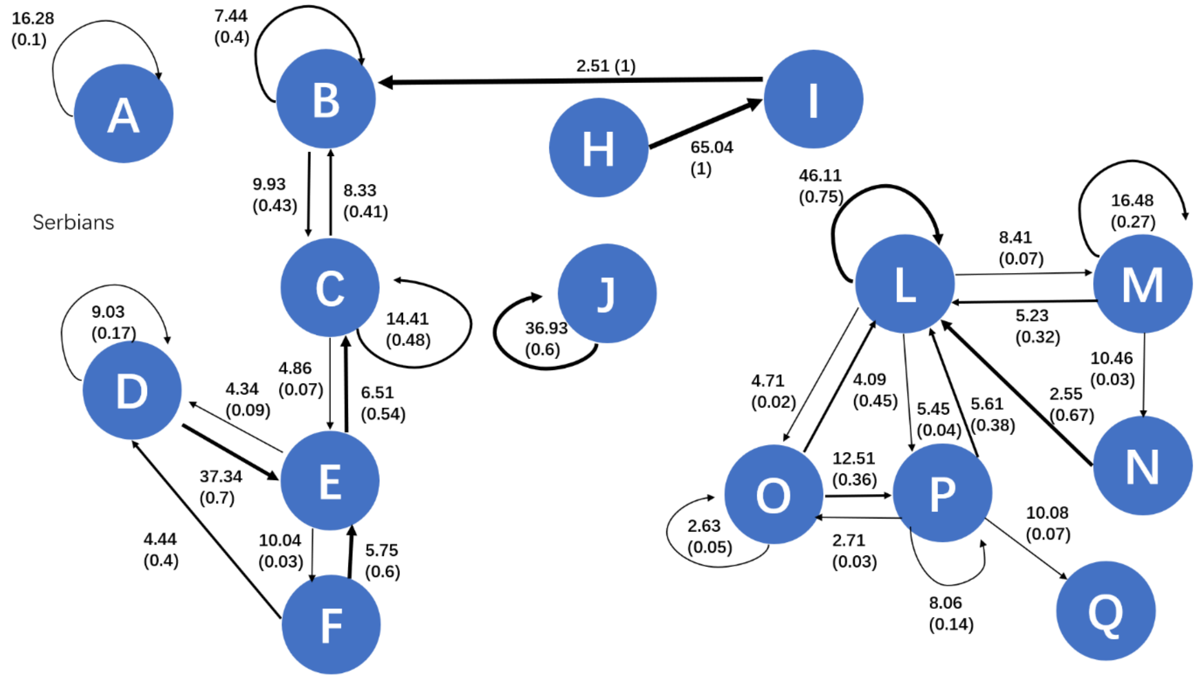

Figure 5. Behavior transition diagram of Serbian students

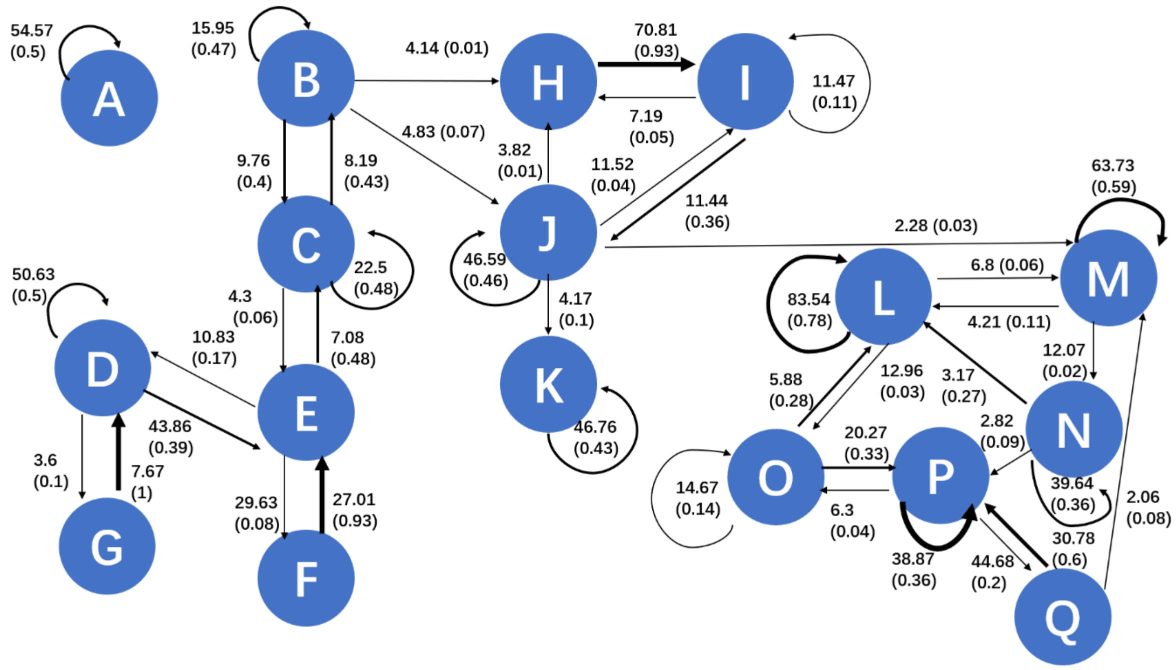

Figure 6. Behavior transition diagram of Chinese students

These behavior transitions were then discussed from three perspectives, namely learning approach, discussion behavior and team building, based on Hofstede's National Cultural Dimensions (see the next subsequent sections).

4.2.1. learning approach

It is seen that all students, regardless of their cultures, started by gaining a generic idea about all the course content, by viewing each course module (B→B). They then started reading each module and finishing it (B→C). The probability of this transition (B→C) was almost the same between all the students from the three cultures (41% for the Arab culture, 40% for Confucian culture and 43% for Serbian culture). It is also seen that all the students uploaded the associated assignment, and further updated it (E→F). The probability of this transition (E→F) was almost the same between all students from the three cultures as well (11% for the Arab culture, 8% for the Confucian culture and 9% for the Serbian culture).

Kruskal-Wallis test was then calculated to investigate the difference of these behavioral transition patterns among the three cultures. As shown in Table 4, no significant difference is found ($p > .05$). Therefore, it can be deduced that these learning behavioral patterns are typical, where all students generally follow them regardless of their cultures, where they start by seeing the whole course content to know its focus. They then start carefully reading and finishing each course module. In this context, Vermunt and Vermetten (2004) have concluded based on several empirical studies that "relating and structuring" is frequently observed in learning. This means that students intend to relate elements of the subject matter to each other and to prior knowledge; structuring these elements into a whole, before they start the learning process. Thus, our finding aligns with former studies and confirms that this typical learning strategy is prevalent in online learning.

Additionally, it is seen that students from both the Confucian and Arab cultures used forums to ask questions to better learn the course content in each module (B→H) or were involved in discussions to reflect on their assignments (G→D). However, students from the Serbian culture were involved differently, and did not engage with their peers, where they followed a more reflective approach, by reading discussions and then going back to the learning materials (I→B). For instance, the probability of the transition B→H was the same, 10%, for the students coming from the Confucian and Arab cultures, however it was 0% for Serbian students. Also, the probability of the transition I→B was 100% for the students coming from the Serbian culture, however it was 46 % and 38% for the students coming from the Confucian and Arab cultures, respectively.

Kruskal Wallis H test was further conducted to investigate if there is a significant difference between these transitions. As shown in Table 4, it is seen that there was a significant difference of only the transitions B→H and I→B between the three cultures. Post-hoc analysis further revealed that students from the Serbian culture scored the lowest B→H transition pattern compared to the Arab culture ($t = .1$, $p = .04$) and Confucian culture ($t = .9$, $p = .03$), while having the highest I→B transition pattern compared to both cultures.

From the Hofstede's model (see Figure 1), it is seen that all the three cultures have high power distance and low individualism. Therefore, it is expected that the students from these three cultures would prefer to engage with their peers in order to understand something, rather than with their teachers as they highly respect them, and do not dare ask them questions (Gómez-Rey et al., 2016; Hofstede, 2011). However, interestingly, this was not the case for the Serbian culture. This might be further explained by the impact of the educational traditions. Specifically, in Asia and in the Arab region, social networks, such as WeChat and Facebook, are frequently used in education (between students, students and their teachers and even between the administration and both students and teachers) where groups are created to discuss several educational topics (Saif, Tlili, Essalmi, & Jemni, 2019; Xu, Chen, & Chen, 2020). This might affect their learning behaviors and enable them to be more open to engage in discussions within the course. For instance, UK higher education institutions are now developing strategies to attract and educate Chinese students by utilizing WeChat (Zhu, 2019). However, European countries, on the other hand, rely more on formal communication ways (e.g., emails or office meeting hours). This might explain the reason that made Serbians not be open to engage in discussions while learning as their peers (from Tunisia and China). Studies from Europe have shown that the social media is yet restricted and limited in scientific discipline (Manca & Ranieri, 2016).

Additionally, it is found that students from the Confucian culture saw their peers' course achievements and then moved to see their achievements (N→P). This might be to compare their course achievements and progress with that of their peers, and this was not the case for students from the Arab and Serbian cultures. As shown in Table 4, Kruskal-Wallis test showed a significant difference of this behavioral pattern (N→P) among the three cultures, where post-hoc analysis revealed that the Confucian culture had the highest frequency of this transition behavior compared to both the Arab culture (t = 2.37, p = .01) and Serbian culture (t = 1.57, p = .01). This resonates to both theoretical and empirical conclusions. Masculinity, which is an important index of Hofstede's model, indicates to what extent a system value cooperation or advancement. According to Hofstede, cultures with high masculinity encourages competition and teachers value only excellence. Particularly, the Confucian culture in our study is categorized with high masculinity (see Figure 1). Hence, Chinese students were accomplishment-driven and valuing competition. In the same context, Liu et al. (2016) also pointed out that that students from the Confucian culture value learning certificates, as it gives them a sense of achievement.

Table 4. Results of the Kruskal Wallis H test for the learning behaviors

Behavior	Culture	Mean Rank	Chi-Square	df	Sig
B→B	Con	131.02	.72	2	.69
	Ara	129.19			
	Ser	142.30			
B→C	Con	125.98	2.32	2	.3
	Ara	132.37			
	Ser	149.48			
E→F	Con	132.13	1.25	2	.53
	Ara	131			
	Ser	131			
B→H	Con	138.72	6.39	2	**.04****
	Ara	125.84			
	Ser	125.43			
G→D	Con	133	1.53	2	.46
	Ara	130.78			
	Ser	128.50			
I→B	Con	140.41	8.32	2	**.01****
	Ara	123.91			
	Ser	126.4			
N→P	Con	142.24	9.85	2	**.00***
	Ara	126.82			
	Ser	108.05			

Confucian (Conc), Arab (Ara) and Serbian (Ser)

Statistical significances are boldfaced and reported as *p < .01 and **p < .05

4.2.2. Discussion and interaction behaviors

It is seen that students from the three cultures behaved differently in participation in the forum. Each time when students from the Confucian culture subscribed to a given discussion, they get involved in it by posting answers (I→H). They also used discussions to see the profile of some peers (J→M), who may give some interesting answers during the discussion. Tunisian students, on the other hand, engaged in a different way to Chinese students. Every time they read a discussion, they went on to create a new discussion topic (J→H). Finally, Serbian students were more passive, as every time they subscribed to a discussion, they went back to view the course to complete the module (I→B). Based on the above, it can be deduced that the students from the three cultures used discussions in three different ways. Chinese students engaged in discussions and then ended up doing some social networking by viewing other peers' profile. This could be explained based on their high scores related to "long term orientation" index (see Figure 1), unlike Serbians and Tunisians. Therefore, Chinese students aimed to make use of discussions to further establish or develop relationships with their peers. Kipnis (1997) stated that it is typical of Chinese people to establish personal relationships, which are usually naturally occurring or created and maintained over time.

Tunisian and Serbian students, on the other hand, used discussions for a more reflective approach. For instance, it is seen that Serbian students used discussions to reflect on what they learned and revisited again the given learning materials. However, Tunisian students used discussions to reflect on what they learned and further asked new questions by creating new discussions. These questions could be invoked while reading the discussions of their peers. Nonetheless, the two different ways of using discussions for Tunisian and Serbian students suggest that the students from both cultures aimed to limit their exposure to making mistakes and to ensure correctness of their responses. This is in accordance with their scores in the "uncertainty avoidance" index (see Figure 1). According to Hofstede, strong uncertainty avoidance cultures are typical with constraints in rules. However, as shown in Table 5, Kruskal-Wallis test showed that there is no significant difference of these behavioral patterns among the three cultures ($p > .05$).

4.2.3. Team building

As students had to form teams (4 to 5 persons) with their peers for the competition at the end of the course, their social networking behavior patterns were observed. It is seen that both Tunisian and Chinese students saw the achievement reports of other peers before they start seeing specific profile of their peers (N→M for Tunisians, and Q→M for Chinese). This implies that both Chinese and Tunisians were driven by the course achievements to choose their peers for the competition. However, this was not the case for the Serbian students where they focused on seeing the total peers' list before they see a specific profile of a peer (L→M).

Based on the indulgence index of the three countries (See Figure 1), it is seen that all these three countries have low in indulgence score index, which means that their cultures regard leisure as something less prioritized in the society. Therefore, it is expected that students will make relationships not "for leisure", and it will be mostly for work. However, this was the case only for Chinese and Tunisian students. Hutchings and Weir (2006) stated that Chinese culture and Arabic culture both regard relationships as more valuable creation of opportunities (Hutchings & Weir, 2006). This achievement-driven mindset, by selecting those who have high achievements, led the students to select whom they are going to work with as a team member, for the competitions in order to increase their wining chances. However, the behavior of

Serbian students does not align with their indulgence index. On the contrary, they tend to network with people they might be familiar with (i.e., people from Serbia) instead of people with accomplishments. This may have to do with Serbia's kinship reciprocity, which remains strong in a rapidly industrializing society (Simić, 1973). This strong bond among relatives, acquaintances and friends leads students to team up in an educational setting. However, as shown in Table 5, Kruskal-Wallis test showed that there is no significant difference of these behavioral patterns among the three cultures ($p > .05$).

Table 5. Results of the Kruskal Wallis H test for the interaction and team building behaviors

Behavior	Culture	Mean Rank	Chi-Square	df	Sig
I→H	Con	133.39	3.8	2	.14
	Ara	130			
	Ser	130			
J→M	Con	131.27	.27	2	.87
	Ara	130.70			
	Ser	135.48			
J→H	Con	135.53	5.55	2	.06
	Ara	128.76			
	Ser	126.5			
N→M	Con	130.63	1.6	2	.43
	Ara	132.89			
	Ser	129.50			
Q→M	Con	132.76	2.52	2	.28
	Ara	130.5			
	Ser	130.5			
	Ara	129.94			
	Ser	130.17			

Confucian (Conc), Arab (Ara) and Serbian (Ser)

5. Conclusion and lessons learned

This paper investigated the impact of cultural differences on learning behavioral patterns from the Hofstede's National Cultural Dimensions (NCD). The obtained results revealed that culture can impact the way students use forums while learning or the motivation that drives them to learn (e.g., accomplishment driven). The results also showed that some of the learning behaviors were not in line with their students' cultures based on NCD, calling for further investigation in this regard. For instance, students coming from high power distance and low individualism are expected to interact with each other and use forums. However, this was the case for students from the Confucian and Arab cultures, but not for students from the Serbian culture. It is also seen, when it comes to team building, that the way of doing business in a given society may also affect their learning behaviors (case of students from the Confucian and Arab cultures). This can be explained with culture is a broad concept which can cover other dimensions that researchers should pay attention to as well. For instance, in this study, it is found that the educational traditions (i.e., the use of social networks in education) may affect students' behavior online. Therefore, based on this study, it is concluded that culture should not be taken as a generic concept, and should be investigated deeply to see other associated dimensions that may affect students' online behaviors.

Marrone, Mantai and Luzia (2013) suggested the principles of Universal Instructional Design (UID) for designing culturally inclusive learning environments. However, it is suggested, based on the findings of this research, that cultural diversity is a complex dimension that should be deeply investigated and it is beyond the capabilities of UID. While learning design might be one of the solutions to overcome cultural-issues, it should be also noted that students' individual factors, such as personality, could be one of the solutions too. While education is moving towards open learning environments, students should have more open personalities to accept others' differences online and learn from each other.

Finally, it is also seen, based on the findings of this study, that despite the students were from three different regions (Africa, Asia and Europe), they had a lot of similarity in their cultures based on NCD (see Figure 1), suggesting for a more cultural dominancy rather than diversity. Similarly, Bozkurt and Aydın (2018) also noticed that there is a cultural dominancy in online-networked learning spaces. While cultural differences exist, not enough findings are found so far to explore this heterogeneity for enhancing online learning.

While the current study contributes to the growing interest related to culture and online learning behaviors, some limitations should be acknowledged and further investigated. For instance, this study covered only three cultures, and the sample size of the Serbian students was relatively small. This might affect the obtained LSA results, where students with few behaviors might not be fairly treated. Also, there might be other factors other than cultures that influenced Serbian students' behaviors, due to the limited sample size. Additionally, this study relied on Hofstede's tool to calculate the NCD values for each country, and the students did not complete any culture survey. Therefore, future research could focus on applying structural equation models to investigate how students' perceived culture, for each of the six dimensions, could impact their online learning perceptions and behavioral patterns. Future research directions could also focus on applying the two-step lag behavioral patterns of students to further investigate not only direct transitions, but also the sequence of transitions (Liu, Cheng, Liu, & Sun, 2017).

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Appendix A

Table A1. Z-score of navigational behaviors of Tunisian students

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
A	**57.28**	0.52	-3.32	-1.11	-1.15	-0.36	-0.11	-0.14	-0.22	-1.05	-0.04	-0.53	0.03	-0.15	-0.35	-0.58	-0.15
B	0.48	**14.29**	**13.25**	-4.67	-20.84	-6.61	-1.2	**3.16**	-3.27	**2.74**	-0.75	-18.24	-5.89	-2.71	-5.1	-5.39	-2.81
C	-3.31	**7.95**	**23.73**	-10.19	**3.35**	-6.21	-0.26	-2.34	-3.8	-17.62	-0.71	-20.06	-10.57	-2.54	-4.44	-7.51	-2.64
D	-1.1	-12.57	-18.23	**27.56**	**55.71**	-2.06	**4.48**	-0.78	-1.26	-5.64	-0.23	-7.1	-3.31	-0.85	-1.98	-2.07	-0.88
E	-1.13	-6.74	**6.69**	**14.18**	-5.63	**36.43**	-0.64	-0.8	-1.3	-6.18	-0.24	-6.62	-4.85	-0.87	-1	-1.89	-0.9
F	-0.36	-6.54	-5.99	-2.07	**35.47**	-0.67	-0.2	-0.25	-0.41	-1.96	-0.08	-2.52	-1.89	-0.28	-0.65	-1.1	-0.29
G	-0.11	0.4	-1.87	**4.46**	-0.65	-0.2	**16.34**	-0.08	-0.12	-0.59	-0.02	-0.76	-0.57	-0.08	-0.19	-0.33	-0.09
H	-0.14	-1.21	-2.35	-0.78	-0.81	-0.25	-0.08	-0.1	**57.76**	-0.74	-0.03	-0.95	-0.71	-0.1	-0.24	-0.41	-0.11
I	-0.22	0.26	-3.42	-1.27	-1.32	-0.41	-0.12	-0.16	**19.58**	**7.55**	-0.05	-1.54	0.65	-0.17	-0.4	-0.67	-0.18
J	-0.03	-4.33	-16.04	-0.84	-6.24	-1.95	-0.59	**2.11**	**10.22**	**56.14**	**4.5**	-5.11	1.13	-0.8	0.37	0.52	-0.83
K	-0.04	-0.74	-0.71	-0.24	-0.24	-0.08	-0.02	-0.03	-0.05	**4.48**	-0.01	-0.29	-0.22	-0.03	-0.07	-0.12	-0.03

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
L	-1.34	-15.98	-23.02	-5.34	-8.01	-2.51	-0.75	-0.95	-1.54	-6.99	-0.29	**78.43**	**8.72**	-1.03	**8.87**	**2.13**	-0.05
M	0.02	-0.3	-14.52	-1.12	-5.71	-1.9	-0.57	-0.72	-1.17	0.03	-0.22	**3.6**	**36.13**	**12.66**	0.48	0.01	-0.81
N	-0.14	-0.77	-2.45	-0.82	-0.85	-0.27	-0.08	-0.1	-0.16	-0.77	-0.03	**2.29**	**3.47**	27.48	-0.26	-0.43	-0.11
O	-0.35	-2.8	-5.98	-1.99	-2.07	-0.65	-0.19	-0.24	-0.4	-1.88	-0.07	**8.39**	-1.24	-0.27	**14**	**21.47**	-0.28
P	-0.57	-2.43	-9.01	-1.04	-3.43	-1.08	-0.32	-0.41	-0.66	-3.13	-0.12	**5.02**	-1.61	-0.44	**13.78**	**35.42**	**28.4**
Q	-0.15	-2.1	-2.55	-0.85	-0.88	-0.28	-0.08	-0.1									

Statistical significances of Z-score are boldfaced

The non- significant data are colored in light grey

Table A2. Z-score of navigational behaviors of Serbian students

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
A	**16.28**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0	**7.44**	**9.93**	1.58	-10.2	-1.55	0	1.26	-1.2	2.15	0	-14.85	-4.35	-1.2	-0.99	-4.22	-2.41
C	0	**8.33**	**14.41**	-4.54	**4.86**	-1.56	0	0.02	-1.21	-11.65	0	-16.79	-7.1	-1.21	-2.37	-4	-1.8
D	0	-6.22	-7.96	**9.03**	**37.34**	-0.43	0	-0.33	-0.33	-2.91	0	-4.9	-1.46	-0.33	-0.9	-1.64	-0.66
E	0	-1.32	**6.51**	**4.34**	-3.27	**10.04**	0	-0.39	-0.39	-3.81	0	-4.17	-0.49	-0.39	-1.05	-1.92	-0.77
F	0	-1.54	-1.57	**4.44**	**5.75**	-0.08	0	-0.06	-0.06	-0.59	0	-0.93	-0.36	-0.06	-0.16	-0.3	-0.12
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	-1.2	-	-	-	-	0	-	**65.**	-	0	-	-	-	-	-	-

			1.21	0.33	0.39	0.06		0.05	**04**	0.46		0.72	0.28	0.05	0.13	0.23	0.09
I	0	**2.51**	-1.21	-0.33	-0.39	-0.06	0	-0.05	-0.05	-0.46	0	-0.72	-0.28	-0.05	-0.13	-0.23	-0.09
J	0	-1.8	-10.31	-0.85	-3.84	-0.59	0	-0.45	-0.45	**36.93**	0	-6.17	0.06	-0.45	-1.23	-0.33	-0.91
K	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L	0	-13.46	-18.48	-3	-6.08	-0.93	0	-0.72	-0.72	-7.07	0	**46.11**	**8.41**	-0.72	**4.71**	**5.45**	-0.62
M	0	-1.93	-6.93	1.06	-2.43	-0.37	0	-0.29	-0.29	-2.05	0	**5.23**	**16.48**	**10.46**	0.55	2.23	-0.57
N	0	-1.2	-1.21	-0.33	-0.39	-0.06	0	-0.05	-0.05	1.9	0	**2.55**	-0.28	-0.05	-0.13	-0.23	-0.09
O	0	-2.79	-3.29	0.27	-1.06	-0.16	0	-0.13	-0.13	-1.24	0	**4.09**	0.6	-0.13	**2.63**	**12.51**	-0.25
P	0	-0.49	-5.18	-1.62	-1.92	-0.29	0	-0.23	-0.23	-2.23	0	**5.61**	0.92	-0.23	**2.71**	**8.06**	**10.08**
Q	0	-2.18	-2.22	-0.6	-0.71	-0.11	0	-0.08	-0.08	-0.83	0	-0.42	-0.51	-0.08	-0.23	9.3	29.59

Statistical significances of Z-score are boldfaced

The non- significant data are colored in light grey

Table A3. Z-score of navigational behaviors of Chinese students

	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**	**P**	**Q**
A	**54.57**	-0.23	-1.77	-0.64	-0.56	-0.15	-0.04	-0.14	-0.2	-0.61	-0.06	1.2	-0.36	-0.07	-0.14	-0.24	-0.11
B	0.59	**15.95**	**9.76**	-10.75	-19.19	-5.23	-0.54	**4.14**	-5.73	**4.83**	-2.08	-16.66	-9.68	-1.99	-3.1	-5.58	-3.61
C	-1.76	**8.19**	**22.5**	-13.45	**4.3**	-4.78	-1.44	-4.56	-6.5	-19.62	-1.91	-17.51	-10.42	-2.39	-4.04	-5.61	-3.26
D	-0.6	-16.	-19.	**50.63**	**43.86**	-1.7	**3.6**	-1.	-2.3	-6.4	-0.6	-6.8	-3.0	-0.8	-1.5	-1.9	-0.5

	4	97	9			2		64	4	6	9	3	9	6	8	6	2
E	-0.55	-7.52	**7.08**	**10.83**	-4.6	**29.63**	-0.45	-1.42	-2.03	-5.96	-0.59	-3.65	-3.28	-0.74	-0.6	-0.59	-1.14
F	-0.15	-5.18	-4.16	-1.11	**27.01**	-0.4	-0.12	-0.39	-0.55	-1.67	-0.16	-1.6	-0.97	-0.2	-0.37	-0.64	-0.31
G	-0.04	-1.56	-1.44	**7.67**	-0.46	-0.12	-0.04	-0.12	-0.17	-0.5	-0.05	-0.48	-0.29	-0.06	-0.11	-0.19	-0.09
H	-0.14	-3.96	-4.57	-1.65	-1.45	-0.39	-0.12	-0.37	**70.81**	-1.59	-0.15	-1.53	-0.93	-0.19	-0.35	-0.61	-0.3
I	-0.2	1.46	-6.52	-2.35	-2.06	-0.55	-0.17	**7.19**	**11.47**	**11.44**	4.38	-2.18	-0.54	-0.27	-0.5	-0.88	-0.42
J	-0.61	-1.21	-17.44	-4.22	-6.22	-1.66	-0.5	**3.82**	**11.52**	**46.59**	**4.17**	-4.34	**2.28**	-0.83	-0.82	-1.01	-1.27
K	-0.06	0.27	-1.91	-0.69	-0.6	-0.16	-0.05	-0.15	-0.22	0.94	**46.76**	-0.64	-0.39	-0.08	-0.15	-0.26	-0.12
L	-0.59	-15.83	-18.09	-5.55	-6.02	-1.6	1.71	-1.53	-2.18	-6.44	-0.64	**83.54**	**6.8**	-0.8	**12.96**	1.21	-0.37
M	-0.36	-6.64	-11.21	-2.37	-3.67	-0.98	-0.29	-0.93	-1.33	-0.26	-0.39	**4.21**	**63.73**	**12.07**	-0.9	-1.56	-0.75
N	-0.07	-1.97	-2.4	-0.87	-0.76	-0.2	-0.06	-0.19	-0.27	0.45	-0.08	**3.17**	1.62	**39.64**	-0.19	**2.82**	-0.16
O	-0.13	-1.93	-3.99	-1.57	-1.37	-0.37	-0.11	-0.35	-0.5	-1.51	-0.15	**5.88**	-0.88	-0.18	**14.67**	**20.27**	-0.28
P	-0.24	-3.87	-6.8	0	-2.41	-0.64	-0.19	-0.61	-0.87	-2.64	-0.26	1.66	-0.87	-0.32	**6.3**	**38.87**	**44.68**
Q	-0.11	-1.43	-3.19	-1.31	-1.14	-0.3	-0.09	-0.29	-0.41	-1.25	-0.12	-0.33	**2.06**	-0.15	-0.28	**30.78**	-0.23

Statistical significances of Z-score are boldfaced

The non- significant data are colored in light grey