A Ubiquitous Model of Emotional Tracking in Virtual Classes: From Simple Emotions to Learning Action Tendency

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***Abstract*— Researchers in the field of ubiquitous learning assert that emotional presence management leads to promising results in the teaching-learning process. However, are there predominant emotions in virtual classes? How can emotional clusters be created? Is it possible to obtain action tendencies in virtual classes? In response to these questions, we propose a ubiquitous emotional model for virtual classes, recording the simple emotions from participants´ faces, checking whether these emotions can produce emotional clusters, and using these clusters to infer action tendencies within the context of virtual classes. The experimentation was carried out in a real virtual class. To evaluate the model, the experts verified the results of the ubiquitous model, and it is confirmed that the action tendency obtained by the model coincides with the criteria of the experts. Inferring these action tendencies are very important, since the teacher, unlike a face-to-face model, has difficulty observing all the students with the use of cameras in virtual classes, making it difficult to understand the student´s behavior online.**

***Index Terms*— Action Tendency, Emotion Recognition, Ubiquitous Model, Virtual Classes.**

I. INTRODUCTION

USE of digital technology in the teaching-learning process of Higher Education Institutions in Latin America HEIs - LATAM faces different challenges considering demographics and potential barriers. Among the factors that limit the use and prevent the effective implementation of Technology Enhanced Learning in HEIs - LATAM are teacher training, limited technological resources, internet access and effective feedback.

However, Latin America has seen an increase in the popularity of online learning recently, particularly as a result of the COVID-19 pandemic. The region struggles to provide high-quality education due to a few factors, including few resources, poor infrastructure, and social inequities. By granting access to education to a broader audience, regardless of location or economic background, online education has the potential to address some of these difficulties [1-2].

The promotion of online education has received substantial attention from several Latin American nations. For example, the Brazilian Ministry of Education has initiated a series of projects to increase online learning, including the development of a national distance learning platform [3].

However, there are still a few difficulties for online education in Latin America. Lack of infrastructure, such as reliable internet connectivity and access to devices like laptops and smartphones, is one of the main problems. A high level of motivation and self-discipline is also needed for online learning, which can be challenging for certain students. To ensure that students can achieve the same learning outcomes that they would in a traditional classroom, there is a requirement for high-quality online educational content and successful pedagogical practices [4].

Hence, the need arises to implement innovative learning methodologies to face these challenges and support decision-making not only for teachers but also for those responsible for formulating policies to defend the teaching-learning process based on technology [5-6].

Technology makes it possible to identify feelings through facial recognition, thus facilitating the identification of affect even in uncontrolled environments. It has been determined that emotions are directly related and directly reflect the student concentration index in an e-learning context using facial emotion analysis, whose analysis helps to improve the learning process [7-8].

Artificial intelligence (AI) has come a long way in recognizing and understanding human emotions. This is done using various technologies, such as facial recognition, speech recognition, and natural language processing. In the context of classroom performance, emotions play an important role in shaping students' learning experiences [9]. Positive emotions such as interest, excitement, and curiosity can enhance motivation and engagement, leading to better learning outcomes. Conversely, negative emotions such as anxiety, frustration, and boredom can interfere with learning, resulting in poor academic performance [10]. In addition, the set of these emotions can configure groups, which can then be interpreted as tendencies towards a specific behavior [11]. This is very

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helpful in the educational feedback process, because analyzing this behavior allows the teacher to know the emotional behavior action tendency of each student in the development of a class. For example, if a student shows signs of agonistic or interrupting, the teacher can modify the lesson to make it more engaging or provide additional support to help the student.

However, it should be noted that relying solely on AI to measure students' emotional states is not always accurate. Human emotions are complex and subtle, and AI algorithms may not always capture the full range of emotions students experience [12].

These considerations go hand in hand with the present study, since the concept of error is considered with the application of Receiver Operating Characteristic (ROC) curves and of course the point of view of the human experts, who helped to verify the results [13].

Moreover, since in these virtual contexts it is difficult to achieve a total control of student emotions by the teacher, it is necessary to apply intelligent multi-modal algorithms that benefit the educational environment and its ubiquitous game rules. In face-to-face settings, this does happen. In fact, it is recommended for maintaining positive emotional contexts [14-15].

TABLE I

AUTHORS WHO DEAL WITH EMOTIONAL MANAGEMENT AND HUMAN BEHAVIOR IN VIRTUAL, MIXED AND FACE TO FACE ENVIRONMENTS

Year	Author	Proposal
2020	A. Petrova, D. Vaufreydaz, and P. Dessus.	Prediction of human behavior through global moods in unimodal analysis.
2020	A. Raes, P. Vanneste, M. Pieters, I. Windey, W. Van Den Noortgate, and F.	Analysis of learning environments and their emotional impact on students in synchronous contexts.
2020	J.P. Rowe and J.C. Lester.	Identifying human behaviors through patterns based on the visual attention of individuals.
2020	R.F. Behnagh.	Identification of constructs and emotional energy, with the aim of controlling emotions based on emotional recording in videos.
2020	A. Kaviani.	Assessment of learning experiences and the relationship with the teacher’s methodology.

Table I shows the authors whose proposals allow us to consolidate the hypothesis namely whether the emotions influence the virtual classes.

Researchers propose that emotions affect virtual classes, but Are there predominant emotions in virtual classes? How can emotional clusters be created? Is it possible to obtain action tendencies in virtual classes?

The contribution of this work is to determine whether the set of emotions causes a human behavior guided by the action tendencies in virtual classes. We worked with an emotion recognition software[1] based on convolutional neural networks that provides a probabilistic emotional classification, to detect the simple emotion (Fig. 1) of 33 students within virtual classes. The output of the emotion recognition software was assessed using the ROC curves for each of the participants [16], with the observations made by human experts acting as the ground truth.

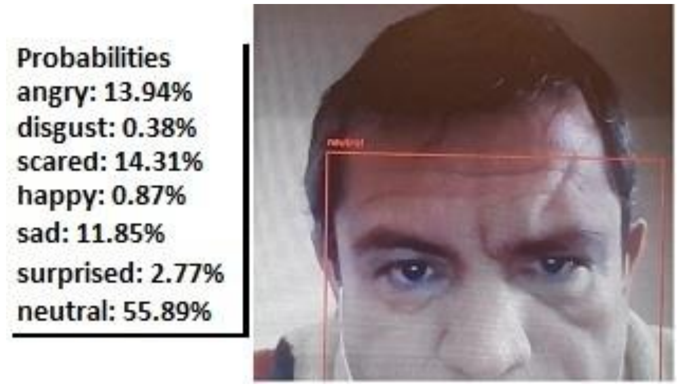

Fig. 1. Facial emotion identification software.

The experiment took place at the Universidad Técnica de Ambato, during the COVID-19 pandemic, when students and teachers were forced to keep the camera on during the virtual class. This experiment obtained the approval of the Ethics Committee of the Universidad Técnica de Ambato, where the students signed an informed consent form to record the virtual classes. Although emotions may be altered when students sense they are being watched, as also occurs in face-to-face classes, we consider that the alteration is minimal once some of the class time has elapsed or when it becomes a "standard practice".

We examined emotions based on the Pareto principle [17], where 20/80 of emotions are significant and need to be analyzed. The Pareto output show that the neutral emotion is a simple emotion, its detection is of the utmost importance as it can be interpreted as a lack of interest or demotivation in the class, since emotions are expected to be more frequently positive.

Emotions are then grouped by means of the KMEANS algorithm [18-19]. The result of the KMEANS algorithm is a set of emotional clusters that can lead to a type of human behavior.

KMEANS output allows us to infer emotional human behavior by using an emotion ontology (EMO[2]), through its Action Tendency class, which is defined as an urge to perform certain expressive or instrumental behaviors and is linked to a specific emotion [20 - 23]. In EMO, there are classes used to describe, categorize, and infer action tendencies from the semantic axioms and ontology reasoner. In this work we use the Pellet ontological reasoner to infer the action tendencies.

To test our model, two experts watched the videos to identify the MAJOR and MINOR action tendencies. A MAJOR action tendency is the action tendency most frequent, while the MINOR action tendency is the least frequent action tendency.

The level of agreement between experts was measured through the Kappa method with moderate agreement [24].

[1] "GitHub - omar178/Emotion-recognition: Real time emotion recognition." GitHub. https://github.com/omar178/Emotion-recognition (accessed Jan. 17, 2023).

[2] OBO Foundry." OBO Foundry. http://www.obofoundry.org/ontology/mfoem.html (accessed Jan. 17, 2023).

Therefore, this results in MAJOR and MINOR action tendencies, which are compared with the EMO Pellet reasoner output. Results show coincidences between the experts and the output of the Pellet reasoner in the ontology.

Algorithm and semantic steps necessary to obtain the emotional human behavior –Action Tendency class– are explained below in Section 2. Section 3 describes how the proposed approach is experimented. Discussion and future work of this research is presented in Section 4. Finally, we present the conclusions in Section 5, which allows to recommend this ubiquitous model as a base tool for the identification of action tendencies in virtual classes.

II. METHODOLOGY

The methodology applied to obtain the action tendencies in virtual classes is set out below:

1) The students are informed that the class will be recorded and that their faces will be recorded on video while the class is underway.
2) Faces are registered; they are analyzed by recording the emotions on the face. The software outputs a file of the set of participants' emotions recorded during the virtual classes.
3) Pareto is applied to observe which emotions are the most prevalent; this procedure can be performed individually or in a group setting, depending on the match sought to obtain when applying the methodology [25].

$$\left(f_{i(e)}\right)20\% \qquad (1)$$

whereby:
fi = frequency; e = emotion.

4) KMEANS algorithm is applied to group the most prevalent emotions. In the same way, this process can be carried out both individually and in a group setting.

$$J = \sum_{i=1}^{m}\sum_{k=1}^{K} w_{ik} \left\|x^i - \mu_k\right\|^2 \qquad (2)$$

whereby: w_{ik} =1 for data point x^i if it belongs to cluster k; otherwise, w_{ik} =0. Also, μ_k is the centroid of cluster x^i.

5) KMEANS outputs clusters of emotions. Each cluster is instantiated in the EMO ontology and active Pellet axioms to obtain Action_Tendency.

The work environment allows the following scenarios for student alone and all students in virtual classes:

- Emotions during the virtual classes are registered using software.
- Most representative emotions are selected (Pareto).
- KMEANS obtains the emotional clusters in virtual classes.
- Emotional clusters are sent to the EMO to obtain the action tendencies.

To test the methodology, it is necessary to have two experts, specialized in psych pedagogy, so that the videos are analyzed by them, and information is obtained to calculate the Kappa Index. The result of the analysis serves to determine the reliability of the semantic results.

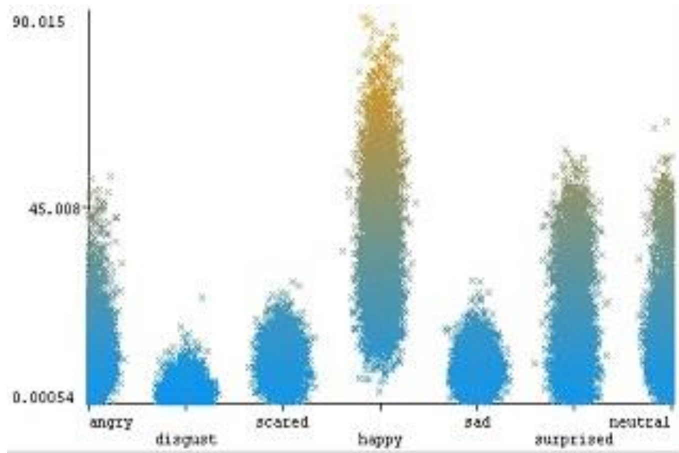

Fig. 2. Simple emotions of an individual student: The registration of simple emotions in virtual classes is linked to their percentage.

An example of applying the emotion registration software on a face is shown in Fig. 2. In this case, it was applied to a single student.

There are emotions that commonly appear during the teaching-learning process. Fig. 3 shows an emotional cluster that has the *Interest* emotion which is used as input for the axioms to infer the Attending action tendency.

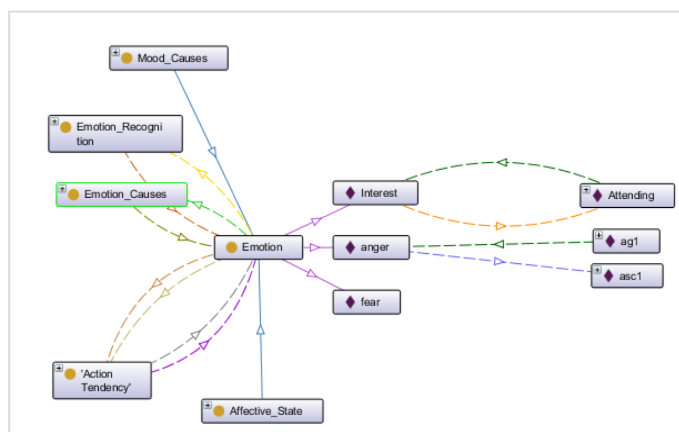

Fig. 3. A student´s emotions in virtual classes: The emotional clusters are instanced in Emotion class and human behavior is generated through the Action Tendency class.

III. EXPERIMENTATION

A simple emotion recognition software was used on the 33 students' faces in a real virtual class. The output was individual files that collect the emotion and its percentage. The videos were recorded in the real virtual class, while the teacher was explaining and, the students listened and asked questions, that is, the videos correspond to the entire virtual class and not only to specific moments of it. The videos were used to detect the emotions of the faces in order to obtain the action tendency, and no interaction with other elements of the context was recorded. It is important to note that the participants signed an informed consent for their participation in the experiment, allowing only the recording of their videos but not of other interactions in their own computer environment.

A. Results of the Emotion Recognition System: ROC Curve

To assess the performance of the emotion recognition system, ROC curves are used, with the experts' judgement acting as the ground truth. Fig. 4 shows the ROC curve for 5 of the 33 cases (Table II).

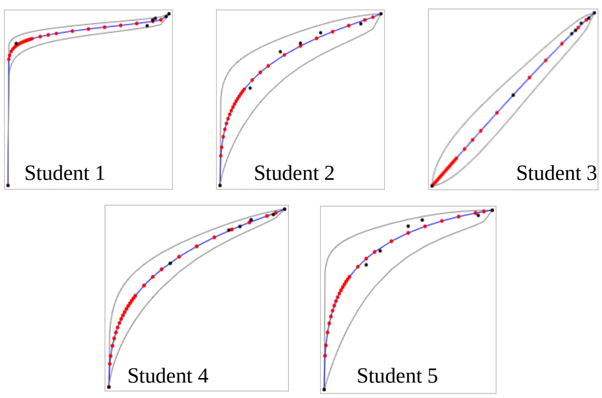

Fig. 4. ROC curves analysis of the emotions set registered on the student' faces.

TABLE II
ROC CURVE DATA

No. Participant	AUC
1	0,61
2	0,52
3	0,72
4	0,85
5	0,87
6	0,62
7	0,4
8	0,44
9	0,54
10	0,61
11	0,64
12	0,64
13	0,64
14	0,51
15	0,54
16	0,48
17	0,9
18	0,87
19	0,61
20	0,71
21	0,53
22	0,55
23	0,54
24	0,54
25	0,67
26	0,72
27	0,72
28	0,9
29	0,87
30	0,42
31	0,89
32	0,45
33	0,61

Table II shows the results where the tests fluctuate between fair and good, basing on the interpretation of the area of the curve. Given that the ROC curve cannot discriminate values below 0.5, the results are considered acceptable [26] because 28 of the 33 cases exceed the value of 0.5 and in fact, 21 exceed the value of 0.61.

B. Pareto Principle

Pareto shows (Fig. 5) that neutral and angry emotions (80%) are affected by scared, sad, happy, surprised and disgust emotions (20%), based on the principle 20/80 [27].

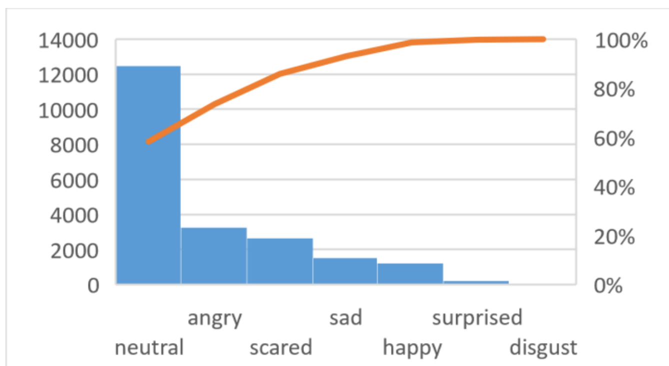

Fig. 5. Histogram Pareto Chart: simple emotions

C. KMEANS and Semantic validation

The 28 individual files that collect the emotion and its percentage was the input to KMEANS. Then, KMEANS algorithm provided individual emotions' clusters.

Then, each individual cluster is instantiated in the EMO to infer Action_Tendency class.

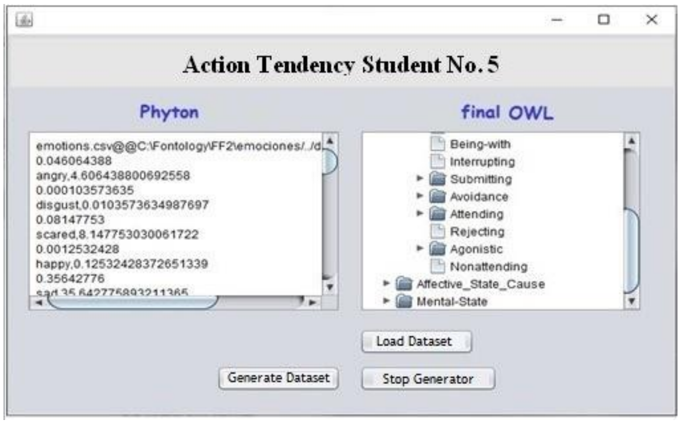

Fig. 6. Individual action tendencies inferring.

Fig. 6 shows the Action_Tendency class that has been instantiated using the Pellet axioms. Definitions of emotional behavior via the Action Tendency facilitate an algorithmic identification of the base semantic structure for academic feedback.

This is another contribution as a high-level finding of the ubiquitous cusp of emotional human behavior. Indeed, feedback processes must be guided by individual emotional behavior and not only by opinion or by the planning of learning resources in virtual classes.

To test our model, the experts in Psycho-pedagogy analyzed the 28 students’ videos and reflected the results based on their knowledge, this being a necessary step when verifying the ontological results (Table III). Each video had an average duration of one hour.

Table III shows the results of the work carried out by the experts in psycho-pedagogy. Experts in psychology were instructed on the semantic interpretation of behavior in the ontology (Action_Tendency).

In this regard, the experts individually watched the videos, and classified the behavior according to their expertise and the semantic concepts (Summiting, Avoidance, Attending, Agonistic, Rejecting). This allowed the experts to identify the MAJOR and MINOR action tendencies and the comparison with the Action_Tendency value provided by the ontology.

MAJOR action tendency refers to the human behavior that had more records in the expert's observation. MINOR action tendency refers to the human behavior that is registered but fewer occasions.

For example, for student 1, the MAJOR action tendency is Agonist and the MINOR action tendency is Dominant, which coincides with the axiomatic execution of the ontology in the Action_Tendency column (Table III). The coincidences between the results of the execution of the axioms and the expert's point of view are observed, which serves to verify the certainty of the results.

Kappa Index obtained is 56.8%, which implies moderate agreement between the two observers.

IV. Discussion

Methodological application of this work involved to obtain participants´ action tendency. This work can be complemented with others that allow corroborating results and consolidating conclusions as the possibility of configuring groups of emotions, which can then be interpreted as tendencies towards a specific behavior [11].

The ubiquitous model was implemented in an environment of real virtual classes, so the model can be part of educational feedback systems, to support the teacher when monitoring students in each academic semester.

Although other works [28-31] analyze the emotion, we also cover semantic interpretation necessary for feedback processes [32], given that the group and individual behavior conceive semantic relationships. We can use ontologies to create instances of emotional classes and verify the Action tendencies such as the interpretation of behavior that is recorded in the teaching-learning process.

Decisions that can be made from the semantic conclusions of the emotional behavior are the basis for educational improvements.

This methodology finds its support solely in individuality, although also in the group sense. It can identify the phenomenon towards a student as well as towards the group.

Therefore, it acts as a simulator of face-to-face emotional surveillance, which is generally undertaken by the teacher [33-34].

The ability to feel and express emotions appropriately, highlights vast differences between men and women in virtual classes [35], and the presented proposal facilitates their study in future works.

Likewise, the degrees of belonging of a student to an emotional group may be verified, this would be very important since individual treatment can be given to each situation of the teaching-learning process. To find out which cluster a student belongs to, a classification system can be used, according to the clusters encountered. For example, a neural network can be applied where the classes would be defined by the dominant emotion, which is proposed as a future work.

To accomplish this, in our future work, we will explore the application of techniques as fuzzy logic and neural networks to obtain the degree of belonging to an emotional group and the emotional group classification of each student.

In the present study, only videos were recorded to obtain the action tendency from the emotions expressed in students’ faces, but no other input was considered. Considering students’ interactions with other elements outside the online classroom but inside the own computer environment may imply privacy issues. We consider that the action tendency may give the teacher a cue whether the student is attending to the class or to other elements, in face to face or mixed context (virtual and face to face). However, we will explore the possibility of capturing other interactions for further analysis and better feedback in future work. Last, in a next stage, we will study the pedagogical approach to provide suitable feedback from the student’s action tendency and the possibility of integration in hybrid environments.

TABLE III
EXPERTS VS ONTOLOGY RESULTS SUMMARY
* The major action tendency is marked in bold in the Ontology Action_ Tendency column.

	EXPERTS		ONTOLOGY Action_Tendency
	MAJOR action tendency	MINOR action tendency	
Student1	Agonistic	Dominating	***Agonistic**-Dominating
Student2	Agonistic	Agonistic	**Agonistic**
Student3	Being with	Agonistic-Dominating	**Being with**-Agonistic-Dominating
Student4		Being with	Being with
Student5		Nonattending	Nonattending
Student6	Agonistic	Interrupting	**Agonistic**-Interrupting
Student9	Dominating	Dominating	**Dominating**
Student10	Agonistic		**Agonistic**
Student11	Agonistic-Interrupting	Being with	**Agonistic-Interrupting**-Being with
Student12	Being with-Agonistic		**Being with-Agonistic**
Student13	NonAttending	Submitting	**Nonattending**-Submitting
Student14	Submitting-Being with		**Submitting-Being with**
Student15	Submitting	Being with	**Submitting**-Being with
Student17	Interrupting	Nodefine	**Interrupting**-Nodefine
Student18	Avoidance	Being with	**Avoidance**-Being with
Student19	Being with	Submitting	**Being with**-Submtting
Student20	Submmiting	Interrupting	**Summiting**-Interrupting
Student21	Agonistic	Being with	**Agonistic**-Being with
Student22		Being with-Submitting	Being with-Submitting
Student23	Interrupting	Nodefine	**Interrupting**-Nodefine
Student24	Avoidance	Submitting	**Avoidance**-Submitting
Student25	Agonistic	Interrupting	**Agonistic**-Interrupting
Student26	Avoidance	Interrupting	**Avoidance**-Interrupting
Student27		Agonistic	Agonistic
Student28	NonAttending	Avoidance	**NoAttending**
Student29	Agonistic	Avoidance	**Agonistic**-Avoidance
Student31	Attending	Submitting	Submitting-**Attending**
Student33	Submitting		**Submitting**

Table III shows the MAJOR and MINOR action tendency identified by the experts versus the Ontology Action_Tendency class. The MAJOR column shows only the action tendencies in which the experts agreed. In cases where the experts did not agree, an empty cell is displayed. The same is true for the MINOR column. Matches were found between the results from the experts' column and the inferred results in the ontology action_ tendency column.

V. CONCLUSIONS

During the teaching-learning process, emotions play a fundamental role in what each student learns. Emotional control in face-to-face environments is mediated by the teacher, who can control the teaching process, guided by the observed face-to-face emotional responses of students.

However, what occurs in virtual classes? Are there predominant emotions in virtual classes? How can emotional clusters be created? Is it possible to obtain action tendencies in virtual classes?

This work proposes a methodology that starts by recognizing simple emotions on participants' faces automatically, which are grouped into emotional clusters that allow semantic interpretation to be performed. This model has been tested and implemented for virtual classes, which are currently very widespread; it has not been tested in other environments such as face-to-face as it requires the recording of the face by a camera. When the alarm system to take actions is developed in a future work, it will be studied how to integrate it in mixed environments.

We applied Pareto principle to respond to the question: Are there predominant emotions in virtual classes? This suggests that neutral and angry emotions represented the 80% of virtual class predominant emotions. This result can be used in a general way, to verify how is the basic behavior of a students` group and with it, to provide feedback to the teaching-learning process.

About the possibility to create emotional clusters, individual clusters are created according to the percentage of emotions with KMEANS.

Once individual emotional cluster is generated, they are instantiated in EMO ontology to obtain the Action_Tendency class, which is the possible reaction of the student from the semantic viewpoint. Therefore, it is possibly to obtain action tendencies in virtual classes, responding to the third above mentioned question.

EMO axioms, which are executed with the Pellet reasoner, allow the student's human behavior to be inferred and will be the basis of the feedback of the teaching-learning process [36-37].

Student human behavior has been analyzed in this study from the outlook of experts with the MAJOR and MINOR action tendencies, with an acceptable Kappa index of 56.8%.

The observation results by the experts reflect coincidences with the Action_Tendency class of the ubiquitous emotional model. This will surely entail improvements in the teaching-learning process for virtual classes.

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