Emotion-based decision support tool for learning processes

An application with undergraduate students during Covid-19 pandemic

Eduardo Puraivan
Escuela de Educación
Universidad Viña del Mar
Viña del Mar, Chile
Escuela de Ingeniería Informática
Universidad de Valparaíso
Valparaíso, Chile
eduardo.puraivan@postgrado.uv.cl

Marcelo León
Escuela de Ingeniería y Negocios
Universidad Viña del Mar
Viña del Mar, Chile
Escuela de Ingeniería Informática
Universidad de Valparaíso
Valparaíso, Chile
Marcelo.leon@uvm.cl

Jarnishs Beltran
Facultad de Economía y Empresas
Universidad Diego Portales
Santiago, Chile
Escuela de Ingeniería Informática
Universidad de Valparaíso
Valparaíso, Chile
jarnishs.beltran@gmail.com

Fabián Riquelme
Escuela de Ingeniería Informática
Universidad de Valparaíso
Valparaíso, Chile
fabian.riquelme@uv.cl

Abstract — **Student stress is a problem that hinders the teaching-learning processes, and that has increased considerably since the beginning of the Covid-19 pandemic. This article introduces a framework for the development of an emotion-based decision support tool for learning processes. As a case study, we consider undergraduate students starting their academic year virtually in the context of a pandemic. Through the application of the PANAS questionnaire and NLP techniques on free-text responses, students' emotions are automatically classified as positive and negative, as well as a level of basic emotions of the Plutchik model. The results allow to identify the most frequent sentiments in students. Also, they show concordances between both measurement instruments and a high capacity for the classification of emotions.**

Keywords - e-learning; sentiment analysis; PANAS; Covid-19; decision support tool.

I. INTRODUCTION

The SARS-CoV-2 (Covid-19) pandemic has changed our life routines; work, health, shopping, among others, moving to a reality strongly mediated by information and communications technology (ICT). In this new context, it is urgent to gather evidence to understand the new reality.

In education, student stress levels were already high before the pandemic. However, since 2020 these levels have intensified [1]. The latter is relevant because there is a relationship between emotions and the teaching-learning processes [2], [3]. Currently, it is possible to measure emotions from various disciplines, such as Psychology and Computer Science. However, these instruments do not usually complement each other.

Sentiment analysis is understood as opinion mining, which covers a wide range of methods, from natural language processing (NLP), information extraction, artificial intelligence, machine learning (ML), and data mining. These methods seek to automatically classify a text into positive and negative sentiments [4] and even some of Plutchik's basic emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust [5], [6]. Data processing is based on statistical and association relationships, not on linguistic analysis [7]. Medhat et al. [8] classified the main sentiment analysis techniques into two large groups: the machine learning-based approach and the lexicon-based approach. Lexicon-based techniques use a dictionary or a set of words with predefined emotional weights, generally formed of adjectives, the type of words that provide more information when analyzing sentiments [9], [10]. The development of these techniques for the Spanish language is in full swing, and its applications include education [11] and social network analysis [12].

From Psychology, Positive and Negative Affect Schedule (PANAS) is a questionnaire created in 1988 [13] to measure positive and negative affect about something in a specific environment. PANAS was originally applied to college students but it can be applied to students of different ages. Besides, other variants have appeared, such as PANAS-C, for children [14], or PANAS-X, which adds 11 specific affects [15]. Based on the latter, PANAS-t was developed as a psychometric scale to measure feelings on Twitter [16]. Supported by deep learning

This work was partially funded by the Escuela de Ingeniería Informática, Universidad de Valparaíso, Chile, through the grant No. 01.016/2020.

2021 16th Iberian Conference on Information Systems and Technologies (CISTI)
23 – 26 June 2021, Chaves, Portugal
ISBN: 978-989-54659-1-0

(DL) techniques and natural language processing (NLP) techniques, PANAS-t has recently been used in the tourism field during the Covid-19 pandemic [17].

This article proposes a framework for the development of an emotion-based decision support tool for learning processes. As a case study, we aim to identify emotions when starting a university course in a Covid-19 context. Since the respondents are students, we prefer to use the original PANAS instrument. Likewise, the questionnaire also included a free text field to express the students' emotions more openly. Thus, using NLP techniques on these texts, we seek to compare these results with the responses obtained from PANAS for the classification of emotions. This study also analyzes the relationship between computational techniques of sentiment analysis and the application of the PANAS questionnaire to measure positive and negative affects on students. We hope these results will help to improve decision-making processes in the educational context during health and social crises.

The article continues as follows. Section II describes the work methodology, including both measurement instruments (PANAS and NLP). Section III presents the case study and a description of the analysis tools and techniques used. Section IV discusses the results obtained, and Section V ends with the main conclusions of the work.

II. Methodology

The analysis methodology used by the emotion-based decision support tool is illustrated in Figure 1. The components are detailed as follows:

1) When starting a university course, students are asked to produce an "authentic text" (not limited in length) aimed at describing how they feel to face the course. Additionally, and immediately, the PANAS questionnaire is applied [13]. PANAS is formed by two higher-order scales of 10 items each:
   - Positive affect: Attentive, Active, Alert, Excited, Enthusiastic, Determined, Inspired, Proud, Interested, Strong.
   - Negative affect: Hostile, Irritable, Ashamed, Guilty, Distressed, Upset, Scared, Afraid, Jittery, Nervous.

   Each item is evaluated with a score between 1 (not at all) and 5 (very much), depending on how the respondent feels. From the sum of the positive and negative scores, it is possible to obtain a balance score, which allows determining whether the respondent's balance category is predominantly positive or negative. Factor analysis is performed on the PANAS results to empirically validate the theoretical structure of the instrument.

2) Student comments are manually pre-processed. As the Spanish language has lexical gender distinctions (e.g., in Spanish "nervioso" and "nerviosa" are used to refer to the masculine and feminine of nervous, respectively), some words must be unified to be recognized by the dictionary in the next step. After this, the punctuation marks are removed, and the strings are lowercased. From the unified texts of the previous step, terms are extracted from the document and crossed with NRC Lexicon. For each word of each comment, one of the eight basic Plutchik emotions is associated [5]. The latter is done through R's `syuzhet` package [18].

3) Emerging coding is carried out on the authentic text under the grounded theory. Subsequently, considering the PANAS items, the dimension of the emerging codes is reduced. In other words, the emerging coding is grouped, prevailing the PANAS concepts.

4) Correspondence analysis is performed between the NLP-based sentiment analysis results and the PANAS items.

III. Experimental Setting

As a case study, an online survey was conducted in the third quarter of 2020 during the Covid-19 pandemic. First-year students from various careers of a Chilean university who started the common course of Mathematical Logical Thinking were considered. This course is mandatory, and it aims at leveling students' skills in Mathematics.

The survey was conducted in the first class of the course. This survey consisted of the PANAS questionnaire, in addition to the following question: "How do you feel about starting the Mathematical Logical Thinking course in the COVID-19 context?" Unlike the previous questions, the last one had to be answered through a text field (not limited in size). The idea was to collect the student's impressions at the time of starting their new academic cycle. Study participants conducted the survey voluntarily and with informed consent.

This course was chosen because it has been taught in virtual format for more than three years. Also, its teaching resources used have been successfully tested in previous versions, complying with the standards of the specialized unit of the university in the delivery of courses in a blended and online format. Due to the above, we can understand that students, regardless of the pandemic (which led to taking all the courses in 100% online format), know in advance that the subject considered will be online, i.e., there was no change concerning the original form of dictation. In this way, we seek that the emotions collected can be attributed to the general Covid-19 context and not to a change in the course methodology.

From the above, we obtained a sample of 40 students, from these careers: Public Administration (1), Law (3), Engineering in International Business Management (1), Pedagogy in Differential Education (19), Public Relations (2), and Social Work (14). Of these students, 4 are men and 36 women, with 23 years old on average. This unequal distribution of participants in the different careers is not considered a problem in the context of this work since no analysis will be carried out by age groups, race, sex, among other possible classifications of this type.

IV. Analysis and Results

A. PANAS validation

As mentioned in Section III, exploratory factor analysis is performed to verify the original structure of PANAS, that is, the subscale of positive and negative affects. In this case, the

2021 16th Iberian Conference on Information Systems and Technologies (CISTI)
23 – 26 June 2021, Chaves, Portugal
ISBN: 978-989-54659-1-0

KMO value obtained was 0.66, which indicates that the factor analysis is adequate. Bartlett's results of 637 and a p-value of 0.00 indicate that the correlation matrix is different than the identity matrix. Using the Cattell criterion, two components were selected. The factor loadings are presented in Table I.

The factor analysis shows that the sample recognizes the original PANAS structure; that is, the dimension of *positive* and *negative affects* is verified. This result is fundamental, and it is used as a validity measure since the text production is carried out together with the PANAS application (see Figure 1).

TABLE I. FACTOR LOADING MATRIX

Emotion	Factor 1	Emotion	Factor 2
Nervous	0.92	Inspired	0.83
Scared	0.89	Interested	0.79
Afraid	0.88	Enthusiastic	0.78
Jittery	0.83	Attentive	0.75
Distressed	0.82	Proud	0.72
Irritable	0.74	Determined	0.71
Upset	0.70	Strong	0.63
Guilty	0.47	Active	0.60
Ashamed	0.46	Excited	0.59
Hostile	0.45	Alert	0.55

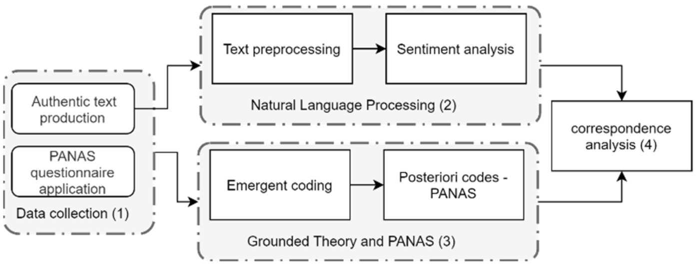


Figure 1. Analysis methodology for the emotion-based decision support tool.

Figure 2 shows the variables (vectors) and observations (numbered points) in the rotated space, using principal component analysis. The X-axis corresponds to factor 1 of negative affects, and the Y-axis corresponds to factor 2 of positive affects. For variables, we must look at the vectors and the angles they form. The more parallel the vector is to an axis, the more the variable contributes to that factor. Small angles between vectors indicate a high correlation between the corresponding variables.

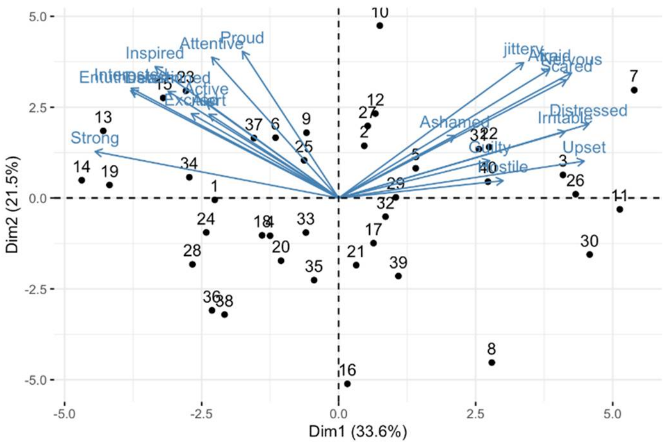
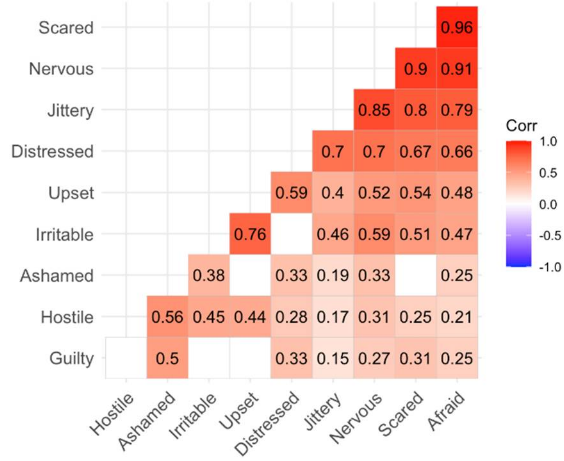
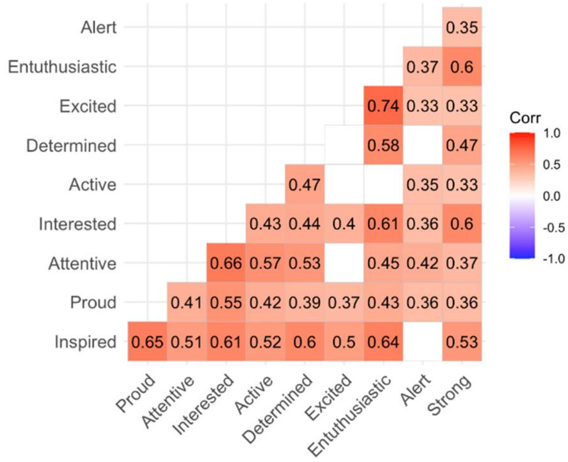


Figure 2. Variables and observations in rotated space.

Figure 3 shows the levels of correlation between the subscales. For positive affects, the highest correlation (0.74) is between Excited and Enthusiastic; for negative affects, it occurs between Scared and Afraid (0.96). Regarding the observations (numbered points), the closer points represent groups of observations with similar characteristics. In this case, one could identify students who are optimistic (high scores in positive affects), pessimistic (high scores in negative affects), and inconsistent (high scores in positive and negative affects).



(a) Positive emotions



(b) Negative emotions

Figure 3. Correlation matrix in each PANAS subscale.

B. Natural Language Processing

The algorithm used associates the opinions of the students with the words contained in the dictionary. If a word of the student's opinion appears in the dictionary, it is weighted with a value to determine the predominant emotion. Initially, sentiment analysis focuses on calculating the polarity of a text. However, using R's `syuzhet` package [18], Plutchik's eight emotions can be considered. The process considers dictionaries made up of unigrams that have a predefined score for each sentiment. The `syuzhet` package allows analysis in

ISBN: 978-989-54659-1-0

Spanish. Thus, from each opinion expressed by a student, each word is taken and automatically compared with the dictionary. If the word is in the dictionary, it is assigned a value of 1 in the corresponding sentiment; if the word has no associated sentiment, it is assigned 0. At the end, a count is made of the 1's and 0's obtained in each opinion. Figure 4 illustrates the analysis results. Note that fear (negative) and anticipation (positive) are the predominant sentiments in students' opinions. Fear has a survival function and is activated when a threat is perceived, while anticipation is related to exploration and the feeling of being prepared for future situations. On the other hand, when comparing the positive sentiments (anticipation, trust, joy, and surprise) with the negative ones (fear, sadness, anger, and disgust), their total distribution is very similar, being 167 and 160, respectively.

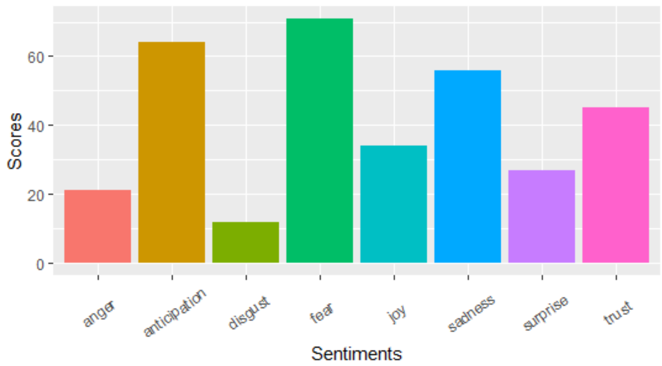


Figure 4. Scores obtained with NLP for the Plutchik's emotions.

C. Text analysis with grounded theory

The text analysis was carried out on the only open question, which did not belong to the PANAS questionnaire (see Section III). The responses were subjected to an emergent categorization based on Grounded Theory [19]. After that, a post-coding process was applied, using the categories of the PANAS scale. This method allowed us to identify the words that best represented the group's sentiments, identifying 19 words that resulted in the highest frequencies out of a total of 1566 words processed (see Table II).

TABLE II. POSTCODING USING PANAS CATEGORIES

Spanish word (original)	Traduction	Frequency	Percentage
Ansias	Cravings	47	0.03
Espectativas	Expectations	94	0.06
Inquieta	Restless	16	0.01
Insegura	Insecure	63	0.04
Molesto	Upset	157	0.10
Motivada	Motivated	63	0.04
Temor	Fear	31	0.02
Tranquila	Calm	16	0.01
Asustada	Scared	94	0.01
Desafío	Challenge	16	0.01
Estusiasmada	Excited	125	0.08
Frustración	Frustration	31	0.02
Fuerte	Strong	110	0.07
Inquietud	Restless	31	0.02
Miedo	Afraid	125	0.08
Ansiedad	Anxiety	94	0.06
Preocupada	Concerned	172	0.11
Ansiosa	Anxious	157	0.10
Nerviosa	Nervous	125	0.08

In general, both positive (generating liking) and negative (generating dislike) emotions are appreciated. The most frequent are negative emotions ("preocupación", "molestia", and "ansiedad"; which mean worry, annoyance and anxiety, respectively), followed to a lesser extent by some positive emotions ("entusiasmo" and "fuerza", which mean enthusiasm and strength, respectively). Presumably, the negative emotions are reflected with greater intensity due to the pandemic context.

1) PANAS scale and Plutchik's wheel of emotions model: As detailed in Section II, a sentiment analysis with natural language processing was also performed [20], considering the same sample of students and based on the same responses to the open question. Consistent with Plutchik's model, this analysis revealed the underlying basic emotions in the context of a pandemic (see Table III).

TABLE III. PLUTCHIK SCALE CATEGORIES

Sentiment	Frequency	Percentage
Anger	21	0.06
Anticipation	64	0.19
Disgust	12	0.04
Fear	71	0.22
Joy	34	0.10
Sadness	56	0.17
Surprise	27	0.08
Trust	45	0.14

Unlike PANAS, Plutchik's basic emotions are only eight categories, but they essentially measure PANAS-like aspects to determine emotional states. Therefore, it seems reasonable to know if both instruments allow us to measure sentiments concordantly and with an acceptable margin of variability.

2) Homologation of the PANAS scale and the simplified Plutchik model: From Plutchik's reduced model of only eight categories, all categories of the PANAS scale, made up of ten

2021 16th Iberian Conference on Information Systems and Technologies (CISTI)
23 – 26 June 2021, Chaves, Portugal
ISBN: 978-989-54659-1-0

positive and ten negative categories, were homologated (see Section II). The grouping was carried out through a bibliographic review of the classification criteria of the complete Plutchik model [20] and the Spanish version of Pultchik's gradations reported in [21]. The homologation results are shown in Table IV.

TABLE IV. HOMOLOGATION BETWEEN PANAS AND THE PLUTCHIK MODEL

(Simplified) Plutchik model	%	PANAS scale	Spanish word (original)	%
Anger	0.06	Hostile, Upset	Molesto	0.10
Anticipation	0.19	Attentive	Preocupado, Expectante	0.17
Disgust	0.04	Guilty	Insegura, Frustración	0.06
Fear	0.22	Scared	Miedo, Asustada, Temor	0.16
Joy	0.10	Enthusiastic	Entusiasmada	0.08
Sadness	0.17	Distressed	Ansiosa, Ansiedad, Ansias	0.19
Surprise	0.08	Nervous	Nerviosa, Inquieta, Inquietud	0.11
Trust	0.14	Strong	Fuerte, Motivada, Desafío, Tranquila	0.13

For each Plutchik's basic category, one or more categories of the PANAS scale were associated, which in turn were related to the emerging categories from the grounded theory analysis. Although the intensity of emotional concepts may present variability in terms of their frequencies, it will correspond to the determination of a concordance index that allows evaluating their goodness of fit.

D. Concordance among the models

1) Concordance among both scales through ICC: To measure the concordance between the PANAS scale and the Plutchick model (see Table IV), we use the Intraclass Correlation Coefficient (ICC). Due to the absolute variability between both scales, ICC is more suitable than Pearson's correlation coefficient since the latter can present high levels of correlation but low levels of concordance [22].

The intraclass correlation coefficient was significant for the average measurements between the scales, with a value of 0.914 (p-value < 0.003). The interaction between the scales obtained reliability of Cronbach's alpha of 0.903.

2) Concordance among both scales through Bland-Altman plot method: A more appropriate way to analyze concordance, which would later be called *limits of concordance*, was defined in [23] (see also [24]). The idea is to evaluate whether the comparison of the methods allows one to replace the other with sufficient precision. For this, two key aspects must be considered: how well the methods agree on average and how well they agree for individuals. The average concordance is evaluated by comparing the average of the differences of the measurements of the individuals. The above can be done with a Student's t-test for paired samples, assuming no difference as a null hypothesis. The estimation of the difference is contemplated with confidence intervals of 95%, which is obtained approximately as the average difference ±2 the standard error of the differences.

Next, the limits of concordance are plotted on a Bland-Altman diagram, i.e., a dot plot showing the difference between measurements (y-axis) with their average (x-axis). This diagram shows if there is any relationship between the difference (y-axis) and the measurement level (evaluated by the average of the measurements, x-axis). This graphic quantifies the range of values that can include the concordance for most of the sample. What we expect to find is that the points are distributed without following a defined pattern, such as a direct or inverse relationship between the variables. If any relationship is observed (e.g., as the average increases, the difference between the methods increases; or as the average increases, the variability of the differences increases), Bland and Altman propose using transformation techniques [24], [25]. The limits of concordance can be interpreted as follows: for a randomly selected individual from the population on which the results are expected to be inferred, the difference between the two evaluations is expected to be between the limits with a 95% probability. Figure 5 illustrates the distribution of the differences for each item with respect to the mean difference.

The differences of each item are within the range of two standard deviations from the mean. Therefore, we can conclude that the PANAS scale and the Plutchik model show concordances in the measurements they perform regarding emotions.

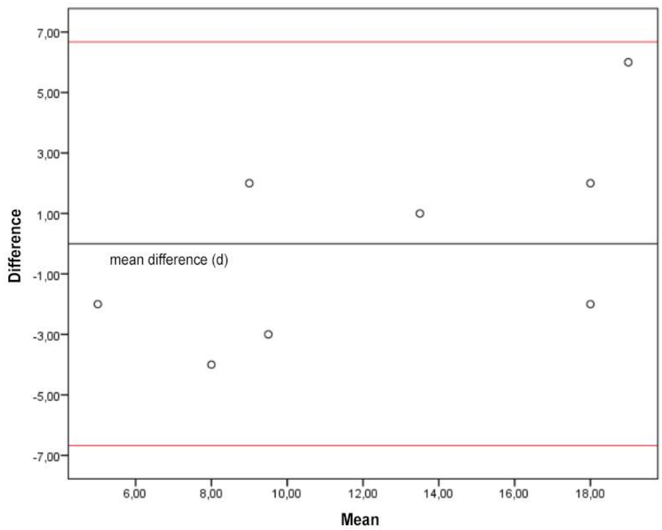


Figure 5. Distribution of the differences for each item with respect to the mean difference.

V. CONCLUSIONS AND FUTURE WORK

In this work, both the PANAS scale and natural language processing techniques were applied to evaluate sentiments in Chilean students at the beginning of a university course in the COVID-19 context. Through factor analysis, the validity of PANAS was verified, obtaining that the sample recognizes the theoretical dimensions of the instrument (that is, positive and negative scale). Natural language processing was applied to an authentic text written by the study participants (developed together with PANAS). The results allowed observing the most frequent sentiments according to the methods described. Then, a concordance analysis was performed between natural language processing (Plutchik categories) and PANAS. To do this, first, an emergent categorization was carried out on the

2021 16th Iberian Conference on Information Systems and Technologies (CISTI)
23 – 26 June 2021, Chaves, Portugal
ISBN: 978-989-54659-1-0

authentic text, which made it possible to identify 1566 words that represented the group's sentiments. These words were subjected to a postcoding process using the PANAS scale categories. The intraclass correlation coefficient was 0.92 with p-value 0.003.

Early identification of sentiments in students can be helpful at different levels. At the micro-level, it could help the teacher identifying the levels of motivation and possible problems of their students when facing the course. At the meso-level, it could serve as a teacher's guide for work teams formation, assigning roles in projects, etc. Finally, at a macro-level, it can be useful in career management, especially if there are historical data to make comparisons. The latter could be a useful input in accreditation and continuous improvement processes in educational institutions.

Besides traditional questionnaires such as PANAS (which already have proven usefulness), the automatic text analysis of responses to open questions constitutes a complementary output for the teacher, who can take the safeguards, mainly in the teaching methodology to achieve the expected learning.

Like any case study, this work has the limitation that it does not have external validation. In future work, the number of participants should be expanded. Further, some processes should be automatized, such as expanding the dictionary by incorporating words from the Spanish context, to reduce pre-processing time. For example, in Spanish, the words "nervioso" and "nerviosa" are used to refer to the masculine and feminine of "nervous", respectively. This union of words that represent different gender was done manually.

Also, as future work, it is expected to consolidate the idea of an emotion-based decision support framework for learning processes. To provide real help to the teacher, a front-end with appropriate usability techniques must be developed, which allow the integration of measurement instruments and the proper visualization of the results.

References

[1] T. Day, I.-C. C. Chang, C. K. L. Chung, W. E. Doolittle, J. Housel, and P. N. McDaniel, "The immediate impact of COVID-19 on postsecondary teaching and learning," *The Professional Geographer*, vol. 73, no. 1, pp.1–13, Oct. 2020.

[2] M. Boekaerts, "Being concerned with well-being and with learning," *Educational Psychologist*, vol. 28, no. 2, pp. 149–167, Mar. 1993.

[3] R. Pekrun, S. Lichtenfeld, H. W. Marsh, K. Murayama, and T. Goetz, "Achievement emotions and academic performance: Longitudinal models of reciprocal effects," *Child development*, vol. 88, no. 5, pp. 1653–1670, 2017.

[4] B. Pang and L. Lee, "Opinion mining and sentiment analysis," *Foundations and Trends in Information Retrieval*, vol. 2, no. 1-2, pp. 1–135, 2008.

[5] R. Plutchik, "A general psychoevolutionary theory of emotion," in *Theories of Emotion*. Elsevier, 1980, pp. 3–33.

[6] A. Mondal and S. S. Gokhale, "Mining emotions on plutchik's wheel," in *2020 Seventh International Conference on Social Networks Analysis, Management and Security (SNAMS)*. IEEE, Dec. 2020.

[7] S. M. Weiss, N. Indurkhya, T. Zhang, and F. Damerau, *Text mining: predictive methods for analyzing unstructured information*. Springer Science & Business Media, 2010.

[8] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," *Ain Shams engineering journal*, vol. 5, no. 4, pp. 1093–1113, 2014.

[9] L. Guthrie, J. Pustejovsky, Y. Wilks, and B. M. Slator, "The role of lexicons in natural language processing," *Communications of the ACM*, vol. 39, no. 1, pp. 63–72, 1996

[10] L. Wang and R. Xia, "Sentiment lexicon construction with representation learning based on hierarchical sentiment supervision," in *Proceedings of the 2017 conference on empirical methods in natural language processing*, 2017, pp. 502–510.

[11] E. J. Castro-Navarro, J. Beltrán Mejía, and I. Miranda Viramontes, "Emociones de estudiantes en clases online sincrónicas que tratan espacios vectoriales." *Paradigma*, vol. 41, no. 2, 2020.

[12] Á. Ortiz Espinoza and A. Espejel Trujillo, "Análisis de sentimiento en las campañas presidenciales México 2018." *Revista Española de Investigaciones Sociológicas*, no. 173, 2021.

[13] D. Watson, L. A. Clark, and A. Tellegen, "Development and validation of brief measures of positive and negative affect: the PANAS scales," *Journal of personality and social psychology*, vol. 54, no. 6, p. 1063, 1988.

[14] A. A. Hughes and P. C. Kendall, "Psychometric properties of the positive and negative affect scale for children (PANAS-c) in children with anxiety disorders," *Child Psychiatry and Human Development*, vol. 40, no. 3, pp. 343–352, Jan 2009.

[15] D. Watson and L. A. Clark, "The PANAS-x: Manual for the positive and negative affect schedule - expanded form," 1994.

[16] P. Gonçalves, F. Benevenuto, and M.Cha, "Panas-t: A pychometric scale for measuring sentiments on Twitter," CoRR, vol. abs/1308.1857, 2013.

[17] A. Peña, J. Mesias, A. Patiño, J. V. Carvalho, G. Gomez, K. Ibarra, and S. Bedoya, "PANAS-TDL: A psychrometric deep learning model for characterizing sentiments of tourists against the COVID-19 pandemic on Twitter," in *Advances in Tourism, Technology and Systems*. Springer Singapore, Nov. 2020, pp. 162–176.

[18] M. L. Jockers, *Syuzhet: Extract Sentiment and Plot Arcs from Text*, 2015. [Online]. Available: https://github.com/mjockers/syuzhet

[19] R. C. Giménez, "Aplicación de la teoría fundamentada (grounded theory) al estudio del proceso de creación de empresas," in *Decisiones basadas en el conocimiento y en el papel social de la empresa: XX Congreso anual de AEDEM*. Asociación Española de Dirección y Economía de la Empresa (AEDEM), 2007, p. 44.

[20] L.-P. Chen, "Text mining in practice with R," *Journal of Statistical Computation and Simulation*, vol. 90, no. 13, pp. 2497–2498, Jun. 2019.

[21] S. Shanker, *Calma, Atención y Aprendizaje: Estrategias de autorregulación en el aula*. Lima, Perú: Cerebrum, 2013.

[22] S. Pita Fernández, "Pértega díaz s, rodríguez maseda e," *La Fiabilidad de las Mediciones Clínicas. El análisis de concordancia para variables numéricas. Cad Aten Primaria*, vol. 10, no. 4, pp. 290–6, 2003.

[23] D. G. Altman and J. M. Bland, "Measurement in medicine: the analysisof method comparison studies," *Journal of the Royal Statistical Society:Series D (The Statistician)*, vol. 32, no. 3, pp. 307–317, 1983.

[24] D. Giavarina, "Understanding bland altman analysis," *Biochemia medica*, vol. 25, no. 2, pp. 141–151, 2015.

[25] C. Bunce, "Correlation, agreement, and bland-altman analysis: Statistical analysis of method comparison studies," *American Journal of Ophthal-mology*, vol. 148, no. 1, pp. 4–6, Jul. 2009.

2021 16th Iberian Conference on Information Systems and Technologies (CISTI)
23 – 26 June 2021, Chaves, Portugal
ISBN: 978-989-54659-1-0