C&C@ITS2018

International Workshop on Context and Culture In Intelligent Tutoring Systems

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Workshop Abstract: International Workshop on Context and Culture in Intelligent Tutoring Systems

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With the internationalization of education, the need for adaptation and flexibility in ITS and other learning systems has never been more pressing, extending to many levels and fields including: the international mobility of learners, teachers and researchers; the integration of international, intercontextual and intercultural dimensions in instructional programs (from primary to higher education and continuing professional development), as well as in the designs, methods, techniques and tools that support them; the international mobility of education viewed through the lens of today's new reality of mass open online courses accessible by a diverse range of learners around the world facilitated by ubiquitous, mobile and cloud learning systems.

In this sense, there is a need for more research about context and culture in intelligent tutoring systems. Teachers and researchers need to develop new adaptation skills and embrace diverse contexts and cultures as well as leverage this diversity to foster the transfers that can enhance learning. Clearly therefore, it is important to make room for this diversity in curricula and learning systems and integrate transfer and adaptation concerns into pedagogical practice. But how can we do this concretely? How can we best manage this complexity and leverage this diversity? How can this materialize in the ITS field, and what are the benefits?

One of the main focuses of current research is to define the boundaries of context and culture (C&C) as a theoretical concept and what constitutes the best methods, techniques and tools in order to collect, analyze and model it from an adaptive learning perspective. Until recently, C&C modelling was considered an intrinsic part of the various classical ITS architecture models. Aspects of C&C were therefore partially covered under the domain, learner, pedagogical and communication models. Now, however, the advent of big data in education and significant innovations in artificial intelligence are opening new doors for us to analyze and model C&C differently, if we are able to take advantage of the information available through the learning analytics process. Big data offers an exciting opportunity for us to look at C&C modelling for ITS through a new lens. Do we need a fifth model? Should we view it as another layer in the ITS architecture? Let's start thinking about it. In today's era of adaptive learning delivering anything learners need, anywhere and at any time, the potential for context and culture-aware ITS could be huge. What would knowledge representation and reasoning mechanisms look like in ITS? What kinds of limits might C&C represent for ITS? How can we identify or measure these limits? Can ocular and biometric measurement play an instrumental role? What are the logical next steps in terms of conducting studies about context and culture-aware ITS and gathering and analyzing data about context and culture?

This C&C@ITS2018 workshop aims to build the foundations of this research stream by forming an international research community and providing new avenues and questions for research. New avenues and questions for research may include the following: Will integrating context and culture mean changing traditional ITS architecture by proposing new models? Is there any interest in using AI innovations (big data, deep learning) with the modelling of context and culture knowledge? Why, knowing that there are many schools of thought? Where do we begin to combine our efforts? Do other modelling methods such as ontological engineering represent a better way to achieve this goal? Is it relevant to use AI techniques for education such as educational data mining or learning analytics to maintain up-to-date knowledge about contextual and cultural diversity? How can an lTS accommodate and leverage this new complexity to gain awareness of contextual and cultural diversity? How can earning analytics support contextual and cultural adaptation, and how can we combine the two? What is the role of the learner in contextual and cultural adaptation? How can contextual and cultural diversity make learning deeper and richer?

In light of the above, submissions are welcomed for this workshop on topics including, but not limited to, the following: Contextual theory; Ontological and cognitive modelling of contextual or cultural knowledge/context or culture-aware ITS; Context-aware collaborative learning; Contextual or cultural knowledge in ubiquitous, mobile and cloud learning systems and various application areas

Context or Culture: What is the Difference?

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Abstract. Literature can sometimes tend to present context and culture almost as synonyms. This creates ambiguity, which can complicate the consideration of contextual and cultural variables in instructional design, learning and teaching. From an ontological point of view, some clarification of these two concepts is essential as each may influence learning and teaching in different ways. Moreover, since context and culture are interconnected to a certain degree, one may influence the other. It is crucial to make a clear distinction between these two concepts in the knowledge models used in Intelligent Tutoring Systems (ITSs) if we want to facilitate 1) their consideration in pedagogical scenarios, and 2) the accumulation of knowledge about different contexts and cultures. This article offers an interpretation of the difference between these two concepts, presenting context as a substrate of culture. Contextual issues in the learning ecology are also discussed, based on this distinction.

Keywords: Context, Culture, Ontology, Learning Ecology

Ontology-Based Context Modelling for Designing a Context-Aware Calculator

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Abstract. This paper reports on the research conducted by a team from the France-Quebec research project TEEC, and its advances. This team is responsible for modelling and designing of a context gap calculator, the MazCalc. The MazCalc is a computer artifact aimed at measuring the effects of two distinct context with the same object of study. In a Context-Based Teaching project such as the one presented in this paper: Context Modelling is essential in identifying the context parameters needed to include in the design of the context gap calculator in order to predict context differences; At the same time, measurements provided by the MazCalc are essential to guide the design of learning scenarios aiming to produce context effects among learners. The article is divided into three parts. First, the contextual modelling is presented, then we discuss the design of the MazCalc, and finally, we address the challenges of this research, namely: (1) the definition of the didactic context and its modelling, leading to the identification and the prediction of context deviations; and (2) the articulation of this modelling with the specifications of the MazCalc artifact. Context modelling is done using an ontological approach. While the iterative design of the MazCalc in connection with the realization of design experiments is conducted according to the Design Based Research method. At the end, we discuss the next steps to be taken.

Keywords: Ontology-Based Context Modelling; Context-Aware System

1 Introduction

Context effects are pedagogical event occurring when there is a clash between student's conceptions, coming from distinct environmental contexts, and about a shared topic being studied. These effects can arise during communications between individuals involved and it allows them to realize the differences that exist in their conception of a same object depending on the context in which it is studied. Context effects can lead to the construction of richer and more complete conceptions on a given subject. The prior identification of differences in contexts relative to the object of study in the two contexts makes it possible to create collaborative learning scenarios aiming to produce context effects [1]. This model is called the CLASH model [1], and the TEEC project wants to test this hypothesis and validate the model using the Design Based Research (DBR) methodology described in [2]. In order to predict the potential emergence of context effects, a computer artifact was designed to parameterize contexts and calculate their differences. The ultimate ambition of this artifact is to provide input needed for the design of learning scenarios based on the effects of contexts.

Context modelling involves conceptualization, and abstraction; where concepts are specified with their components, properties and relationships among each other. It is, for each iteration of the DBR methodology, the first link in the chain that should produce context effects. The context model therefore, guides the learning scenario which in turn determines the (didactic) design experiments for data collection. It enables the researcher to contrast and contextualize and identify parameters. The first instrument used to model the context is the Meta model (ontology). The second is the context gap calculator which informs the specification of the parameters needed for computing the differences. This paper addresses two questions, then it looks at the challenges of this research, namely: (1) the definition of the didactic context and its modelling leading to the identification of parameters to be used in the prediction of context deviations; and (2) the articulation of this modelling with the specifications of the MazCalc artifact. Furthermore, the context modelling is done using an ontological approach. Finally, the next steps and problems addressed in both the ontology-based context modelling and the design of the MazCalc are discussed.

2 Ontology-Based Context Modelling

Ontological modelling dealing with contextual issues is a well-studies research topic[3-7]. However, so far, none of already existing studies have met the challenge of modelling the didactic context. The didactic context of a learning scenario is influenced by sociolinguistic, environmental or socioeconomic factors and their subsequent impact in the learning process. The theoretical framework of the didactic context has been described in [8]. In the TEEC project, our focus has been on studying the external context which concerns the impact of the environment and authentic situations on learning.

Vision and purpose of ontological engineering. Although ontology was initially defined by Gruber as “an explicit specification of a conceptualization” [9], other authors have sought to emphasize essential features of ontology that we feel are important to recall. First, we agree that an ontology be “a formal system with an explicit specification of a shared conceptualization” [10]. This means that an ontology is an abstract model of a world phenomenon whose appropriate concepts are identified (conceptualization). The type of concepts used and the constraints related to their use are defined declaratively (explicitly). In addition, ontology can be translated into interpretable language by a (formal) machine. Finally, an ontology captures consensual knowledge, that is, not reserved for a few individuals, but shared by a group or community (shared).

Moreover, when we speak of articulating ontology to the digital artifact design model, it is to these two definitions that we refer: “an ontology is a hierarchically structured set of terms for describing a domain that can be used as a skeletal foundation for a knowledge base” [11]; which “provides the means for describing the conceptualization explicitly behind the knowledge base” [12]. These definitions recall us that ontological engineering must be based on the final purpose and use of ontology, and on the services it will ultimately render. The purpose of this ontological engineering is therefore to specify a conceptualization (level 1) of the domain of didactic contextualization shared by the members of TEEC, then to formalize it (level 2) and then make it operational (level 3) in the context deviation calculator [13]. And that of context ontology is to describe the skeleton of the MazCalc knowledge base.

Ontological Modelling Process. The goal of this article is not to explain the ontological engineering method used. We rely on the MI2O method [14].

Among preliminary pilots, we selected geothermal energy as a topic that was subject to a detailed analysis [8] and led to MazCalc 1 (1st generation). This created a list of candidate terms. These terms discussed with the team were retained or not depending on their potential to correctly represent the field, that is, to become concepts. At this point, they were inserted into a concept dictionary (Table 1).

Table 1. Excerpt from the MazCalc Ontology Concept Dictionary

Concept	Definition	Property (part-of)	Relation (is-a)
Didactic Context	It is a sub concept of context. It can be social, internal or external (environmental). It is defined by a set of context parameters.	Has set of context parameters.	Is a Context. Is created by someone Is related to a learning scenario.
External Context	It is composed of a set of context parameters. We model the external context (not the social or internal ones).	Has set of context parameters.	Is a Didactic Context.
Context of study	It is an external context which is based on an object of study.	Has one or many context parameters clusters.	Is an External Context.
Context parameter cluster	It is part of Context of study. It is a non-exclusive set of context parameters from various themes. It was formally called: Family.	Has one or many context parameters.	Is a (sub) Context of study.
Learning Domain	Example: geothermal energy, language.	Has many Object of study	Is a Domain
Object of study	It is related to the learning domain and theme. It is dependent on the domain but not on the theme. e.g. in the domain of biology, an object of study is “frog”, and a theme is “nutrition”.	Has one or many themes. Has many contexts of study.	Is a (sub) Domain
Context parameter	A set of context parameters defines a context of study (the state of the context). Each context parameter belongs to one or more clusters. e.g.	Has a list of possible context parameter values.	

Concept	Definition	Property (part-of)	Relation (is-a)
	In the domain of geology, a context parameter is “type of roc.”	Has many types.	
Context gap	It is the gap between two context parameter values due to two distinct given contexts. Context Gap is the result of gap computing.	Has computed values	Is a gap

It should be noted that ontological engineering does not consist of creating a collection of terms (which are polysemous), but rather in extracting the concepts (which are explicit). This is an abstraction exercise that is essential for ontological modelling, and it involves the specification of concepts with their properties, as well as their relationships with other concepts within a conceptual network. In parallel to this process, several versions of an initial conceptual ontology (Figure 1), in the sense of [13], were created using GMOT software [15] and shown to experts in different didactic fields (geothermal energy, socio-history, language/French, environment and sustainable development [ESD]). It should be recalled that four design experiments are context modelling based.

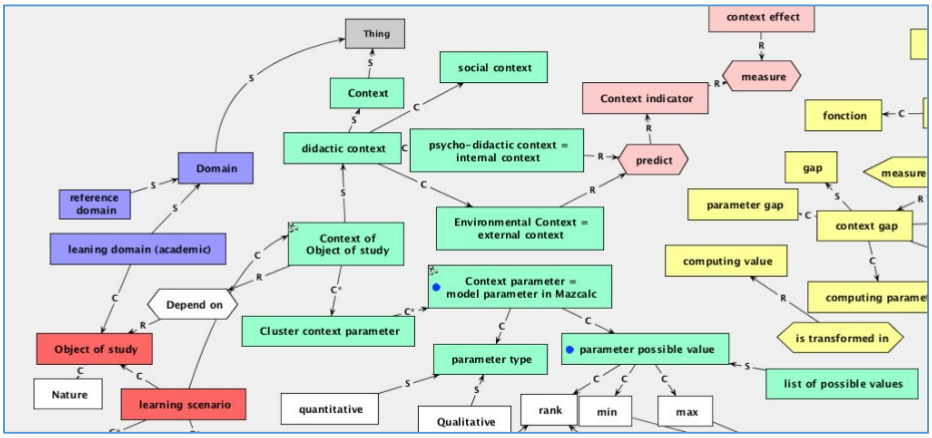

Figure 1. Graphical Representation of the MazCalc Ontology

The evaluation of the conceptual ontology was completed through several collaborative activities with different stakeholders. First of all, the ontology was explained to the content experts in order to verify that we had a common representation of the didactic context. Then, we addressed their feedback on the contextual representation of their didactic domain by replacing the ontology concepts by instances taken from the different versions of MazCalc 1 (MazCalc 1 applied to geothermal energy 2, language, socio-history and ESD). We also consulted about the ontology with the analyst responsible for the MazCalc 2 specifications. This third phase’s purpose was to compare the MazCalc 2 class diagram, a kind of skeleton of its database, with the ontology.

3 Context Gap Calculator: Models and Design

Consistent with Tchounikine's [16] views, MazCalc can be considered as a component of an intelligent tutoring system (ITS) [17] called CAITS, given that CAITS is "a system that works on knowledge," those specific to setting the context of an object of study in a given context, and "that manipulates symbolic representations." In this sense, the problems related to the design of the MazCalc are ITS engineering problems. It is therefore from this angle that we approached the design of the MazCalc and the challenges that flow from it.

MazCalc 1 and 2: genesis of context calculator. The MazCalc's engineering process was carried out in conjunction with design experiments in a connected classroom with collaborative learning, in order to test it. Several iterations of design and design experiments were set up jointly and informed the knowledge used to guide the project. Four phases illustrating the evolution of the project are detailed here.

Phase 1—Ideation during the GOUNOUIJ project: First design experiment whose scenario was based on differences in conceptions of the frog between primary school pupils in Guadeloupe and Quebec [18].

Phase 2—First iteration of MazCalc: MazCalc prototype, the MazCalc 1. First development of a computational tool in the form of a spreadsheet. This prototype enabled the creation of a learning scenario about geothermal energy during the GEOTREF project [8].

Phase 3—Second iteration—alpha version of the MazCalc: Launch of the TEEC project [2]. Creation of a web version of the MazCalc 2 (alpha version).

Phase 4 — Third iteration — MazCalc Beta version (in progress) : MazCalc 3.

MazCalc 3 Modeling. MazCalc 3 is a web computer tool that has been proposed to calculate the differences between contexts and predict their effects. But to successfully design such a tool, context modelling is very necessary to cover all cases and states of any context. The more detailed and clear the specifications, the higher the quality of the software.

Design specification. The specification definition consisted of describing the actors who will use this artifact (Table 2) and three types of design models: the use case diagram, the class diagram (Figure 2) and the sequence diagrams. The use case diagram showing how each actor is involved in a specific part of the calculator development and implementation. The class diagram shows all the objects that the MazCalc 3 tool will contain. The starting point of our work was to consider the assertion [19] that "the context of the study is described using context objects". Thus, modelling a study object amounts to modelling a context relative to its object (Table 2).

Table 2. Actors using the MazCalc

Actors	Roles
Actor 1: Cognitionist	Model a Meta model (Ontology, class diagram); Update the parameters of the Meta model.

Actor 2: Expert Designer of the Study Object	Model an object of study (related to the didactic field); Specify the parameters of an object of study; Specify the properties of parameters; Update the parameters of a study object.
Actor 3: Specialist of the object of study in its context	Instantiates an object of study in a given context = create a context; Assigns parameter values for a context model; Add a context parameter Update the values of the parameters.
Actor 4: Instructional Designer	Access the deviation calculation of each parameter; Access the result of the global calculation of the difference between the contexts.

Class diagram. The diagram that has caught our attention the most is the class diagram, as we see it as the design model for an ITS [16]. This model is the most important, it is the one that will be used as a comparator with the ontology of the didactic context, and how the two can be linked (see section 4). The object of study is defined by a set of parameters. These parameters are of the “qualitative” or “quantitative” type with “continuous” or “discrete”, “bounded” or “not bounded” values. Each parameter belongs to one or more clusters (families). It can have a list of possible value. A parameter can derive from another parameter [8]. These specifications have been grouped into “Models” and “ModelParameters” tables, as well as their link with the “Family”, “paramfamily”, “paramValueTypes” and “ParamPossibleValues” tables (Figure 2). The table “Models” represents the model of an object of study and not its instance (with actual values). That is to say, Model is the skeleton of an object of study only. The field referenced in the “ModelParameters” table refers to its parent parameter. Here, the model of an object of study is constructed independently of the context to be studied.

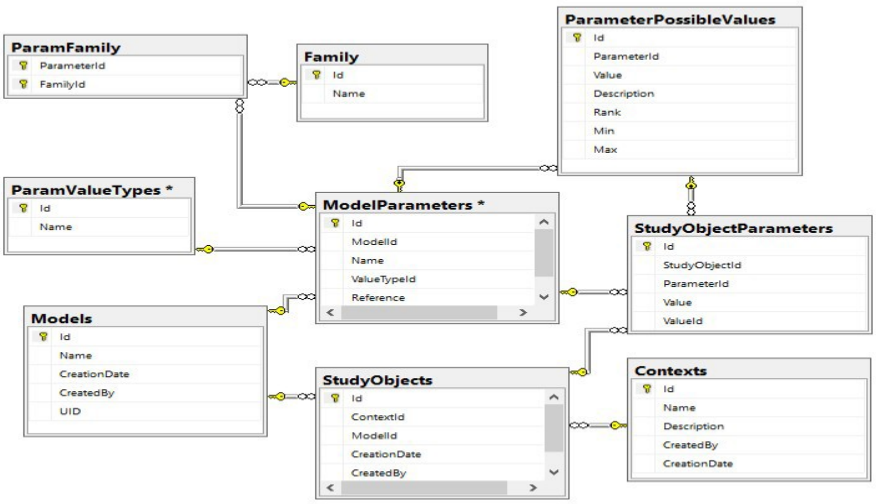

Figure 2. MazCalc3 Class and Object Diagram

The object of study in a context must have only one value for each parameter. Therefore the model is developed to produce to an object of study defined in the "StudyObjects" table, which is relative to a context. This relationship is respected by the link between the "Models", "StudyObject", and the "Contexts" tables (figure 2). Each parameter of the model of an object of study must have a unique value among its list of possible values. This value, for each parameter, is stored in the "StudyObjectParameters" table and is extracted from the existing values in the "ParamPossibleValues" table. This explains the link between the "StudyObjects", "StudyObjectParameters", "ModelParameters", "ParamPossibleValues" tables (Figure 2).

MazCal 3 Conception and Implementation. The MazCalc 3 database is created based on the class diagram. It allows to define, via MazCalc 3, all types of study objects independently of the context, which makes MazCalc a generic tool. It allows to create several objects of study, and to instantiate several contexts in relation to a single object of study. In order to calculate the difference between two contexts, we calculate the difference between each parameter of these two contexts. The formulas for calculating the context gap are under discussion.

The MazCalc 3 tool is still under development. And, yet many tasks have been completed. For instance, the database is implemented, but it can evolve according to the evolution of the modelling of the objects of studies as well as the formulas for the gap computing, as stated by the DBR methodology [2]. The main human-machine interfaces have also been created: the one for the generation of models, one for the definition of parameters and their value types, one for the definition of all possible values for each parameter as well as the instantiation of contexts with respect to the object of study.

4 Challenges in Modelling and Articulating its Models

4.1 Models to Understand Theories and to Design Artifacts

On the one hand (Challenge 1), we had to model to understand what is meant by "didactic context" in order to serve the needs of the TEEC project, i.e. to measure contextual gaps. Starting from the concept dictionary (Table 1), we now wish to give an overview of the discussions conducted to reach a consensus during the modelling. Especially around terms which have been difficult to define such as the term "Family".

Examples of problems related to Metamodel modelling. "Family" Case.

For some members of the Modelling team, "Family" was understood as a theme, a learning area, or a scale. But, for others, it was seen as a grouping of context parameters. For them, the concept of "Learning Domain" which is a well-defined concept, could not be associated with "Family", since in an ontological view, it is quite clear whether a term corresponds to a concept or not: one tries to construct the specification with components, properties and relationships, and if one does not succeed, then this term probably does not have the status of a concept in this ontology. Thus, if the term does not pass the test of conceptualization, this is probably because it is already taken into account somewhere else with another label.

Examples of problems related to domain context modelling. “Language” Case. Let us take the case of the design experiment “Language”. This experiment is experimental in the sense that it is more difficult than others to quantify in order to calculate the differences in context. Thus, we encountered the problem of representing the “quantification” of context parameters in order to calculate the context gap.

Other very beautiful problems of transposition of theories into models have also arisen. For example, the “oral nature of the narrative situation” cannot be modelled as a sub concept of “Intrigue”. We must therefore find another idea to place orality in ontology. To better understand the problem, let us try to explain it differently: in ontology, we have the concept “object of study”. In the case of the didactic situation Language, perhaps the object of study is “the story”. For the “object of study” concept to respond well to the principles of ontological engineering, a sub concept of the “Object of study” concept would have to be created.

Table 3. Illustration of a modelling problem

Concept = Object of study= tale; o Subconcept = oral story (=orality, event, actors, space-time dimensions, unforeseen); o Subconcept = written story (=document, whether or not a transcription of the oral story).

With this example, we see that we can, in the written tale, make a reference to the oral tale. It must therefore be included in the ontology so that it is representative of all possible cases of the target domain to represent. The two previous examples clearly show the similarity between the modelling problems of the class diagram and those of ontological modelling. This brings us to our challenge: articulating these two types of resulting models.

4.2 Models to Design Artifacts

On the other hand (Challenge 2), we had to define and model the design intent of the artifact [16]. This is software engineering work leading, among other things, to the production of a class diagram.

Example of a problem related to challenge 2. Modelling of the “Parameter (context implied)” class. One of the main problems encountered concerns the modelling of context parameters, the latter leading to the calculations of context deviations. In particular, we have tried to answer the following questions: What defines a parameter? What are its attributes (type, nature, properties)? Should the parameters be prioritized? Should parameter values be differentiated according to their type (constant or variable)?

4.3 Articulation of Models

Articulate models to understand theory and models to design the artifact (challenge 3) [20]. The difficulty was to completely transpose the “theoretical” model, the ontology resulting from the work of the “Context Modelling” team, to the design model, the class diagram, resulting from the "Context Calculator Development" team. However, we soon realized that we were facing the same modelling problems. Before we spoke, we had encountered problems in representing certain concepts/classes. A concrete example of a common problem we faced was to represent the concepts of "Context parameter", "Parameter value" and "Possible parameter value". Questioning each other and sharing our representations has allowed us to improve both models.

5 Next Step in an ITS Point of View

Next steps concerning the context modelling. The problem of merging between the Context Modelling team and the design Experiment teams is still to be developed in TEEC. It is a weak link in the TEEC project, which is engaged in a chain of production of context effects: modelling with calculation of the gap and probability of context effects, learning scenarios, experiments and data analysis. Fortunately, with the DBR methodology, we are able to deal with "real life" and learn from each iteration of the production chain for the next.

In addition to the context ontology, we plan to construct a domain ontology for each contextualized domain. Next, the line between the meta-model (ontology) of the context and the domain model must be drawn. Normally, ontology governs models as instantiation, which inherit them. If this is not possible, it is because either the Meta model has a flaw, or the domain model must conform to it.

We also plan to build an ontology of context effects. Next, the line between the meta-context model and the meta-context effects model must be drawn.

Next steps concerning the context gap calculator. So far, MazCalc has been developed as an independent tool, and will remain like this until its design and implementation are completed. But ultimately it will be part of a context-sensitive learning software suite (with authoring and tutoring services), and it is the core of the CAITS, a "Context-Aware Intelligent Tutoring System" [21]. The CAITS comprises three main components: The Context-Sensitive Domain Model (CSDM); the Context-Sensitive Teaching Model (CSTM) and the Context-Sensitive Learner Model (CSLM). MazCalc will share its results with the CAITS component by connecting with its CSDM; this connection will make it possible to provide the ITS with context effect information which will drive the domain model behaviour [22]. This is why the MazCalc 3 was designed as an API web application (to exchange services to the CAITS), rather than a simple web application.

Ultimately, once the development of the MazCalc is completed, it should be able as well to provide a service to the learning designer to specify and adjust the instructional scenario (Actor 4); and serve as a reference in the analysis of experimental data to validate the CLASH model [1]. Indeed, one of the mandates of the Data Analysis team is to detect weaknesses in the elements of our causal chain that are supposed to produce context effects: the context modelling for each iteration, the scenario, the experimentation, and the data collection device. So, the quality of the MazCalc is essential, since it conditions the other elements.

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Ontological Support for the Cultural Contextualisation of Intelligent Learning Environments for Adaptive Education

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Abstract. Within ITS research, most systems rely on data in order to train models for decision making and for customising system behaviour. The inherent bias has been traditionally in favour of developed nations. This paper examines the issues involved in contextualising interactive intelligent educational systems using a semantic approach that leverages the meaning of data rather than common patterns within data. It presents a trio of ontologies for relating conceptual knowledge to sociolinguistic terms in the context of a student's cultural influences and background. The paper argues that if an ITS can model students culturally, model their languages, and model their cultural concepts, then it would be possible for an ITS to start communicating with students socially and conceptually in a culturally appropriate way. The paper explains the rationale behind the need for ontological concepts when adapting aspects of instruction, how they relate to cultural lexical terms, and examples of when these terms may be suitable for use in educational content and instructional events.

Keywords: Ontologies, Cultural Semantics, Student Modelling, Sociolinguistic Contexts, Content Adaptation, Semantic Analysis

1. Introduction

In 2010, there were approximately 1,991 million Internet users worldwide [11]. Compared to 2016, that figure increased to 3,385 million. Not only has the sheer volume of users increased, the cultural backgrounds of these users are being quickly diversified. In just under 10 years, the proportion of Internet users from the developing world has almost doubled in relation to those from the developed world. In 2008, the ratio of developed world users to developing world users was approximately 4.2. In 2017, that ratio is now 2.0. Moreover, 70% of the world's youth (aged 15-24) are online and they make up the largest group of Internet users [11]. Two interesting points arise from these statistics. Firstly, a lot of data is being generated daily and this will continue to increase. Secondly, as the human sources of this data change, so does the quality of the data, and more importantly the cultural bias.

Within ITS research, most systems rely on data in order to train models for decision making and for customising system behaviour. The inherent bias has been traditionally in favour of developed nations [2] and this makes sense since most users in the past have been predominantly from these areas. ITS research would have therefore been driven by the cultural backgrounds and biases of the researchers who produced the systems and the student users who produced data that fed the research. The problem here is that data biases affects the design of an ITS and the eventual decisions made by the system. The bias can be positive or negative, and educational systems need to be more acutely aware of this because of the impact on learning and rates of success. For instance, statistical analysis of large amounts of data allows prediction of various types of instructionally relevant events that might take place next with a fair level of accuracy. This allows models to be built based on the observation of patterns in the data which help to give an indication of the details of some domain of interest. The flexibility of the patterns that are detected however, depend heavily on the kinds of data that the models are trained on which in turn affects the scaleability of the system overall [8].

Culturally-aware ITS design is a reasonable way of dealing with this lack of flexibility since, as the statistics show, the landscape of the student audience is changing and systems need to evolve or risk irrelevance. It is difficult however to transfer and extend intelligent learning environments to different cultural contexts for several reasons [14,19]. Diversity arises from differences between cultures. While tangible and concrete in many instances, such as language, dress, food, gestures, and music, culture at its deepest level is intangible and non-deliberate. Furthermore, the multiple factors and influences that shape an individual person's cultural awareness come through interactions, perceptions and knowledge of other cultural groups. Culture itself is therefore challenging to model computationally in a holistic sense and even more complex when aiming to do this for an individual learner within an ITS. It necessitates organising cultural semantics and data from heterogenous sources to reduce bias and also because individual data points such as country of origin or language are insufficient for meaningful modelling.

Semantic web technologies have been around for many years but widespread uptake has not been achieved [18]. This is subject to change in the upcoming years as the importance of linked data becomes evident with the need to organise and structure data [5]. This paper argues that rather than taking a data centric approach towards cultural inclusiveness, a semantic approach is preferable since it allows the meaning of the data to be leveraged rather than common patterns. Ontological modelling of cultural contexts would allow data from heterogenous sources to be filtered, disambiguated and combined. The paper describes a trio of ontologies that were developed for modelling cultural contexts in intelligent learning environments. The ontological representations covers three main areas: modelling a student's cultural context, modelling a student's language and cultural expressions, and modelling the cultural concepts (metaphors, idioms, concepts) that are relevant to a student. Each ontology is useful in isolation for various purposes, however when all three are merged, they give insight regarding how to communicate with a student using appropriate sociocultural concepts and language.

The rest of the paper is organised as follows. Section 2 defines the process of cultural contextualisation. Section 3 describes the trio of ontologies: CSM, CERA and

VELO. Section 4 illustrates how concept chains produced when the ontologies are merged result in the identification of appropriate cultural terms and concepts for a given students. It also gives examples of how these may be used in instructional events. The paper concludes in Section 5.

2. Defining Cultural Contextualisations

Culture refers to a cognitive and linguistic framework within which humans interact with and relate to their environment [10,13]. Interactions are governed by societal and ideological systems of thought [12] and result in the construction, distribution and assimilation of shared meanings that originate from individual and group level perceptions. These shared meanings, also called *cultural conceptualisations* [17], result from human cognitive processes of categorising observations and experiences under familiar conceptual categories. These categorisations are intrinsically linked to language which conveys cultural knowledge and allows individuals to understand each other's perspectives when communicating. *Contextual groups* are defined as collections of individuals with common beliefs, characteristics and values who reference cultural conceptualisations through shared linguistic terms. *Cultural contextualisation* is therefore defined as the process of integrating one or more cultural conceptualisations into aspects of a digital learning environment [16]. Cultural conceptualisations manifest as concrete representations of abstract concepts and are comparable to *cultural elements*. Defined in the literature as an observable manifestation of culture, *cultural elements* are categorised as material artefacts or non-material cultural products which represent or embody the shared meanings of a cultural group [4]. For the purposes of this paper, cultural elements and contextual elements are used interchangeably.

3. Ontological Descriptions of Cultural Context

An intelligent learning environment that aims to model cultural contexts will rely heavily on semantic metadata. This is necessary in order to reason about the cultural contexts of educational resources and relate these contexts to a student's cultural background. Many standard upper-level ontologies define general knowledge concepts that relate to cultural descriptions of real-world phenomena and provide foundational semantic bridges between intermediate levels of cultural knowledge abstraction. Upper ontologies have not been designed with the intention of structuring cultural knowledge in particular. Recent work by Blanchard and Mizoguchi [3] describes high-level cultural conceptual entities in an upper ontology of culture (MAUOC) and identify several categories of cultural elements that manifest in a culture. In addition, ontological concepts should be defined such that lexical entries irrespective of the source language are all accessible by these concepts, that is, through ontological mapping and merging. The following subsections describe the trio of ontologies introduced in this paper using UML notation.

3.1. Contextual Student Model (CSM) Ontology

The ontological structure of the CSM is extensible for capturing and modelling multiple cultural backgrounds. Figure 1 shows the main concepts and relationships in the CSM ontology. It is partitioned into three layers consisting of factors and influences originating from various sources. The first layer stores personal demographic data that define a student's core identity. The second layer consists of dimensions from immediate socio-cultural units that play formative roles in a student's life such as family members and close friends. The third layer consists of dimensions from neighbouring socio-cultural units that are of lesser influence but still contribute towards a student's awareness of and exposure to cultural contexts. This is possible because the *Guardian* and *Contextual_Group* concepts (and related attributes) and relationships can be instantiated any number of times with dimension data. This implies that a student's cultural background can be modelled not only from a single temporal perspective indicated by the student's age, but also from a chronological perspective where his/her cultural background may change with age.

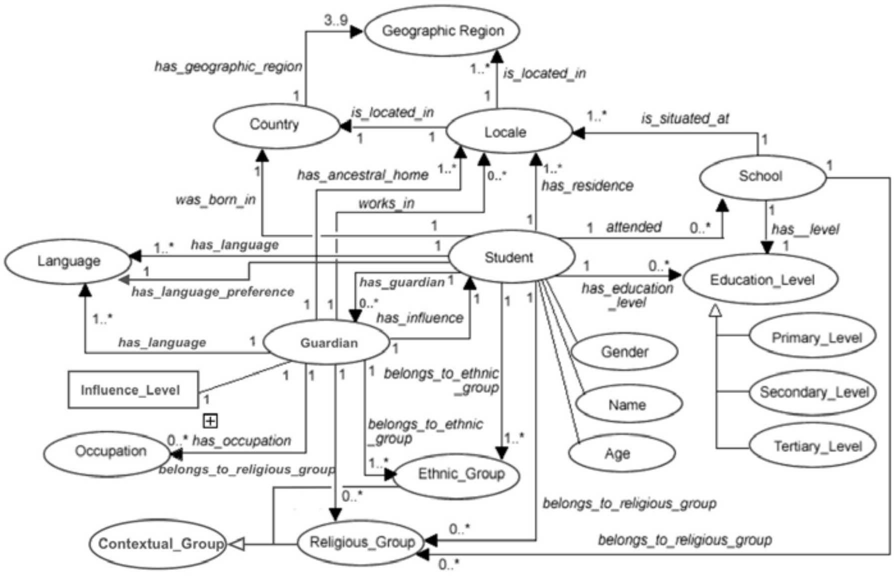

Fig. 1. The Contextual Student Model Ontology

3.2. Contextual Element Resource Annotation (CERA) Ontology

Observable manifestations of culture have been referred to as cultural elements, or more generally, as contextual elements [4]. High level categories that represent language independent abstractions of real world phenomena are described in [3, 15]. Based on these abstractions, the Contextual Element Resource Annotation (CERA) ontology specifies the ontological concepts and relationships that describe the nature and background of a contextual element which is referred to as an *Entity* in Figure 2 which shows the ontological signature of CERA. The More Advanced Upper Ontology of Culture (MAUOC) [3] and SUMO[1] (Suggested Upper Merged Ontology) were used to build the semantic backbone of CERA. SUMO provided a comprehensive hierarchy of spoken human languages used by members of a contextual group and helped to define the language origin of linguistic concepts that are used to describe one or more contextual elements (identified as dark grey concepts in Figure 2). The MAUOC on the other hand, provided high-level classifications of entity abstractions (identified as light grey concepts in Figure 2) namely *Physical Entity, Continuant Entity, Abstract Entity, and Semi-Abstract Entity* concepts which were subsumed by the *Entity* concept in CERA. The Entity concept is linked to a *Contextual_Group* concept.

Fig. 2. The Contextual Element Resource Annotation Ontology

[1] http://www.ontologyportal.org/

3.3. Vocabulary Equivalence Lexicon Ontology (VELO)

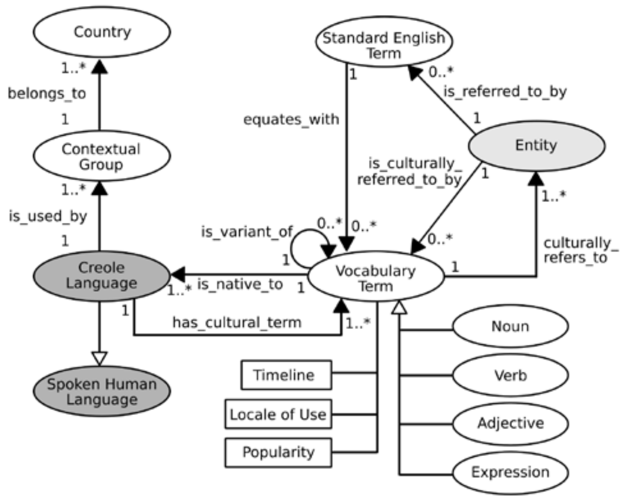

Fig. 3. The Vocabulary Equivalence Lexicon Ontology

The main concepts of VELO, the relationships between the concepts, and the attributes of the concepts are shown in Figure 3. VELO was designed to facilitate the mapping necessary for equating multiple vocabularies accurately. The ontology is based on the conceptual-linguistic approach described by [1], and adopts a similar structure to the ontologies in the DOSE platform [6] and the KYOTO project [21] by referencing upper-level concepts from SUMO and DOLCE. The intention behind VELO is to equate/map Standard English vocabulary to localised equivalents. It specifies the base concepts and relationships needed for achieving lexical equivalence across languages at the semantic level through the *Entity* concept. This can then be used for facilitating queries on communicative acts, language concepts, metaphors, and idioms that are culturally appropriate for a student using an ITS.

4. Deployment in Intelligent Learning Environments

4.1. Ontological Mapping and Merging

Ontological mapping and merging is necessary in order to combine the information distributed across the three ontologies described in the previous section. Figure 4 shows a partial snapshot of the important concepts in the ontological signature of the merged ontologies. Correspondence throughout the merging process is facilitated based on the use of the *Entity* concept in both VELO and CERA. Using the concept chain illustrated in Figure 4, it is possible to determine which contextual elements (referenced by *Entity* concepts) are suitable for a student based on familiarity through a student's affinity to one or more contextual groups in a society. Furthermore, the specific language terms that reference the concept can now be identified, leveraged and integrated into instructional events using rules.

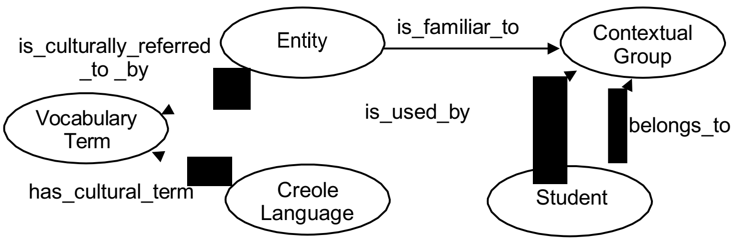

Fig. 4. Merged Partial Ontological Signature of the VELO, CERA and CSM Ontologies

To illustrate, consider two original sentences S1 and S2 which might be used in an ILE to respectively set the frame for a problem description, and give feedback to a student with a Trinidadian cultural context.

S1: Every week, John gives away free apples to the customer with the largest purchase.
S2: You did not answer the question correctly.

When S1 is provided as input to an ILE that uses the trio of ontologies, the resultant sentence S3 below would be produced for the student used in this example.

S3: Every week, John gives away free zabocas to the customer with the largest purchase.

In S3, the cultural reference to 'zabocas', would be matched conceptually under same semantic category through a shared higher level *Entity* concept as that of 'apple'. This cultural term would be used if a Trinidad English Creole vocabulary base is activated in VELO. Consequently, the general reference (apple) in S1 would be replaced with a more culturally-specific and culturally appropriate reference based on the student's cultural background as in S3 using rules. This demonstrates how the cultural semantic context of the educational material was changed while still preserving the learning context. When S2 is provided as input, there are several possible resultant sentences as shown in S4, S5 and S6 below.

S4: You did not answer the question correct.
S5: You eh answer the question correct.
S6: Yuh eh answer the question correct.
S7: Yuh eh answer d question correct.

In S4, the underlined words would be changed by grammatical rules loaded due to the activation of a Trinidad English Creole rule base since the student has a Trinidadian context. This gives an ILE the ability to produce appropriate localised variants of a source text when a particular level of formality is specified. For example, if formal variants are requested for S2, then only S4 would be generated. If very informal, colloquial variants are requested for S2, then S7 would be generated. It should be noted that the rules and ontologies facilitate different languages and cultural backgrounds. The design is not tied to a particular implementation as in this example. Therefore, if a student has a Jamaican context or a Singaporean context, the cultural references used would vary and therefore the output produced would vary.

4.2. Integration into Instructional Events

Instructional design models specify instructional events that take place during the learning process. A popular model often used in educational software was developed by Gagné [9] who identified nine instructional events. Based on the work of Branch [7], who linked culturally-aware instruction to these events, Table 1 was developed. It lists practical ways of using different types of contextualised content produced using the trio of ontologies for some of these types of instructional events.

Table 1. Using Contextualised Content for Instructional Events

Instructional Event	Contextualised Approach
Gaining the learner's attention	Integrate contextual elements, that are appropriate for the student, into instructional content as a form of stimulus change
Informing the learner of instructional objectives	Use a formal language variety that the student approves of and can relate to when stating instructional objectives
Presenting material to be learned	Use cultural references, scenarios, analogies in text, audiovisual or multimedia content
Providing learner guidance	Use a language variety that the student can relate to when giving instructional hints, directions or tips in order to provide meaningful context
Drawing out learner performance	Use familiar language expressions to encourage the learner to reflect using learning probes such as review quizzes
Providing informative feedback	Use familiar language expressions to phrase corrective feedback and inform the learner of the degree of answer correctness

For example, when providing informative feedback or drawing out learner performance for students who use a particular language variety in everyday life, the contextualised intensity of text-based sentences can be varied to create emotive feedback ranging from formal to informal, and also varying in the number of cultural references, metaphors and idioms used.Another example is the use of contextualised images when aiming to enhance retention and transfer or gain the student's attention. Images that depict contextual elements that the student is familiar with and which match the student's cultural background can be used to increase the relevance of the instructional content from a cultural perspective. A final example is the use of contextual elements in unexpected but instructionally and semantically appropriate places within text-based content. These elements when inserted in place of similar, semantically-relevant references in scenarios or questions descriptions can be used to gain a learner's attention or enhance the presentation of the learning material. The approach in the paper is currently suitable for an individual learner using an ILE. Collaborative learning challenges are more complex and require a different strategy for customising an ILE to deal with multiple learners with different cultural influences.

5. Conclusion and Future Work

The self-contained model of a traditional ITS is changing. In the past, the focus was on ensuring quality regarding what students learned. This has progressed to coaching to ensure that students learn effectively [20], and now the focus is on the kinds of students that are involved in learning from an ITS. If we can model students culturally, model their language, and model their cultural concepts, the focus would then be to communicate with them socially and conceptually in a culturally appropriate way. The next steps to consider are whether it is acceptable to communicate in culturally informed ways, and to determine when such communication is acceptable or not. The need to consider cultural ethics and privacy is more important now than ever. For example, students from some cultures may be reserved and having an outward display of (somewhat privately-used) cultural realism in an ITS can be frightening and startling. This might make users uncomfortable and suspicious and which could eventually affect successful usage and uptake of such an ITS in a practical way. The ontologies described aim to mitigate such effects and extend the current efforts to model cultural knowledge for intelligent learning environments. They are a first step in addressing the need for practical, reproducible approaches towards cultural contextualisation from conceptual, linguistic, and cultural perspectives.

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Relevance of the cultural dimensions in affective-cognitive behavior during interaction with an intelligent tutoring system

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Abstract.
Cultural Dimensions, as stipulated by different theoretical perspectives such as Hofstede's, are normally not considered to define student models. These cultural dimensions consist of traits that can be attributed to students and include both cognitive and affective characteristics. Some dimensions indicate students' ability to represent an effect in the affect which may be useful to predetermine affective models. This research project hypothesizes that students' cultural dimension may indicate affect tendency during the use of Intelligent Tutoring Systems (ITS). The methodology consisted of determining students' cultural dimensions, cognitive achievement, and analyzing affective responses (self-reported) when the student used the ITS on an individual way. The results suggested that there are affective behaviors associated to a Hofstede cultural dimension (Power distance index). The implications of these results are that some cultural characteristics may predict students' affective behaviors employing an ITS for mathematics. Additionally, affect models could be used to predefine affective-cognitive scaffolding.

Keywords: affective-cognitive states, cultural dimensions, intelligent tutoring systems, secondary education.

1.1 Introduction

The technological tools are current elements that contribute to the teaching- learning process of students at different educational levels, which are shown with contents of topics specialized in some areas.

These tools are designed so that users (students) have innovative elements, however, when referring to the adaptation of the tools to the user, there are several problems in the interaction, since they are not fully developed to adapt to the particular needs or characteristics of each user [1].

However, these reasons have not precluded several researches to identify some relevant characteristics that impact on learning with technology such as collaboration [2], cultural dimensions [3], learning styles [4], motivation [5, 6], affect [7–9] and among others. The aim of this study is to analyze whether students' cultural dimensions are related to both affect and knowledge during interaction with the intelligent tutoring system.

In this research, we focus on individual student factors used in all the interaction with an Intelligent Tutoring System (ITS) for mathematics when they acquire knowledge about variables (numerical and categorical) and the way they represent them. To do this, there are characteristics that are affected by the environment where the student works in a learning process, such is the case of cultural dimensions. Since students' cultural dimensions traits lies in that teaching instructed in the classrooms and the learning environment.

In the association of affection and cognition, particularly, there are several studies applied with technology [10–13], that allude that the affection presents predominant tendencies in the learning process (negative, neutral and positive) [8], which can be regulated for the student to acquire either greater or better knowledge.

On the other hand, the importance of culture in education shows contrasts that impact the cognitive process [14, 15]. Cultural dimensions are divided into five dimensions described by Hofstede, these dimensions alone represent influential factors in society as the Power distance, Uncertainty avoidance, Individuality, Masculinity and Long term orientation [3, 16].

In Mexico's basic education system, it is considered that an environment conducive to learning must indispensably contemplate the recognition of influential physical, affective and social factors in cognitive achievements in an individual and group manner [17], making relevant the study of the characteristics of the students, as well as their behaviors in the classroom.

Considering the above is done the following research question: What cultural dimensions are present and how these influences the acquisition of knowledge and the affect of students during the use of a ITS?

The research focuses on identifying associated cultural behaviors that give indication to be able to define the students' profiles, and thus provide elements considering their cultural and affective characteristics during the interaction with an intelligent tutoring system.

2 Methodology

This work was performed at the secondary school "Federal N. 2 Julio Zárate" in Xalapa, Veracruz, Mexico for four days. It was considered to be a simple random sampling (n=50 students) of five groups (N=110 students) in the first year on 2017 of secondary school with 62% of female and 38% of male with an age range of 12 to 14 years old.

The materials used consist of the intelligent tutoring system "Scooter tutor" [18, 19] in the non-reactive version (without Scooter agent), the two isomorphic tests of learning employed on similar experiments [18], the standardized questionnaires of cultural dimensions [16], the self-report of the affective states, and props. The evaluation was guided under the standards of the Belmont report [20].

Standardized learning tests are isomorphic measuring instruments designed to evaluate students' knowledge of the development of scatter plots before and after interaction with the intelligent tutoring system. To calculate the level of knowledge (test scores) of students, points are obtained in percentage by standard terms of evaluation defined by the system creator [18] and these tests measure the cognitive achievement in such a way as to identify the increase obtained by the students. Achievement is calculated with the following equation:

$$\textit{Cognitive Achievement} = \textit{Score of Post\_test} - \textit{Score of Pre\_test}$$

The registration of affective self-reports is given through a booklet, which presents the five most relevant states in a learning situation with technology [8]. This is through the issuance of student judgments about their affective status at intervals of every 8 minutes during the two sessions of interaction with the ITS. The records of affective trials are composed of images with random faces (emoticons) referring to the states of boredom, frustration, confusion, concentration and the absence of affec- tion of the neutral state. The affective measure reported is given in terms of proportions of cases through interaction, and they are distributed in negative (boredom and frustration), neutral (absence of affection) and positive (confusion and concentration) tendencies.
Cultural dimensions test stated by Hofstede [3] employed in this research is obtained through an adaptation of the instrument of the 1994 version [16], this consists of 20 items with five to six categories of ordinal scale type Likert. In addition, each item is weighted in an equation per dimension providing a representative score of the level, either low (*Index<=33 points*), normal (*33 points>Index<66 points*), or high (*Index>=66 points*). These dimensions present different representations such as Power distance that is defined as the extent to which the less powerful members of community within a society expect and accept the power other person or Uncertainty avoidance is as the extent to which members of community within a society feel threatened by uncertain, unknown, ambiguous or unstructured situations. On the other hand, in Individualism a person is expected to take care of himself and his immediate family, just as Masculinity represents a society in which social roles of gender are clearly different and Long-term orientation represents a society that encourages future re- wards-oriented virtues, particularly adaptation, perseverance and savings.

It is important to mention that this test does not present an adequate validation and reliability [21], however, it is necessary to observe the internal structure by dimension and the biases in the answers.
The experimentation included the application of the tests and the interaction with the ITS. There were four experimentation stages during the mathematics class.

1. *Initial test*: This stage consisted of an explanation of the topic “Scatter plots” (10 minutes), the first learning test (20 minutes) and other questionnaires (20 minutes) in the classroom.

2. *Interaction I*: In this phase, the student first performed the interaction with the intelligent tutoring system for 40 minutes in the media classroom and self-reported affective states in interruptions during the lapse of 8 minutes.
3. *Interaction II*: In the same way that in the stage Interaction I, the student worked with the intelligent tutoring system for 40 minutes in the media classroom and self-reported affective states in interruptions during the lapse of 8 minutes.
4. *Final test*: The student was given the Post-test on a 20-minute period in the media classroom, as well as the cultural dimensions test (15 minutes) and participants were thanked for their participation in the research (5 minutes).

3 Result

The preliminary findings in the interaction with the intelligent tutoring system present relevant characteristics to influence the affective-cognitive student behavior. It is significant to mention that the analyzed information did not assume the assumption of normality, the test score (pre-test and post-test) was measured in percentage points and worked with affective tendencies (negative, neutral and positive) and the results were assessed with nonparametric statistical techniques in R [22] and just considering the cases of positive achievement (*Cognitive Achievement* > 0).
The comparisons (pre-test) between the five groups, showed no significant differences (*K−W chi−squared=3.64, p-value=0.45*). However, all groups showed a high proportion (more than 60%) of neutral affective states during the initial time of interaction with the intelligent tutoring system. In addition, it was observed that all groups in the performance showed *42.75* average proportion score of the positive affective state and *25.75* average score of the negative states and differences by group in the proportion of affective tendencies.

On the other hand, it was observed that only one dimension showed the existence of significant difference *(p-value<0.05)* between the groups of the Power distance (PDI), showing that group 1 manifests a normal level *(mean=34.0, sd=40.30)* to differences of the other groups (see Figure 1-A) and a general average lower (*mean=2.9, sd=49.48*) than the all groups and much variation with respect to their average value. In addition, high levels (*Index>=66 points*) on average identified of Uncertainty avoidance (UAI), Individualism (IDV) and Masculinity (MAS) and nor- mal average index in Long-term orientation (LTO). (see Table 1)

In the same way that significant differences were identified *(p-value<0.02)* be- tween the pre-test and post-test and not in the post-test by group (*K−W chi−squared= 5.94, p-value=0.20*). Moreover, the post-test had a significant association (r_s*=0.323, p-value=0.02*) with the positive affective states, moreover the positive affect with Cultural dimension of the Power distance index (r_s*=0.326, p-value=0.02*).

Nevertheless, it showed a significant difference per group related to the proportion of positive affective states (*K−W chi−squared=10.74, p-value=0.02*), negative states (*K−W chi−squared=18.19, p-value=0.001*), neutral affective states (*K−W chi−squared=11.75, p-value=0.01*) and the Power distance index (*K−W chi−squared=9.07, p-value=0.04*), the results also presented that the some groups with the lowest index (*Index<=33 points*) for Power distances showed less representation in the positive trend of affective states and only the group 2 high proportion of negative trends. (see Figure 1)

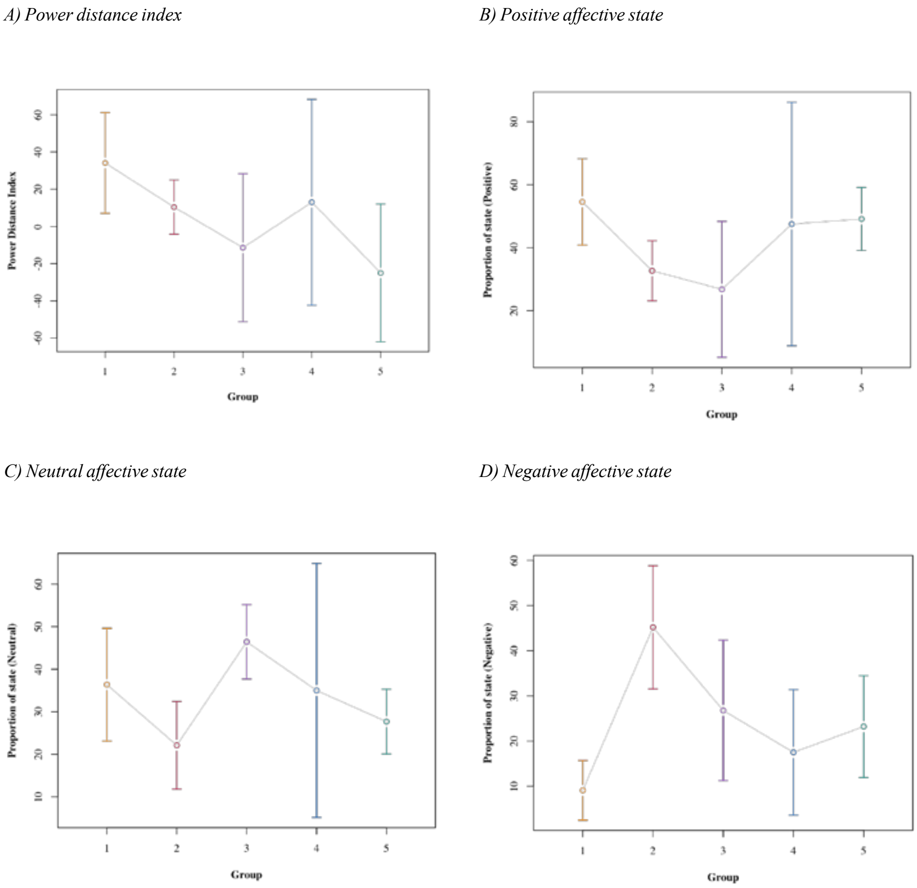

Figure 1. Comparison by group and characteristics (affect and Power distance index)

Figure 2 shows the Principal Component Analysis [23] represent 61.01% varia- tions of the behavior of the affective states association with the Cultural dimension and Learnings scores (pre and post-test), this identifies and confirms that the positive affective trends (AE-Positive) are oriented to Power distance (PDI) and the post-test presents a high association with the pre-test as well as with the Power distance index and positive states. Finally, the negative tendencies (AE-Negative) do not present any significant association with the learning scores when only considering students with a cognitive achievement.

Table 1. Descriptive statistics (Cultural dimensions)

	Cultural dimensions				
Statistics	**PDI**	**UAI**	**IDV**	**MAS**	**LTO**
Number of Observations	50	50	50	50	50
Median	5	92.50	82.5	75.0	40.0
Mean	2.9	83.80	73.8	72.8	43.6
Standard Deviation (n-1)	49.48	71.20	63.18	87.99	22.38
Coefficient of Variation	1706.486	84.96	85.61	120.87	51.34

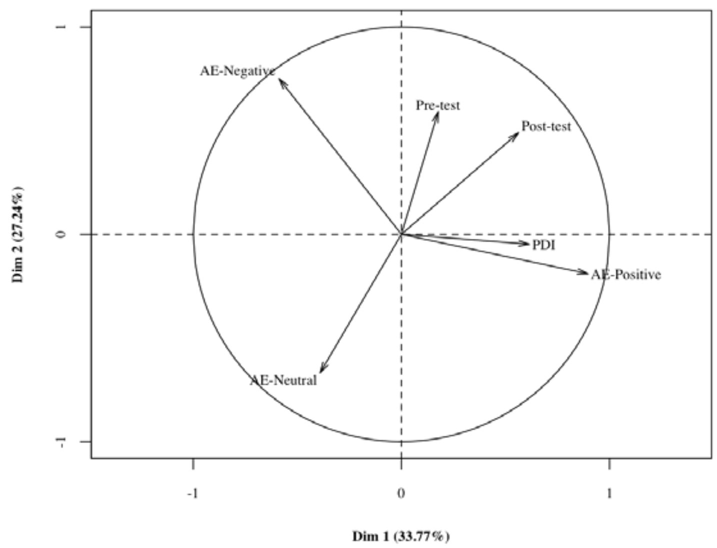

Figure 2. Representation of the characteristics in learning process

4 Discussion

This research project presents results suggesting different patterns of individual student' behavior, which were observed during the use of educational technology (ITS) for mathematics at the secondary level in Mexico. The exploration of independ- ent characteristics (cultural dimensions, affect and cognitive achievement) is relevant because it allows understanding the student profile in a preliminary way during the learning process mediated with technology, contributing with information about the cultural criteria of the student who is likely to affect the academic environment of Mexican students.

The results suggest that there are significant associations between the cultural dimensions (Power distance index) and cognitive-affective states. This can be explained as the positive affective behavior of students may be closely associated to power distance in normal level to obtain higher score in the post-test.

In particular, considering this dimension will allow Mexican students to demonstrate positive states conducive to learning math issues by setting aside levels of traditional academic hierarchy.

However, it is important to mention that the affective measurement of students during the use of technology can be considered as an exploratory measure of the affection that the student presents according to his/her judgement, however, this requires specialized metrics [19] or to measure awareness and regulation [10] of the same over their states.

As a future work, it is proposed to evaluate other characteristics that affect the cognitive process in order to elicit a model of the user who is able to react to factors that are not conducive to learning. This model will allow creating a motor of inference that provides before the interaction of the students a profile to identify if these requires the use of a common intelligent tutor system or one with affective elements of regulation for to increase cognitive achievement and improve the interaction.

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Cultural factors linked to collaborative learning in Intelligent Tutoring System in the Domain of Mathematics

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Abstract. The integration of technology into education requires a thorough analysis of the elements necessary to adapt it to the teaching-learning process, based on appropriate contextual analysis. This article presents the initial identification of elements or variables for the conceptualization of a collaborative model used in a mathematics Intelligent Tutoring System, deployed for secondary school students. Two exploratory studies were undertaken, the first to determine how students will be assigned to collaborative activities as to optimize the learning experience, and the second to identify the elements that influence collaboration and the extent to which collaboration is linked to cultural issues. The main contribution of this paper is to show the results of the second study, in which it was found that the association between collaborative and cultural elements, allow to improve the student's learning gains in collaborative activities use an Intelligent Tutoring System.

Keywords: Collaboration, Cultural Dimensions, Intelligent Tutoring System.

1 Introduction

Socials and cultural factors fundamentals to collaborative learning in technology mediated environment, allow that students improved their learning experiences and get greater benefits in it. To do this, the scales that Hofstede [1] suggest as cultural dimensions, and social elements as organization, participation, dialog, role and responsibly they offer the support to do it.

In several investigations [2], [3], [4], [5] it has been observed that students when interacting with educational technology have the opportunity to increase their level of learning, in addition, if the technology can be adapted within this process of learning, this will provide the necessary assistance that the student requires [6].

On the other hand, the changes of models and educational modalities, lead to certain aspects of migration or improvement in the teaching learning process, one of these aspects is the role of students, their become more dynamic entities in charge of the construction of his own knowledge [7]. Another aspect is the interaction of the student with classmates to carry out academic activities, this communicative and interactive process is given through collaboration where two or more people exchange opinions to create meanings. For this, there are adaptable and intelligent web-based education systems, called AIWBES [8], which adapt the user's preferences and knowledge, individually and in group, during interaction with this system. In this sense, social interactions that promote active and vicarious learning can also be carried out, where students can learn by directly doing exercises or observing activities that others do [9].

The relationship that some students may have with each other, allows each of them to include elements from different contexts, because although they live in similar environments, they may present different personalities, attitudes, knowledge and emotions to face similar situations, this difference is given for the culture that each one presents. Living in the family, at school, on the street, are what denote this difference in individual and collective behavior [10].

Unfortunately in Mexico it is a fact that the mathematics level is below the OECD average, results show that up to 57% of the students do not even reach the basic level of competences, that is, they cannot represent mathematically a Real-world situation, such as comparing the total distance between two alternative routes or converting prices to a different currency [11]. This is an alarming situation, due to this, the interest to include educational technology as a mathematics Intelligent Tutor System within the learning process in secondary school, but not only to include the tutor in this process, but also to adapt in the Intelligent Tutor System, collaborative and cultural elements that further promote student learning.

2 Collaboration in the educational process

Understand by collaboration to the knowledge construction process that originates in the social interrelation of people who share, compare and discuss ideas [12]. It is through this interactive process that the student builds his own knowledge [13].

Within the educational context, collaboration is an interactive form of learning where students must participate as equals, adding efforts, skills, knowledge, talents and competence that lead them to define a series of activities and tasks that allow them to reach their common goal.

By incorporating collaborative activities in the classroom, the teaching-learning process can be enriched, especially if the participation of students is more actively, generating in this way, the construction of their knowledge, fostering collaborative learning and improving the interpersonal relationships.

One of the important benefits of collaboration is the learning that can be obtained from this, when students participate in argumentation and negotiation activities, share and discuss ideas from each person's perspective and reach the consensus of the collaborative group [14]. Collaborative learning is a didactic technique that allows students to be guided in an educational environment, where they can interact with classmates and teachers, enriching the teaching-learning process to achieve their academic goals. In an environment of this type, students assume different roles, responsibilities, share experiences, knowledge and must be engaged by participating in joint processes, for the solution of specific activities in favor of their learning.

However, not all forms of grouping students to work collaboratively, leads to the best outcome [7]. Adequate group formation and structured interactions are important elements to increase the possibility of having a beneficent collaboration in a pair students [14].

As the formation of work groups is analyzed to obtain learning benefits, it should also be studied whether collaborative elements hat influence the learning process of students. One of the collaborative components used as part of this experiment to measure the collaboration of students was the Collaboration Test [15], which consists of 12 multiple-choice questions of nominal scale, from which information is obtained with relationship to five subscales of collaboration such as organization, participation, dialogue, role and responsibility. This test was applied with the goal to understand the kind of collaboration the participants think they had during the interaction with their teammate in the collaborative activity. Each of these subscales included in the test collects information on some of the questions as shown in table 1.

Table 1. Subscales in collaborative test.

Subscale	Question
Organization (S1)	Q1, Q6, Q8
Participation (S2)	Q3, Q4, Q5
Dialogue (S3)	Q2, Q3, Q5, Q9, Q12
Role (S4)	Q6, Q7, Q8, Q11
Responsibility (S5)	Q10, Q11

3 Cultural dimensions

The social behaviors observed in different countries are influenced mainly by thoughts and customs of the own culture [16]. Geert Hofstede is a research sociologist who explains the discrepancy between the behavior of different cultures, through a theory called cultural dimensions, this theory offers a panorama to examine how cultural values affect the behavior of people to act in a or another way.

The cultural dimensions of Hofstede are indicators that show the behavior of a complete society, not a single individual, however, this does not mean that one culture is better than another or has more value, but that the behavior of each is different from the other or not, according to the region [16], even within the same culture, there can be several subcultures which make up a global culture [17] within which can be observed different behaviors and opinions.

The first dimension to which Hofstede refers is the power distance index (PDI), here we can see how the members of a society, question or not, to the people who have the highest hierarchy, that is, in a society with great power distance, the members of a society do not question those who have higher levels, however a society with low power distance, each person has equal power between members of a group or community.

A second dimension is individualism (IDV) versus collectivism, in which it is observed if the members of a society are integrated in a group, or the link between one person or another is weak, that is, he prefers to make individual decisions and focuses only on the "me" and not on the "us".

Another dimension is masculinity (MAS) versus femininity, which refers to the way in which roles are distributed in society through gender. In a highly masculine society people are driven by competences and results, they are ambitious. Within society with low masculinity or femininity, people are more focused on building good relationships and ensuring a high quality of life for all.

The uncertainty avoidance index (UAI) refers to the way in which people feel in unfamiliar situations, in cultures with strong UAI, people avoid risks and unexpected situations since you are creating stress and anxiety. People with low UAI are more tolerant in unexpected situations, they are more relaxed and flexible.

People with long term orientation (LTO) encourage to be thrifty and to invest, respect traditions and fulfill social obligations such as respecting their elders and people of different ranks, on the contrary, those with short term orientation are encouraged to spend and want to make immediate profits, these people believe that the status between members is not important, unless they can get some benefit from them.

Although Hofstede's work has been done to know the influence of culture on the values that people have at work, and that their research gives an idea of what other cultures are like, and which factors are predominant in the organizational scope, its results have prevailed over time and its dimensions have been used even in the educational field, adapting the questionnaire to be applied to students [16].

The Hofstede cultural dimensions test consists of 20 questions, four questions for each of the five dimensions, the purpose of this test was to find some element that intervened positively in the results of the students.

4 Intelligent Tutoring System

The beginning of Intelligent Tutoring Systems gave rise to the moment when Artificial Intelligence (AI) was being worked on to imitate natural intelligence through the creation of machines that could achieve a human thought, these systems have been an important part in the area of IA in Education to create an environment of instruction that resembles a teacher in his teaching process.

These Intelligent Tutors Systems began to be developed with the purpose that knowledge could be imparted in some intelligent way to guide and assist a student in their learning process, so that they sought to emulate the behavior of a human tutor who could adapt to the behavior of the student, identifying the way in which this can solve a problem to provide the cognitive help required, when required and tailored to the student.

Intelligent Tutors Systems by their own nature were created to be used individually, however, it has been shown [18] that students in Mexico work collaboratively, even when it is an Intelligent Tutor, they get up from their places to ask questions to their classmates and complete their activities.

There is an Intelligent Tutor System for the area of mathematics called Scooter the Tutor [19], which teaches students to solve scatterplots and assists them with the necessary help and feedback so they can understand the subject and continue to solve exercises. This Intelligent Tutor System will be taken to include a collaborative model that helps secondary school student's work collaboratively in their math activities to benefit their results.

This Intelligent Scooter Tutor System is a desktop system tested on Windows 95 to Windows 8 operating systems, however, it is being migrated to a web system to be compatible with any browser and operating system, in order to students can use the system in the school, or remotely from your personal computer or mobile device.

5 Methodology

In the methodological process to find which elements or variables have an important degree of significance for the elaboration of a collaborative model, several tests were applied to a group of students, such as the collaboration test which identifies in five subscales (organization, participation, dialogue, role and responsibility) [15], the degree of collaboration of the students after carrying out a joint activity and the Hofstede cultural dimensions test adapted for educational situations that identifies the influence of the culture in students in the secondary school No. 2 "Julio Zarate" in Xalapa, Veracruz, México, in relation to the power distance index (PDI) towards their teachers, uncertainty avoidance index (UAI) in a collaborative activity, individualism (IDV) versus collectivism, masculinity (MAS) versus femininity and long term orientation (LTO).

5.1 Study units

The subjects involved in the development of this project were 116 morning hours students constituted in five school groups 1, 2, 3, 4 and 5 of the first grade (equivalent to seventh grade in the United States) of the General Secondary School No. 2 "Julio Zarate" located in the city of Xalapa, Veracruz, Mexico.

5.2 Procedure

The study was carried out in four days during the 50-minute math class in the media classroom, this is a computer lab used by teachers and secondary students, the classroom has capacity for 50 students at the same time and it consists of 34 computer equipment available with Windows operating system.

On the first day of interaction was the thematic induction, in this case scatter plot in a time of 10 minutes, later a standardized pre-test was done to know what the student's initial knowledge was, this test was done in a time of 20 minutes, a learning styles Kolb test [20] was applied in a time of 15 minutes, this test was applied because in the first study it was found that the best way to associate students in a collaborative activity is grouping them according to the same learning styles, this association allows students to obtain higher learning gains, than if students with different learning styles will join in the activity. The participation of the students on this day was individually. Once the learning style tests were taken, they were evaluated by the researcher for the conformation of the work couples of the following day.

For the second and third day, with the Intelligent Tutoring System, the interaction was done in a collaborative way by students pairs previously defined, this was done in a time of 40 minutes.

On the fourth day of interaction, the standardized test (post-test) was carried out in a time of 20 minutes, then the test of collaboration to answer it in 10 minutes and the last the test of cultural dimensions in 15 minutes. The collaboration test was applied in order to know the type of collaboration that existed between students. The cultural dimensions' test to know if any dimension affected or not, the performance of students during their collaborative activity.

The activities and execution times of this study can be seen in table 1.

Table 1. Activities and execution times of the exploratory study.

No.	Activity	Day	Execution time in minutes
1	Induction scatter plots	1	10
2	Pre-test		20
3	Learning styles test application		15
4	Work teams formation		---
5	Collaborative activity with the STI Scooter	2	40
6	Collaborative activity with the STI Scooter	3	40
7	Post-test	4	20
8	Collaboration test application		10
9	Cultural dimensions test application		15

6 Results

The tests carried out during the experimental scheme were, the pre-test to know the initial student's knowledge in the scatterplot topic, the test of learning styles, so that the students could be put together in pairs according to their same learning styles, the test of collaboration to know the type of collaboration (organization, participation, dialogue, role and responsibility) that existed during the activity, the test of cultural dimensions to know if any dimension affected or not, the student's performance during your collaborative activity. As for the analysis performed in the tests that were applied in the groups in the experiment, it was observed that there is no significant difference (*p-value=0.0866*) between the groups initially, presenting an equal knowledge in the pre-test, another aspect that was shown is that there is no an association between the learning styles and the groups evaluated (*p-value>0.05*), as well as the relationship between learning styles and the five sub-scales of collaboration measured during the interaction with the tutor. However, in the post-test it is identified that there is a significant difference between the groups (*p-value=0.02439*) as shown in Figure 1.

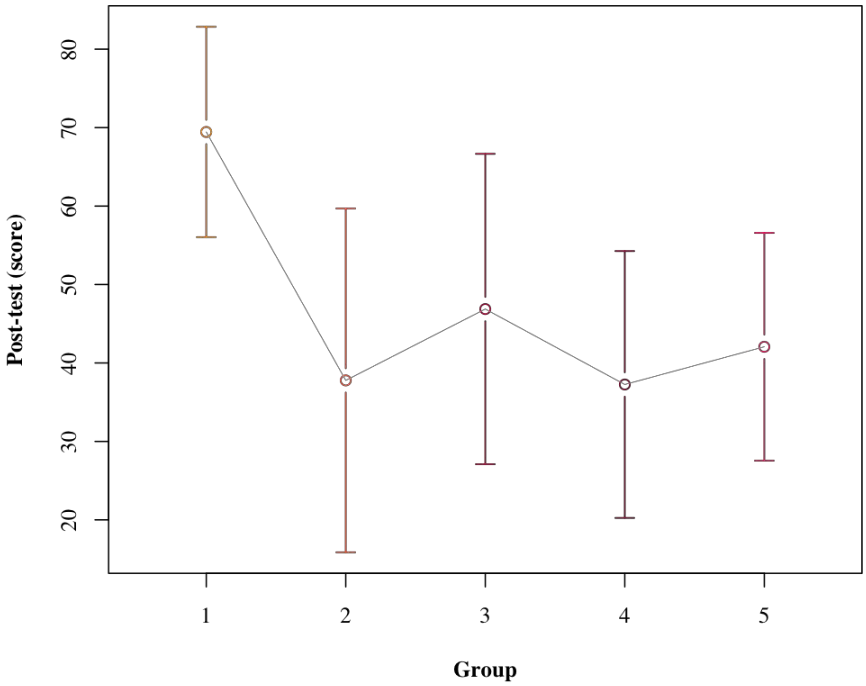

Fig. 1. Result of the post-test of groups.

In the analysis individually for each of the groups, it was found that the variables of both collaboration and cultural dimensions in some of its elements are related, that is, some behaviors are distinguished that do not occur naturally by themselves, but they are added with other characteristics, in this sense the collaboration is directly linked with characteristics of cultural dimensions or vice versa, this in benefit of the improvement of the result in the post-test of the students.

Of the five sub-scales, organization, participation, dialogue, role and responsibility evaluated in the collaboration test, and the five cultural dimensions defined in the Hofstede test, the power distance index 'PDI', uncertainty avoidance index 'UAI', individualism 'IDV' versus collectivism, masculinity 'MAS' versus femininity and long term orientation 'LTO' there was mostly an association between them in a particular way for each group.

In group 2 (G2) the relationship between UAI and Responsibility was observed with a value of *p-value=0.0498*, MAS with Participation (*p-value=0.0497*), as well as LTO with the same dimension of collaboration Participation (*p-value=0.0036*), in addition to MAS and role (*p-value=0.0024*). In group 3 (G3) the relationship between UAI and Organization was observed (*p-value=0.0307*). Group 4 (G4) showed relationship in UAI with Organization (*p-value=0.0102*), MAS and LTO with Responsibility with values of *p-value=0.0439* and *p-value=0.0001* respectively. On the other hand, group 5 (G5) only showed a relation of IDV with Conversation (*p-value=0.0054*). Group 1 (G1) did not present any relationship between cultural dimensions and collaboration sub-scales. You can see these results in table 2.

Table 2. Results of relationship of cultural dimensions and collaboration subscales.

	PDI	UAI	IDV	MAS	LTO
Organization		0.0307 (G3) 0.0102 (G4)			
Participation				0.0497 (G2)	0.0036 (G2)
Conversation			0.0054 (G5)		
Role				0.0024 (G2)	
Responsibility		0.0498 (G2)		0.0439 (G4)	0.0001 (G4)

Table 2 shows that the union of both elements, cultural dimensions and collaboration are present in the behavior of the groups, however, by themselves, they do not show any type of behavior, which indicates that both characteristics must be associated for obtaining better results.

With the results that are observed of the relationship between some cultural dimensions and some collaborative elements, the intelligent tutoring system to which the model going to include, should mediate this type of aspects. For example, if it is observed that the lack of responsibility is linked to the high student's uncertainty to work in a collaborative activity, then, we should include in the intelligent tutoring system, an element that explains more in detail, how to solve the exercise, with the goal to eradicate the student's uncertainty when they doing the activity. In this way, we would seek to eliminate or reduce the uncertainty so that the student is responsible in the development of their activity. Just as the system would be modified in this relationship, modifications would also be made for the other relationships between cultural dimensions and collaborative elements.

7 Conclusions and future work

It was observed that the group is a factor that affects the post-test, the learning style is an element that affects learning independently, that is, it is not linked to any cultural dimension or to any collaborative elements, and last, that the union of the collaborative and cultural elements must be associated to obtain better results.

As future works are the integration of variables for the formal definition of the collaborative model, considering the multiple linear regression approach to study the relationship between the variables of interest, to calculate the response variable through the estimation of the best linear predictor, in this case would be the post-test. Also the inclusion of it in a mathematics Intelligent Tutoring System and the evaluation of the model to check the predictions of it. All this will be done so that students can work collaboratively with an Intelligent Tutoring System to help them get better results in their math assessments.

An example of how it would be the inclusion of the model in the Intelligent Tutoring System is if the model predicts that the student would have a greater post-test if the student when doing a collaborative activity, will talk more with his classmate, then the Intelligent Tutoring System will have to include elements such as a forum, a chat, an editor, or any aspect that promote conversation in the collaborative activity. In this way, all the elements indicated by the collaborative model needed to improve the student's post-test would be added to the system.

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