Measuring Cultural Dimensions of Learning in Online Courses

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ABSTRACT

Online courses lower geographic barriers to educational access and attract learners from around the world. The resulting cultural diversity in online courses has implications for learning preferences, behaviors and outcomes, but established measures of culture are not adapted to educational contexts. We adapted and tested a survey instrument of cultural dimensions of learning that is grounded in cultural psychology research and spans four dimensions: knowledge construction, pedagogical orientation, uncertainty tolerance, and consensus building. We collected 600 responses in two online courses, conducted an explanatory factor analysis, and compared responses across five countries. We found that the instrument has a clear factor structure with high internal consistency, and it can distinguish cultures between countries. The instrument can be used to better understand learners and their culture in the process of course design and evaluation.

CCS CONCEPTS

• **Social and professional topics → Cultural characteristics**; • **Applied computing → Distance learning**.

KEYWORDS

cultural differences, survey measures, online education

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1 INTRODUCTION

Massive Open Online Courses (MOOCs) attract learners from around the world and the global demand for online education has further accelerated during the COVID-19 pandemic [23]. The resulting levels of cultural diversity in these online course can offer valuable opportunities for social learning and feedback [10, 10]. However, gaps in learner persistence and achievement also tend to correlate strongly with geographic and cultural characteristics of learners in these courses [e.g., 8, 9, 17]. These gaps may be related to variation in learner behavior. Several studies found behavioral heterogeneity in MOOCs between learners from different nations and cultures, including differences in in-course navigation strategies [4], in the distribution of learning activities that are used [13], and in self-regulated learning strategies [7, 26]. These findings raise questions about how current course design practices account for the geocultural diversity of learners. Commonly adopted course designs in MOOCs, including the choice of learning activities and assessments, might be imbued with traditional Western values and epistemology, as they originated in the US higher education system [1, 20, 24]. This could lead those who are unfamiliar with Western values and epistemology to experience additional challenges to follow, comprehend, and master the learning content in MOOCs. The role of culture in online education is important but has received relatively little attention historically [28], inspiring recent work to argue for adapting online course designs to fit diverse cultures [19, 29].

How culture is measured plays a critical role in efforts to understand cultural differences between learners and how to respond to them. Prior research on culture in educational contexts relies on country-level measures that originate from large-scale surveys conducted in countries around the world, most notably those by Hofstede [5]. However, the measures used to gauge cultural differences that are relevant to education are often coarse (one score for an entire nation) and frequently uni-dimensional (e.g., the epistemology belief inventory [22], the need for closure scale [21], and self-construal scale [3]). This may overlook consequential variation within a country [25], such as those found across different regions in China [2, 25]. A uni-dimensional measures may be unable to distinguish between several important sources of cultural variation in learning that are relatively orthogonal to each other.

The current study presents a multi-dimensional survey instrument that measures learners' beliefs about learning practices. This instrument is intended to capture the assumptions that educational stakeholders, including students and instructors, make about which pedagogical approaches maximize learning outcomes. Understanding these assumptions can yield important insights for developing online courses for a global audience. This research contributes to advancing our understanding of cultural differences among learners in online education.

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2 BACKGROUND

Cultural psychologists have argued that culture influences people's social cognition and preferences, as well as their epistemological beliefs [5, 11, 15]. This has important implications in educational contexts. To organize cultural differences in education, Parrish and Linder-Vanberschot [16] proposed the Cultural Dimension of Learning Framework (CDLF) grounded in cross-cultural psychology research [e.g., 5, 11, 15]. The framework posits that culture shapes three key aspects of learning: social relationships, epistemological beliefs, and temporal perception. The social relationships component is about how students view themselves in relation to instructors and peers in class. The epistemological beliefs component is about what students believe about the nature of knowledge and the acquisition of knowledge. Finally, the temporal perception component is about how students perceive time and measure their learning progress. Careful consideration of these three components in the development of lessons can help provide effective learning for a culturally diverse group of learners. The temporal perception component may be less of a concern in online courses as they are often shorter, asynchronous, and self-paced. That is why we focus our research effort on cultural factors related to social relationships and epistemological beliefs.

Social relationships are shaped by cultural factors related to interdependence, power distance, and masculinity. First, people in collectivist cultures tend to see themselves in relation to others, whereas those in individualistic cultures see themselves as a separate entity from a group [15]. The distinction between interdependent and independent views of the self matters in classroom settings. In collectivist cultures, the class is more likely to pursue the group's interest; for example, the instructor nudges students become the best performing class in the school. In contrast, in individualistic cultures, there is an emphasis on individual students' personal growth; for example, the instructor encourages students to find their own passion for learning [12]. Second, cultures have varying levels of power distance, defined as the extent to which less powerful members of a group accept the uneven distribution of power [5]. Instructors have power over student outcomes and in a culture where hierarchical relationships are more pronounced, students may perceive the instructor as having more authority, which shapes their interactions. Third, culture also influences attitudes towards competition. In a more masculine culture, competition is more prevailing and ambition to succeed is more cherished [5]. This cultural tendency can manifest in educational context, such that competition between students is fostered and students desire to be the best in their class.

Epistemological beliefs, or beliefs about knowledge and learning, are shaped by cultural factors related to uncertainty avoidance, categorical thinking, and causal attribution. First, certain cultures tolerate uncertainty and ambiguity more than others [5]. Students from a culture that is less tolerant of ambiguity may be more comfortable with pursuing the right answer instead of trying to construct their own argument and logic. Second, ways of processing information systematically differs between cultures with categories. For example, when grouping *panda*, *monkey*, and *banana*, children raised in America, a Western culture, tend to group *panda* and *monkey* based on their taxonomic category (animal); in contrast, children raised in China would group *monkey* and *banana* based on their relationship (monkeys eat bananas) [15]. Third, in addition to categorical inferences, East Asians, compared to Americans, have been found to accept seemingly contradictory information and apply multiple criteria other than logical rules to evaluate information [15].

3 METHODS

We selected and revised statements from the Cultural Dimension of Learning Framework (CDLF) questionnaire [16] to adapt it for online education. We consulted with experienced instructors who have been offering online courses to culturally diverse groups of learners for many years. The adapted instrument consists of 25 items focusing on two high-order categories in the CDLF framework: social relationships (12 items) and epistemological beliefs (13 items). The response scale of the questionnaire is bi-directional with two statements presented as two extremes for each item. Respondents are asked, "do you agree more with the statement on the left or with the statement on the right? 1 = strongly agree with the left statement; 6 = strongly agree with the right statement." An example item is shown in Figure 1.

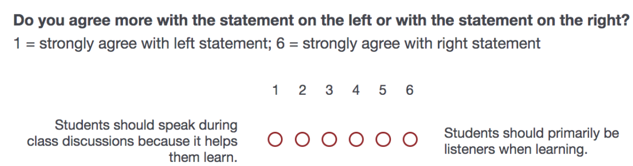

Figure 1: Example of Survey Format.

The survey was embedded at the end of two online courses, *Network Climate Action: Scaling Up Your Impact* (NCA) and *Environment-Science Technology Engineering & Math Education* (E-STEM). The courses were offered in 2020 by a large university in North America, in English, to learners located worldwide via the EdX Edge platform. A total of 600 course participants completed the survey (NCA: 305, E-STEM: 295). According to the survey, participants were from 48 countries (China: 312, 52%; USA: 105, 18%; Iran: 52, Nigeria: 26, 9%; India: 11, 4%; all other countries had fewer than 10 participants each). The majority identified as women (420, 72%; 38% men) and were college educated (Bachelor: 258, 43%; Master: 207, 35%; PhD: 30, 5%; Associate: 26, 4%). Respondents' average age was 33.8 (SD=11.5).

We performed minimum residual factor analysis with varimax rotation for factor extraction and item reduction, using the *psych* R package [18]. We excluded items and reran factor analysis until no item showed a factor loading less than 0.4. We selected the final model based on three fit measures: standardized root mean square of the residuals (SRMR), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA). We confirmed the inter-item reliability for each factor by computing Cronbach's alpha. We labeled each factor based on the statements grouped together. To test if the survey instrument yields cross-country differences in scores, we performed a one-way ANOVA to compare scores of course participants from the five most represented countries in the sample: China, USA, Iran, Nigeria, and India (N = 505).

Table 1: Final Survey Items with Four Factors. Each item consists of two statements and participants choose where they stand between the two on a 6-point scale, from the left end (1) to the right end (6).

Factor	Item	Left End	Right End
Knowledge construction (KC)	1	Students should help decide what is discussed and what activities occur in class.	The instructor's syllabus should be followed without deviating.
	2	Discussions are more important for learning.	Lectures and readings are more important for learning.
	3	Students should speak during class discussions because it helps them learn.	Students should primarily be listeners when learning.
	4	Learning how to solve problems and how to learn on one's own are the most important outcomes of education.	Learning content knowledge is the most important outcome of education.
	5	Learning how to express one's thoughts is the most important part of the learning process.	Understanding what experts have to say is the most important part of the learning process.
Pedagogical orientation (PO)	1	Improving oneself is more important than being the best.	Being the best student is most important.
	2	Failure is an opportunity to learn.	Failure represents wasted time.
	3	Students learn more when they work collaboratively.	Students learn more when they work competitively.
	4	Praise is good for every student, at any level of learning development.	To demonstrate expectations, only the top students should be praised.
Uncertainty tolerance (UT)	1	There is always a correct or best answer, and students should be expected to know it.	Correct answers are less important than critical thinking and problem-solving processes.
	2	It is best to avoid conflicting information in learning.	Multiple resources of information are useful to provide different perspectives.
	3	The instructor's role is to answer students' questions.	The instructor's role is to help students to answer their own questions.
	4	Students should answer questions only when they are confident that the answer is correct.	Students should always attempt to answer questions. It is OK to be wrong if they learn as an outcome.
	5	Students need structure and direct guidance from the instructor.	Students need room to explore and make their own decisions.
Consensus building (CB)	1	Students should challenge others if they feel that they know a better answer or course of action.	Good working relationships are more critical than being correct.
	2	Debating various perspectives is more useful for learning.	Building harmony and trust with others is more useful for learning.
	3	If there is a contradiction, students should argue their case to arrive at the right answer.	If there is a contradiction, dialogue should be used to come to consensus on an acceptable answer.

4 RESULTS

The minimum residual factor analysis suggested a four-factor structure, indicating four dimensions. We excluded 8 items in total, 3 items from the social relationships component and 5 items from the epistemological beliefs component, which left 17 items in the model. The final model achieved SRMR = 0.02, TLI = 0.97, and RMSEA = 0.04, which indicates that the model was a good fit for the data [14]. Items for each factor in this model also reached inter-item reliability (α) above 0.7 (Figure 2). The final set of items is shown in Table 1. We labeled the four factors after reviewing the items: knowledge construction, pedagogical orientation, uncertainty tolerance, and consensus building. We describe each factor in more detail.

Knowledge construction explains the role of instructors and peers in the learning process. It consists of survey items that were originally proposed in the social relationship category from the CDLF. The items address how inequality is handled (e.g., instructor-student relationships) and whether individualistic or collectivist values prevail (e.g., pursuing individual vs. group interests) in the learning context. Some students believe that knowledge is co-constructed with peers and instructors (left end of the item). In contrast, other students believe that knowledge is handed down from experts and instructors (right end of the item).

Pedagogical orientation is concerned with which students' learning attitudes are fostered. For example, should students aim to become the best student or pursue personal goals? How much achievement is valued? All items came from the social relationships category in the framework. In our adaptation, the items compare two pedagogical environments, one in which students learn in a nurturing manner for individual growth (left end of the item) and the other in which students learn in a disciplined manner for selection as the best among others (right end of the item).

Uncertainty tolerance measures beliefs about learning, especially about how ambiguity is addressed in the learning process. It assesses

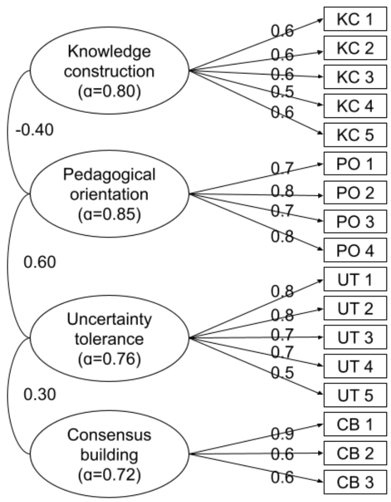

Figure 2: Final Factor Analysis: factor loadings shown on arrows; numbers on the arches between factors indicate correlations between them; inter-item reliability shown in parentheses.

if students believe knowledge is flexible or fixed, and what learning activities should be provided accordingly. It is comprised of items from the epistemological beliefs category in the CDLF. The items contrast two trends of beliefs, learning as mastering established knowledge (left end of the item) and learning as exploring alterable knowledge (right end of the item).

Consensus building is about the process of developing knowledge as a group. The items address the preferred way to manage disagreement, such as which value is more important, logical reasoning or relationship maintenance. The construct compares two values, achieving rigor (left end of the item) and maintaining harmonious relationships (right end of the item) in group-based learning.

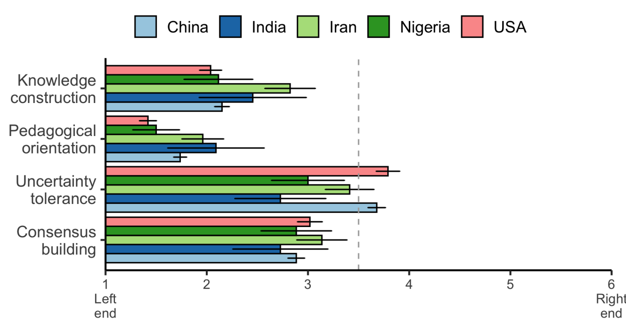

Figure 3: Mean Scores in Five Countries For Each Factor with Standard Errors.

One-way ANOVA revealed significant differences between countries in *knowledge construction* ($F[4, 500] = 3.40, p = 0.01$), *pedagogical orientation* ($F[4, 500] = 2.94, p = 0.02$), and *uncertainty tolerance* ($F[4, 500] = 2.83, p = 0.02$), but not in *consensus building* ($F[4, 500] = 0.49, p = 0.75$). Tukey's HSD test showed that participants in the USA and in Iran were significantly different in knowledge construction ($adj.p = 0.01$) and pedagogical orientation ($adj.p = 0.04$). Those from Iran and China also differed significantly in knowledge construction ($adj.p = 0.01$). No other differences found between countries in other factors were statistically significant at p=0.05.

5 DISCUSSION

This research developed and tested a multi-dimensional survey instrument that measures cultural dimensions of learning. Our survey items were based on the Cultural Dimension of Learning Framework (CDLF) [16], a framework that was proposed based on theories and empirical studies in the literature of cultural psychology.

We found small amounts of variation in the scores between countries (Figure 3), though the measure was sensitive enough to capture some national differences between participants. We consider this to be a conservative test of the instrument due to the nature of our sample. All participants took courses about the same topic, environmental education and action, which itself emphasizes learning as a community and adapting practices to local contexts. Moreover, the survey was distributed at the end of the course and therefore reached only 40% of registrants who managed to complete the course. We therefore expect to find higher levels of variation in responses to our instrument in courses that attract a more diverse audience of learners, such as entry-level course on a popular topic in programming, statistics, social science.

The instrument requires further validation to test its psychometric properties and validity in larger samples. First, a confirmatory factor analysis needs to be conducted on a separate data set to verify the four-factor structure. Second, additional validity testing is required to assess if each factor is correlated with conceptually similar constructs. We plan to pursue these steps going forward.

Once the instrument has undergone formal validation, future research can start to identify connections between the assumptions that learners make in different cultures and course design characteristics. For example, in our study, course participants from the United States and Iran showed a difference in pedagogical orientation. The US-based participants assumed a preference for personal growth, a nurturing learning environment, and collaboration. This difference potentially affects a degree of preference for collaborative learning activities such as group projects and motivational (as opposed to evaluative) feedback on the learning progress. Parrish and Linder-Vanberschot [16] suggest providing alternative pedagogical choices for learning activities and assessments in multicultural classrooms to address differences among students from different cultural backgrounds. Similarly, online course designs could provide alternatives, possibly taking advantage of technology that enables adaptive learning environments and personalization of learning content delivery [e.g., 6, 27].

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