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# LEARNING ANALYTICS TO UNDERSTAND CULTURAL IMPACTS ON TECHNOLOGY ENHANCED LEARNING

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## ABSTRACT

In this empirical study, we investigate the role of national cultural dimensions as distal antecedents of the use intensity of e-tutorials, which constitute the digital component within a blended learning course. Profiting from the context of a dispositional learning analytics application, we investigate cognitive processing strategies and metacognitive regulation strategies, motivation and engagement variables, and learning emotions as proximal antecedents of tool use and tool performance. We find that cultural diversity explains a substantial part of the variation in learning dispositions and tool use. The design of personalized learning paths will, therefore, profit from including national cultural dimensions as a relevant design factor.

## KEYWORDS

Blended Learning; Cultural Diversity; Dispositional Learning Analytics; E-Tutorials; Learning Feedback; Learning Dispositions

## 1. INTRODUCTION

Increasing internationalization of higher education goes hand-in-hand with increased diversity within the classroom. Diversity, not only with regard to prior schooling, and related, prior knowledge, extends to other aspects, including cultural traits and learning dispositions. In order to address these multi-faceted diversities, new instructional models are applied in higher education, especially at stages when this diversity is most pronounced: introductory courses. Flipping the classroom and allowing learners with limited prior knowledge and cultural specific understanding of the host-educational context to adapt instruction time on individual needs are building block of such new instructional models (Tempelaar & Verhoeven, 2016), as in blended learning through the creation of extra practicing and testing opportunities. The application of learning analytics (LA) may be well-suited to provide learners with useful insight of these personal needs (Tempelaar, Rienties, & Giesbers, 2015a).

In this empirical paper, we will investigate the role of cultural traits (as characterised by Hofstede's cultural dimension scores) and the importance of using instructional models that allow for personalized learning paths in a large introductory mathematics and statistics course with high diversity. The instructional model designed to address this diversity includes components of blended learning, combining problem-based face-to-face learning with the use of e-tutorials and a flipped classroom design, supported by dispositional LA (see: Buckingham Shum & Deakin, 2012) to optimize learner feedback. The aim of this research is to focus on the crucial role of cultural diversity, as one of the 'dispositions' in the dispositional LA approach as an antecedent of the intensity of use, and the type of use, of e-tutorial tools.

### 1.1 Dispositional Learning Analytics

A broad goal of LA is to apply the outcomes of analysing data gathered by monitoring and measuring the learning process, whereby feedback plays a crucial part to assist regulating that same learning process. "Traditional" LA applications are based on system trace data of process and output type, such as track data

from learning management systems. Buckingham Shum and Deakin (2012) proposed a ‘dispositional LA’ infrastructure that combines learning activity-generated data with learning dispositions (i.e. values and attitudes measured through self-report surveys), which are fed back to students and teachers through visual analytics. In previous research of the authors (Tempelaar et al., 2015a; Tempelaar, Rienties, & Giesbers, 2015b, 2016), we have demonstrated the power of integrating formative assessment track data (e.g., mastery of concepts, formative assessment scores) into prediction models based on dispositional LA. In this study, we extend this type of analysis by including cultural traits as an additional dispositional factor.

## **1.2 Cultural influences in Online Education**

Previous research has identified that cultural traits may play an important role in the ways that students from different cultural backgrounds approach the use of online educational tools (see, for example: Economides, 2008; Gunawardena, 2014). Thorne (2003), for instance, argued that web resources are not ‘culturally neutral,’ and that some aspects, such as online communication, are heavily influenced by engrained cultural norms. This is demonstrated in research, such as Al-Harhi (2005)’s qualitative analysis of differences in online learning experiences of Arab students in the United States. Further research has highlighted differences in learning motivations and assumptions between those of different cultures (Hedberg & Ping, 2005; Hu, 2004). Sachau and Hutchinson (2012) additionally demonstrated built-in cultural assumptions in website design and its role in diverse users’ interaction with online tools. One suggestion, therefore, may be that cultural traits can explain, to some degree, measurable differences in student behaviours online. However, there is currently need for more research on online learning that considers the role of cultures, as suggested by Zawacki-Richter (2009) and Uzuner (2009). This is of particular dearth in the learning analytics field.

## **1.3 Characterising Cultural Differences**

In the characterisation of cultural differences, research by Hofstede (Hofstede, 1980; Hofstede, Hofstede, & Minkov, 2010) takes a prominent position. Based on an analysis of attitude survey questions obtained from employees in more than 50 countries, Hofstede identified six major dimensions on which cultures differ. Power distance (PDI) refers to the extent to which less powerful members of organisations and institutions accept and expect unequal distribution of power. Uncertainty avoidance (UAI) refers to society’s tolerance for uncertainty and ambiguity, indicating the extent to which members of a culture feel threatened by ambiguous and uncertain situations. Individualism versus collectivism (IND) signals the degree to which individuals are integrated into groups: from loose ties between individuals and self-agency, to integrated and strong, cohesive societies. In masculine societies (MAS), emotional gender roles are rather distinct, whereas, in feminine societies, these roles overlap. Long-term orientation (TOWVS) distinguishes societies in being directed towards future rewards, or the fulfilment of present needs and desires. The final and most recently added cultural dimension is that of indulgence versus restraint (IVR) and signals the degree to which a culture allows or suppresses gratification of needs and human drives related to hedonism and consumerism. While the original aim of Hofstede’s research was to investigate the impact of cultural differences on leadership styles, the cultural dimensions identified by Hofstede appeared to impact learning and teaching styles as well (see, for example: Hofstede, 1986, 2001; Hofstede et al., 2010)

An additional consequence of the interplay of cultural dimensions and learning related activities is that the optimal design of educational systems does have important dependencies on cultural backgrounds of the host society. For example, student-centred education (such as PBL) is an outstanding example of a learning and teaching paradigm that suits students familiar with low power distance, and weak uncertainty avoidance. Thus, student-centred learning may be more appropriate for societies that are characterized by such a constellation of cultural dimensions, as the Netherlands, and Nordic European and Anglo-Saxon countries. In a similar way, motivating students by incorporating competitions seems most effective in masculine, individualistic societies, such as the US and German-speaking countries, but less so in more feminine and egalitarian-oriented countries, such as the Netherlands and Nordic European countries (Hofstede et al., 2010). These examples make clear that cultural diversity does not need large geographical distances, given the rather different characterisations of, for example, Dutch and German societies, as evidenced in Tempelaar and

Verhoeven (2016). With these considerations in mind, this present study considers how cultural diversities influence their online tool use.

## **2. METHODS**

### **2.1 Setting and Context**

This study took place at Maastricht University, which was ranked 14th in the Times Higher Education's Top 100 Most International Universities in the World for 2015. Participants in this study included over 3000 first year undergraduate students in business and economics, and took place during the academic years 2013/14, 2014/15, and 2015/16. In our sample, 41.0% of the participating students were female. Less than one-quarter of the students (22.0%) received a Dutch secondary education, and the remaining 78.0% completed their high school education outside of the Netherlands. Thirty-nine nationalities were present in the dataset, whereby the largest group consisted of students from countries with a Germanistic culture (39.9%). Dutch students were the second largest cohort, comprising 24.2% of the students. The third largest nationality was Belgian, representing 9.2% of the students. The remaining quarter of students was categorized along the following country clusters: Anglo Saxon (2.1%), Eastern Europe (5.1%), Latin Europe (4.8%), and Asia (1.6%).

All participants in this study were enrolled in a university bachelor programme that incorporated problem-based learning (PBL) curriculum and instructional principles. Thus, the curriculum emphasises self-directed learning, with teachers taking a facilitation role rather than acting as lecturers. Educational materials in the program consist of open-ended, unstructured problem cases. In terms of Hofstede-based cultural characterisation, PBL curriculums favor low power distance, feminine values, and low levels of uncertainty avoidance. Dutch society as a whole and its educational system in general already distinguishes itself from neighbouring cultural regions by the same unique combination of low power distance and uncertainty avoidance, as well as high femininity. However, a substantial part of the international students at Maastricht University originate from Germanistic and Eastern-European cultures, with rather opposite characterisations on these three cultural dimensions.

### **2.2 Instructional Design and Tools**

In this study, the educational system in which students learn mathematics and statistics is best described as a 'blended' or 'hybrid' system. The main, required component is in a face-to-face, problem-based learning (PBL), setting, where small groups of approximately 14 students are coached by a content expert tutor (Tempelaar, 2016). The online component of the classroom is optional, and includes practice and testing e-tutorials through MyMathLab and MyStatLab.

These e-tutorial systems are generic digital learning environments for mathematics and statistics, and are developed by Pearson. MyLabs are primarily environments for short, task-related instructions, as well as practice activities and self-assessment. Each step in the learning process is initiated by submitting a mathematical or statistical task. Students are encouraged to (attempt to) answer each (sub)question (see Figure 1 for an example). If they do not master a question, students can either ask for step-by-step help to solve the problem or ask for a fully worked example. After receiving this feedback, a new version of the problem loads to allow the students to demonstrate their newly acquired mastery. When students provide an answer and opt to 'Check Answer', additional feedback is provided. Thus, one investigation of this paper centres on student preferences for these alternative feedback modes.

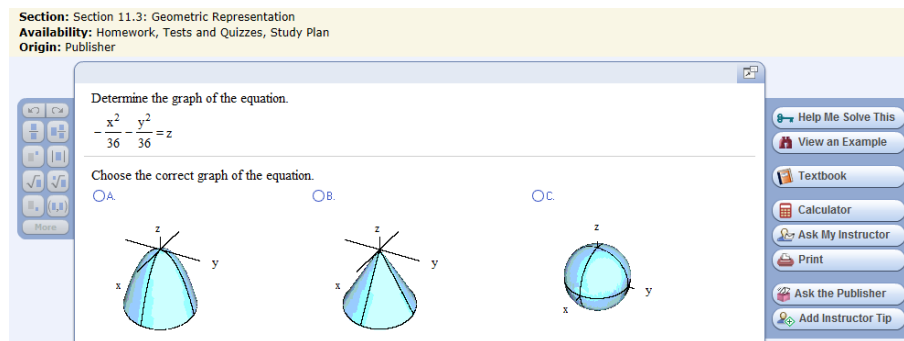


Figure 1. MyMathLab sample window with feedback options

## 2.3 Measures, Data and Statistical Analysis

The methodological approach adopted in this study is based on correlational analyses. In order to better facilitate the interpretation of the correlations, we have opted to present them in graphical format, rather than providing tables of correlation coefficients. This study builds on data measured at two levels. First, cultural dimension data is used to describe cultural differences between nations or clusters of nations. Using country-specific cultural dimension scores from Hofstede et al. (2010) (see also: <http://www.geert-hofstede.com/>), as highlighted in section 1.3. Secondly, we considered individual difference data that describe individual student profiles, which were measured with three self-response surveys: the Inventory of Learning Styles (ILS), the Motivation and Engagement Scale (MES), and Achievement Emotions Questionnaire (AEQ). Dissemination of these surveys is incorporated in the course as part of the curriculum design.

The Inventory of Learning Styles (ILS) instrument, developed by Vermunt (Jan D Vermunt, 1996; Jan D. Vermunt & Vermetten, 2004), has been used to assess preferred learning approaches. Vermunt distinguishes in his learning styles model four domains or components of learning: cognitive processing strategies, metacognitive regulation strategies, learning conceptions or mental models of learning, and learning orientations. Each component is composed of five scales. The two processing strategies (relating and structuring, and critical processing) together compose the 'deep learning' strategy. Memorizing and rehearsing, together with analysing, compose the 'stepwise learning' strategy (also called surface learning). Similarly, the two regulation scales, self-regulation of learning processes and learning content, together compose the strategy 'self-regulation', hypothesized to be prevalent in deep learning students. The two regulation scales, external regulation of learning processes and external regulation of learning results, constitute the 'external regulation' strategy, supposed to be characteristic for stepwise learners.

The Motivation and Engagement Scale (MES) incorporates Martin's 'Motivation and Engagement Wheel' (Martin, 2007, 2009; see also: Tempelaar, Niculescu, Rienties, Gijssels, & Giesbers, 2012). This model considers how behaviours, thoughts, and cognitions play a role in learning. Both are subdivided as such: adaptive behaviour and adaptive thoughts (the 'boosters'), mal-adaptive behaviour (the 'guzzlers') and impeding thoughts (the 'mufflers'). Adaptive thoughts consist of self-belief, learning focus, and value of school, whereas adaptive behaviours consist of persistence, planning, and task management. Maladaptive or impeding thoughts include anxiety, failure avoidance, and uncertainty control. Lastly, maladaptive behaviours include self-sabotage and disengagement.

Affective facets of learning are covered by four scales from the Achievement Emotions Questionnaire (AEQ) self-response instrument (Pekrun, 2006; Rienties & Rivers, 2014; Tempelaar et al., 2012): enjoyment, anxiety, boredom and hopelessness. Pekrun's taxonomy of achievement emotions provides a subdivision into three different contexts of academic settings where students can experience emotions: attending class, studying, and taking exams. For the purpose of our study, we have considered the four emotions categorized in study situations (i.e. the learning mathematics-related emotions). The other assumptions underlying Pekrun's taxonomy are that achievement emotions have valence, which can be either positive or negative, and an activation component, usually referred to as physiologically activating versus deactivating. Considering these dimensional perspectives, enjoyment is a positive activating emotion, anxiety is negative activating, and hopelessness and boredom are negative deactivating emotions. Academic control, in theories

of learning emotions regarded as the principal antecedent, was measured with the perceived Academic Control Scale (Perry, Hladkyj, Pekrun, Clifton, & Chipperfield, 2005). The perceived academic control is a domain-specific measure of college students' beliefs about being 'in control' whilst learning mathematics.

Finally, we considered student behaviours and learning processes. Learning process measurements were taken from MyMathLab and MyStatLab, and were comprised of: the mastery level achieved (Mastery), total connect time (Hours), number of individual attempts (Attempts), and the feedback options of either step-by-step assistance (GuidedSolutions) or viewing fully worked-out examples (SampleProblems). The model of the learning process we hypothesize distinguishes cultural dimensions as distal antecedents of the learning process, and student dispositions as proximal antecedents of the learning process. The learning process itself is described by log data from the two e-tutorials, such as time spent on a problem. The correlational analyses, thus, take two types of correlations into account: correlations between cultural dimension scores and learning dispositions (i.e. between the distal and proximal antecedents), and correlations between learning dispositions and tool use (i.e. between the proximal antecedents and the learning process log data).

### 3. RESULTS

In order to illustrate measurable variations in traits between three neighboring countries we compared cultural dimensions for the three largest groups represented in the freshman population: students from the Netherlands, Germanistic countries and Belgium. Figure 2 highlights scores for the three countries in each of Hofstede's cultural dimensions, with high variations demonstrated. For example, in the case of masculinity (MAS), the Netherlands (MAS=14) is highlighted as a more feminine culture, while Germanistic students (MAS=66) demonstrate more masculine patterns.

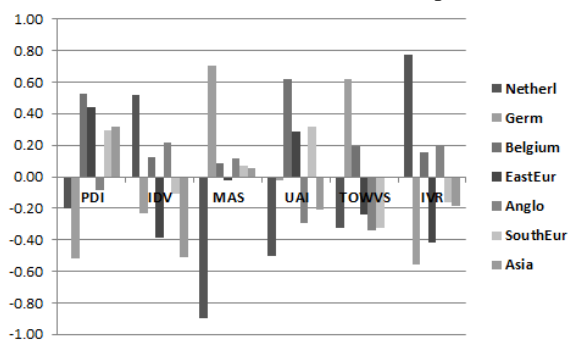


Figure 2. Cultural regions and their cultural dimension scores

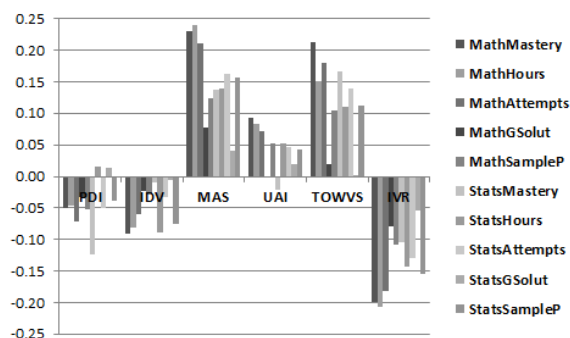


Figure 3. Cultural dimension scores as antecedent of tool use

The effects of cultural diversity as distal antecedents of learning approaches of students are mediated through other learning-related variables (i.e. the proximal antecedents). In the remainder of this section, we will highlight the availability of disposition measures to investigate relationships between cultural dimensions as distal antecedents, while considering learning dispositions as proximal antecedents. The first step in this considers cognitive processing strategies and metacognitive regulation strategies

Figure 5 demonstrates that step-wise processing approaches and external regulations of learning act as proximal antecedents of tool use. For example, deep and concrete learners tend to use their digital learning environment less, while step-wise learners use online tools more intensively. Differences are less articulated for the regulation strategies, but learners in need of external regulation achieve somewhat higher scores than self-regulated learners or learners lacking regulation. A striking observation is that, although learners who lack regulation do use online tools more frequently, they ultimately achieve lower mastery levels. Altogether these findings highlight that the use of online tools varies between students of different learning styles.

We next considered how cultural traits influence learning styles, as highlighted in Figure 4. To this, we found that step-wise processing and self-regulation learning is most strongly related to a more masculine and restraint-focused cultures (such as Germany). However, external regulation and lack of regulation are only weakly related to the six cultural dimensions.

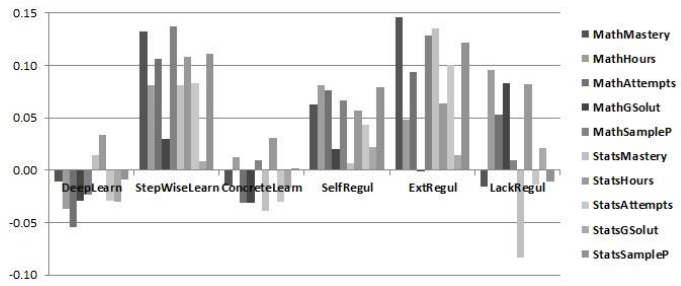
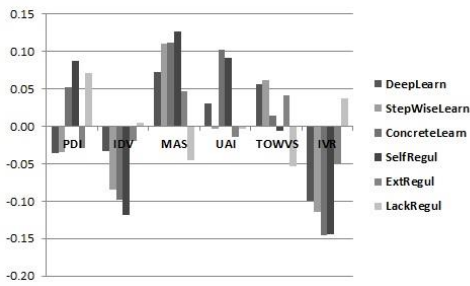


Figure 4. Culture dimension scores and learning styles      Figure 5. Learning styles as antecedents of tool use

The patterns between cultural dimension scores and motivation or engagement mediators are stronger, as highlighted in Figure 6. For example, power distance (PDI) is primarily related to the five maladaptive scales. At the same time, masculinity (MAS) and restraint (IVR) predict adaptive behaviours planning, study management and perseverance, but also the maladaptive anxiety cognition.

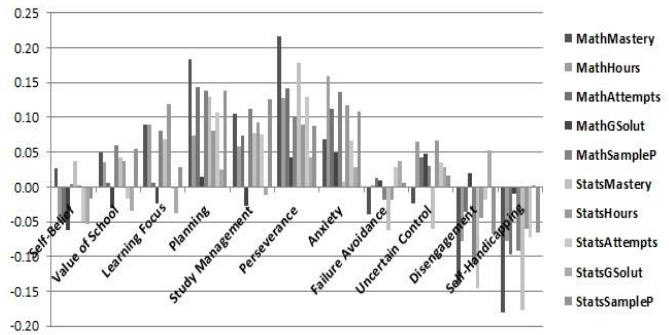
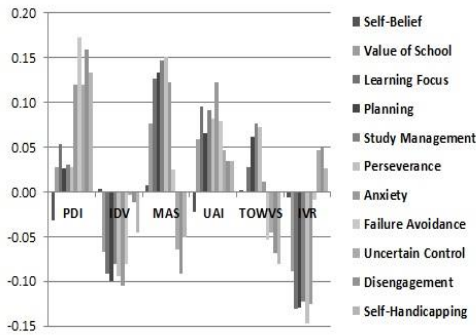


Figure 6. Cultural dimension scores and engagement      Figure 7. Motivation and engagement as antecedents of tool use

Figure 7 demonstrates that student behaviours, both of adaptive and maladaptive types, are antecedents of tool use, with the strongest relationship with mastery levels. We also considered learning emotions and academic control in Figures 8 and Figure 9. Figure 8 suggests that learning enjoyment in particular relates strongly with cultural background, with all culture dimensions except long-term orientation as an antecedent. Learning boredom follows an opposite pattern, but is less pronounced, while academic control is only very weakly related to the cultural dimension scores. Figure 9 depicts that it is again mastery levels, more than the intensity of use variables, which is influenced by learning emotions.

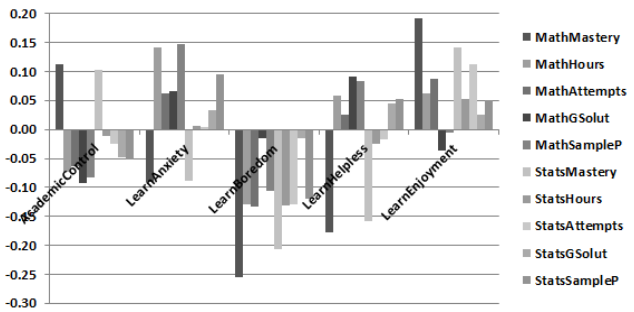
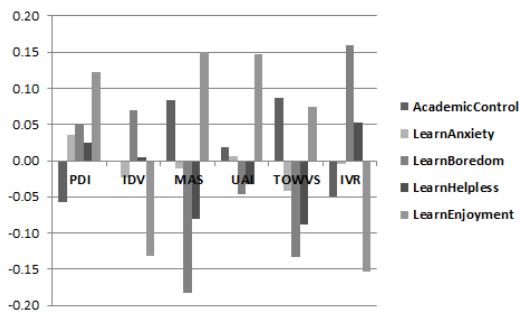


Figure 8. Cultural dimension scores and emotions      Figure 9. Learning emotions as antecedents of tool use

With regard to the use of different feedback modes: evidence from the correlational analyses is mixed. The use of guided solutions in particular, both for mathematics and statistics, is unrelated to the learning dispositions, and unrelated to cultural dimension scores. Yet, this is not the case for calling fully worked out

examples (sample problems). To this, the intensity is related to the step-wise processing approach, external regulation of learning (Figure 5), anxiety (Figure 7), and learning boredom (Figure 9).

These correlational analyses combining relationships between distal and proximal antecedents, and between proximal antecedents and learning process variables, can be formalised by looking at full models. The message these models tell is similar to the above graphical analyses: cultural dimension scores, isolated from disposition variables, explain up to more than 7% of the variation in mastery levels, with masculinity, long-term orientation, and power distance as key variables. Cultural dimensions can also explain more than 4% of the variation in several learning dispositions, like learning boredom and learning enjoyment (with the same three cultural dimensions as main predictors).

## 4. CONCLUSION

LA applications provide crucial learning feedback to allow learners to find optimal learning paths. In previous research (Tempelaar et al., 2015a), we have demonstrated that adding learning dispositions to the LA applications is an attractive step, both in terms of prediction accuracy, and learning intervention opportunities. In this paper, we extend this analysis by including cultural dimensions as distal antecedents in our LA prediction modelling. At first sight, the revenues of doing so are limited; predictive power increases in the order of size of 5% in the strongest cases. However, this revenue is bought at very low costs; the inclusion of national cultural dimensions requires no more than knowing students' country of origin, and the correlational patterns that evolve from the inclusion of these culture dimensions suggest that cultural backgrounds are meaningful. They are, however, dependent upon sufficient cultural diversity in the student population, as was prevalent in the population of this study. Less national heterogeneity, or an international population showing less diverse cultural dimensions, may limit the usefulness of this model.

Yet beyond the predictive benefits of considering cultural dimensions, there are also practical implications worth noting in regards to cultural influences on learning behaviors. As suggested in previous work (Al-Harathi, 2005; Sachau & Hutchinson, 2012; Thorne, 2003), we have highlighted that there are measurable differences between students of different cultures in regards to preferences for and use of online educational resources, as well as learning styles and emotions. Thus, it is worth considering in the future how personalised learning paths may differ between students from different cultural backgrounds.

This study also highlights that students' cultural backgrounds have an impact on the LA data collected by their institutions, even if only distally. This is an important consideration for LA researchers, as current research in the field often considers student behaviours in isolation from the socio-cultural context in which they occur. Our study highlighted that there may indeed be measurable connections between online tool use and cultural traits. Thus, it is important for future LA research to include and consider such socio-cultural influences within the holistic learning environment.

## ACKNOWLEDGEMENT

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