RESEARCH ARTICLE

A Text Mining and Statistical Approach for Assessment of Pedagogical Impact of Students' Evaluation of Teaching and Learning Outcome in Education

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ABSTRACT Technology-enhanced learning (TEL) is now at the heart of teaching and learning process in many higher education institutions (HEIs). Today, educators are faced with the challenges of pedagogically specifying what tools, methods, and technologies are used to support the teachers and students, and to help maintain/sustain a continuous education and practices. This study shows that there is an opportunity in the use of (educational) datasets derived about the teaching and learning processes to provide insights for fostering the education process. To this effect, it analyzed the students' evaluation of teaching (SET) dataset ($n = 471968$) collected within a higher education setting to determine prominent factors that influences the students' performance or the way (TEL-based) education is being delivered, including its didactical impact and implications for practice. Theoretically, the study employed a mixed methodology grounded on integration of the Data-structure approach and Descriptive decision theory to study the rationality behind the students' evaluation of the teaching and performance. This was done through the Textual data quantification (qualitative) and Statistical (quantitative) analysis. Qualitatively, the study applied the Educational Process and Data Mining (EPDM) model (a text mining method) to extract the different sentiments and emotional valence expressed by the students in the SET, and how those characteristically differ based on the period and type of evaluation they have completed (between 2019 to 2021). For the quantitative analysis, the study used a multivariate analysis of covariance (MANCOVA) and multiple pairwise comparisons post-hoc tests to analyze the quantified information (average sentiment and emotional valence) extracted from the SET data to determine the marginal means of effect the different SET types and evaluation period have on the students' learning outcomes/perception about the teaching-learning process. In addition, the study empirically discussed and shed light on the implications of the main findings for TEL-based Education, particularly implemented by the HEI during the analyzed periods. The scholastic indicator from the study shows that while the flexible digital models or instructional methods are effective for continuous education,

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innovative pedagogies, and teaching transformations. It also, on the other hand, serve as an incentive for more robust research that idiosyncratically look into their implications for the students' learning outcomes and assessment done in this study.

INDEX TERMS Text mining, teaching assessment, TEL-based education, learning models, students evaluation, sentiment analysis, educational innovation, higher education.

I. INTRODUCTION

Today, *educational technologies* [1], [2], [3], [4] has become an integral and indispensable part of the modern-day education [5], [6], [7], [8]. One of the effective ways by which educators were able to continue teaching and learning, particularly during the recent global pandemic [9], [10], [11], [12], [13] was through the use of the educational technology otherwise allied to the notion of Technology-Enhanced Learning (TEL) [14], [15]. TEL is an educational practice applied by the educators to improve the teaching and learning processes for the stakeholders (e.g., teachers and students) regardless of where the teaching and learning takes place (face-to-face or remote) through the use of information and communication technologies (ICT) [15], [16], [17], [18], [19], [20], [21].

However, in education, while the TEL-based methods and models have shown to be promising for improving the teaching and learning processes for the stakeholders, for instance, the use of Learning Analytics (LA) and Learning Design (LD), Interactive Whiteboards, Virtual Reality (VR) and Augmented Reality (AR), Massive Open Online Courses (MOOCs), Canvas, Blackboard, Computer-supported Collaborative Learning, Blended Learning, and Flipped Classrooms [1], [14], [22], [23], [24], [25], [26]. On the other hand, there are discourses, both in theory and practice, on the issues and challenges, or what TEL-based methods pedagogically offers toward the transformation or heightening of the educational processes, particularly as it concerns the *flexibility*, *sustainability*, and *scalability* of the new and emerging (technology-based) educational models or instructional approaches [13], [15]. Those challenges include to mention but a few; issues that deal with the social mandate or lack of local capacity to design and build specialized educational technologies, to lack of coalition between the existing educational models and operational policies of the different institutions in respect to the educational labor market [27]. There is also the problem of digital divide or gap (otherwise allied to institutions or persons lacking access to the digital technologies and platforms who are potentially excluded from the vast benefits and opportunities to TEL) [28], [30], [31], [32], to inadequate skills, training, and use of the different technologies by the teachers and students, and inability of educators to leverage the information (educational datasets) that are being recorded and stored at an unprecedented rate in the databases of the different institutions to support the decision making processes and performance strategies [7], [27], [33], [34], [35], [36], [37], [38], [39].

Consequentially, we note that the aforenoted issues and challenges is an indicator for the development of educational models or methods that supports provision of ''innovative pedagogies'' for teaching and learning, that not only integrates the TEL-based initiatives, but can be instructionally used to bridge the gap between the modern and traditional models of teaching, whilst paying attention to the new mechanisms or practices for achieving the much-needed ''flexibility, scalability and sustainability of education''. Indeed, one of the most pertinent ways through which the said goals can be achieved is through conceptual analysis and leveraging of the insights drawn from the readily available educational datasets that explores the learning patterns and performance of the teachers and students [40], [41], for an improved educational practice as done in this study.

A. THE RATIONALE OF THE STUDY

To describe the pedagogical impact, assessment, and evaluation of teaching in context of this research, this study uses information (educational dataset) drawn from the teachers-students learning outcome and experiences (SET) to analyze and understand the impact of the flexible digital models for learning, students' satisfaction and assessment, and how those can be used to determine/develop useful insights and strategies for an enhanced learning and outcomes [4], [7], [12], [13], [42], [43], [44]. The use of educational datasets (e.g., SET) to support the teaching and learning process has become one of the recent and important discourses that have emerged both in the existing literature and in practice [3], [27], [28], [37], [41], [45], [46]. Pedagogically, the dissemination of ''student-generated data'' can be used to provide an increased performance and for addressing the different challenges associated with the TEL-based education [13], [15], [47], [48]. Thus, this study proves that there is a need for innovative methods for extracting useful (education-based) information from the datasets recorded and stored about the students' evaluation of teaching/performance, to help transliterate them into actionable plans for the educators and/or TEL-based education models and curriculum design.

To this end, the study applied a two-step (mixed) methodology grounded on synthesis of the Data-structure approach [49] and the Descriptive decision theory [50], [51] to study the rationale behind the decisions that the learners are disposed to make by means of the textual data quantification (qualitative approach) and statistical analysis (quantitative approach). This was done using the students' evaluation of teaching (SET) dataset collected in a higher education

setting. Qualitatively, we applied the EPDM model (a text mining method) [52] to determine the extent or level of impact (sentiment and emotional valence) of the different comments provided by the students in the SET, and how those may characteristically differ based on the type and period of SET evaluation. For the quantitative analysis, we utilized the extracted information (i.e., the average sentiment and emotional valence) to determine the marginal mean of effect that the evaluation periods (between 2019-2021) and type of evaluation (Students-to-Instructor, Student-to-Students, and Overall recommendation) has on the students' evaluations and outcome, and how those may statistically differ based on the studied period and SET type.

The main research questions of this study are as follows:

1) How can we analyze the (educational) dataset captured about the students' evaluation of teaching (SET) to determine prominent factors that influence the students' performance?
2) Does the students' evaluation and recommendations vary based on the period and type of SET evaluation completed by the students?
3) How can the results and outcome of the study be used to provide actionable insights towards improvement of the TEL-based education?

The main contributions of the study are as follows:

1) It defines a data-structure approach based on the descriptive decision theory to understand the students' perception of the teaching-learning processes and outcomes within the higher educational settings.
2) It provides a two-step mixed method (through a qualitative and quantitative lens) applied to determine the influential factors and marginal means of effects upon how the SET evaluations impacts and differ based on the type and periods of evaluation.
3) It shows the usefulness of the Text mining technique (textual data quantification) in understanding the intensities or impact of the comments provided by the students in the SET.
4) It empirically discusses how educational datasets extracted about the teaching/learning processes can be analyzed and used to provide actionable insights and solutions to the TEL-based education including its implications for practice.

The rest part of the paper is structured as follows: recent and relevant studies in the topic, particularly as it concerns the TEL-based education models and students' evaluation of teaching (SET) are discussed in the Background Information (Section II). Section III consists of description of the research methodology, the SET instrument, data sampling, and experimental setup. The data analysis and results are presented in Section IV. The study empirically discussed and shed light on implications of the results and findings in Section V, including the limitations and directions for future research. Conclusions of the study is provided in Section VI.

II. BACKGROUND INFORMATION
A. STUDENTS EVALUATION OF TEACHING AND ASSESSMENT
Existing studies have looked into the cogency or impact of the students' evaluation of teaching (SET) as an indicator of teachers' performance and assessment [41], [52], [53], [54], [55], [56]. For instance, Boring [53] notes that SET has lately been used not just as a tool to assess the teaching performance of the teachers/instructors, but have also led to studies or researches that look into the qualities or teaching dimensions that the students find important in their teachers [57]. The several studies have shown that a lot of the time, the higher institutions of learning (HEIs) greatly rely on the outcomes of the SET not only for improving or refining the various learning activities and curriculum, but also, are used to define the academic performance of the teachers [48], [53], [55], [58]. In this current study, we note that an important key aspect of the SET should be on its coalition with the educational ecosystem, and how such (educational) dataset can be used to understand the teaching/learning practices, including the identification of steps that can be taken to improve the dynamics of the teaching/learning processes [27], [40]. In this vein, there is a necessity to tenaciously study the concealed benefits of SET in education, and how the underlying information that are derived from such tools can be used to support the decision-making processes, and drive the educational ecosystem forward. The authors believe and prove that studying the comments provided by the students when completing the SET instruments can allow educators to identify the students' learning pathways, experiences, and expectations towards an enhanced learning and teaching practices. This can be didactically done by transliterating the extracted sentiments and emotions expressed by the students in the completed SET into meaningful insights in connection to the teaching-learning process, and to discover the prominent factors that influences the way they rate their teachers and learning outcomes [40], [57], [58].

B. TECHNOLOGY-ENHANCED MODELS FOR LEARNING IN CONTEXT OF SET
The instructional and practical challenges related to ''technological infrastructures'' for learning faced by both the educators and students has led the university' leaders to reinvent learning options that combine the virtual and face-to-face learning modalities [59], [60], [61], otherwise allied to the TEL-based education [15], [43]. Whilst the TEL or hybrid models for learning have shown to be more flexible and caters for continuous education, especially during the recent global pandemic [13], [62], [63]. It on the other hand, could potentially lead to relaxed curriculum. Pedagogically, the hybrid (TEL-based) educational models can be said to come with both opportunities and challenges that the various HEIs need to address and adopt in order to achieve the wide

benefits (instructional and technical) for learning purpose [34], [35], [64], [65]. Thus, the use/analysis of the SET data and information should be of paramount importance in management and heightening of the TEL-based education. For example, whereas the concept of "datafication of learning" which is also allied to analysis of the SET data done in this study, has brought about the emergence of the modern educational models and paved the way for new innovative methods for understanding and improvement of the teaching and learning processes [49], [66], [67]. We note, on the other hand, that the many educational institutions has to also take the extra steps of integrating the derived insights and information from analyzing those educational datasets (e.g. SET) into the curriculum as they are being developed, to be part of the teaching and learning processes, and help maintain/sustain the quality and idiosyncratical capacities of the educational models [1], [64], [68], [69], [70].

C. PEDAGOGICAL AND SOCIO-TECHNICAL FACTORS FOR TEL AND STUDENTS' EVALUATION OF TEACHING

With "transformative education" at the center of the many higher institutions' of learning goals [71], [72], [73], and "technology" spurring the educators to consume, innovate, and transfer knowledge and practices that transcends the stakeholders (e.g. teachers and students) into becoming global voices [74]. Our review of the current literature and state-of-the-art in education/learning delivery shows that the rigidity of the instructions or curriculum can present a threat to ample adoption and implementation of the TEL-based models for learning [75]. On the one hand, while the educational transformations that are experienced by the educators over the years, have led to substantial changes in the teaching and learning processes by adopting the digital technologies (augmented reality, online tutoring, and gamification elements, etc) [76] to foster online asynchronous simulation systems for teaching, and promotion of the learning processes including the wellbeing of students through the use of the technological tools [13], [76]. On the other hand, one of the transpiring challenges hand-in-hand with digital teaching (digitized-education) is the need for scalable strategies for development of the teaching-learning processes and practices. Moreover, the flexible digital models have shown its effectiveness in improving the learning outcomes, satisfaction, and progression for the students [13], [21], [77]. Interestingly, existing studies have shown that online feedback systems, such as the SET instrument described in this study, can be effective for understanding the different pathways or outcome (impact) of the teaching and learning processes, especially used for promotion of students' engagement and success [78].

To summarize the literatures, while the existing studies have shown that platforms such as m-learning or mobile applications have helped the students and educators in continuing education especially during the recent pandemic [18]. Likewise, in the past there are also studies that have fashioned

digital programs to exclusively heighten the quality of teaching and learning for the students [79]. For example, the recent study that looked into pedagogical impact of the technologies within the classroom or educational settings [18], have shown that 53% of the participants agreed that technology has helped them greatly in their virtual learning/teaching process. While 87% disclosed that m-learning applications do motivate them for virtual learning, and 93% still believed that strengthening their digital skills in the use of virtual environments is also paramount to fully benefiting from the TEL-based education. In another study, Rio-Chillce et al. [80] found in a university setting that almost all the participants reported that they frequently use the digital platform for their online classes, with 68% agreeing that video conferencing platforms/tools help them to learn. 72% of the respondents also believed that they need to continue strengthening their digital knowledge, whereas less than 24% also stated that their academic performance has improved due to the new teaching modality or models (TEL-based) [80].

The comparative study of attitude, affect, motivation, cognitive engagement, and perceived behavioral control (ease of use, accessibility, self-efficacy) of students' use and acceptance of emergency online learning due to the recent global pandemic in USA, Mexico, Peru, and Turkey, shows that distance education or TEL-based education is continually experiencing transformation, and the students' cognitive engagement in the classroom settings has increased in many universities across the studied context [81]. Although, the study [81] equally mentioned how important it is to note that it was a challenge providing high-quality education to all students while continuing with the lockdowns or contingency measures during the pandemic, and most higher education institutions, globally, were not prepared with appropriate e-learning resources or online educational platforms to cater for the impromptu (virtual) mode of learning. It is also important to mention the fact that despite the many promising benefits of the TEL-based education and models, our review of the literature such as Suarez [59] noted that most institutions of learning have consequentially relaxed their assessment criteria so that students' academic performance is not affected, which can be used with repercussions or prone to ineffective learning outcomes or curricula. Indigenous communities or universities in the low-tech regions are also at a structural disadvantage as it concerns the TEL-based education [29], [30], [31], [82], as existing disparities and limited access to training, digital literacy and infrastructure between the rural vs urban regions has shown to be a socio-technical challenge or bottleneck to effective use and implementation of TEL-based models for learning [31], [82]. The UNESCO's Global Education Coalition [31] has also mentioned that while the TEL-based initiatives and technologies are promising, their underlying technicalities, educational goals, and services are only accessible to people with access to a computer and networks services, and in consequence, may breed educational ecosystems of social and technological inequality, or at the same time, span measures on how to

scientifically determine and surrogate the pedagogical impact of the digitized-education on learning and outcomes, such as the one done in this study.

III. METHODOLOGY

TEL-based educational models [14], [15], [77] are learning approaches that integrate innovative teaching strategies and cutting-edge technologies, designed to improve the learning experiences of the teachers and students, and ensure continuous education through a combination of different components. As an example, the Flexible and Digital Model (MFD) [77] applied within a university setting is an educational model that consists of the amalgamation of interactive learning contents and activities, technological tools, and learning evaluation framework or assessment. Didactically, the main characteristics of such models (TEL-based) includes the flexibility to deliver learning or education at anywhere, any place, and at anytime, support of collaboration, monitoring, accompaniment, advice and feedback from the instructors, through remote interaction and tools, to availability of digital resources for active learning that are delivered using videos, web pages, canvas, and blackboard, web-conference sessions, and remote assisted work, etc [77]. While prior studies have looked into how best to apply the TEL-based models or initiatives to provide the teachers and students with productive and positive learning experiences [4], [5], [20], [55], [83], [84], [85], [86]. This study notes that the MFD educational model [77] comprises of several years' experience of the HEI in design and delivery of digital education programs aimed at ensuring academic continuity of more than 90 thousand students and 10 thousand instructors [77], [87] within the university setting.

In this study, we note that there is a need to explore pertinent methods for assessment and evaluation of the TEL-based approaches for learning [15]. In turn, while the use of digital (TEL) learning technologies and strategies has proved to be a way of enhancing the learning experiences for the students [4], [88], [89]. On the other hand, considering the students as consumers of the resultant educational models and technologies for learning, we note that there is also a need to monitor the impact or implications of the learning approaches and interventions on the students' performance. To do this, this study applied a two-step (mixed) methodology using the text mining (qualitative) and statistical (quantitative) approach that is grounded on the data-structure and descriptive decision theory to analyze the dataset collected from the students' evaluation of teaching (SET) within the higher institutional setting to help determine and explain the pedagogical impact of the TEL-based models in education and/or learning outcomes and assessment.

A. DATA SAMPLING

The SET instrument designed for collection of information about the students' learning performance and outcomes, referred to as ECOA [90], is an institutional survey applied across 26 national campuses of the host institution where this research was conducted. The survey covers around 14 Schools and Divisions, 78 Departments, and 1082 Courses offered by the institution. For this study, we analyzed a total sample of $n = 471968$ comments provided by the undergraduate students in the survey between 2019 to 2021 during which the MFD model described in this study was implemented (see Methodology – Section III). The main construct and variables considered in the study include (i) the evaluation period between 2019 to 2021, and (ii) the type of evaluation (Students-to-Instructor, Student-to-Students, and overall Yes-No recommendation question) completed by the students.

In our experiment, we analyzed the three categories of SET data provided by the students (Students-to-Instructor, Student-to-Students, and overall Yes-No recommendation) in response to the following questions:

i. Comments provided by the students about the instructors or their learning outcome (*comentarios al instructor*)
ii. What would you say to a student who would like to register on the subject with the teacher? (*qué le comentarías a un estudiante que quisiera inscribir la materia coneste profesor?*)
iii. Why would or wouldn't the student recommend the teacher? (*por qué sí lo recomendarías o por qué no lo recomendarías?*)

From ethical point of view, we note that to obtain an unbiased analysis of the data, the names of the students who have completed the survey were withheld from the data, and the students were also informed about the purpose of the survey before completing the questionnaire, and were not directly involved in the analysis done in this study.

Statistically, the study analyzed a total sample of $n = 471968$ comments after cleaning and removing the incomplete datasets or the students who did not comment in the data. We utilized the sample sizes of $n_1 = 390774$ for the Students-to-Instructors' recommendation (REC), $n_2 = 66934$ for the Students-to-Students REC, and $n_3 = 14260$ for the Yes-No REC question, covering the period of 2019-2021, respectively.

Considering the reliability and validity of the analyzed dataset, we note that the ECOA instrument is an institutional survey administered and maintained by the host university, and has been used for several years by the institution for the purpose of evaluation of the teachers' performance based on answers provided by the students. The instrument has also been validated in previous studies [91], [90], [93]. The analyzed data (i.e., comments provided by the students) were a free choice open-ended question, and the estimated minimum sample size for this research purpose was 40 participants that we considered to be the scientifically acceptable size ($n > 30$ or 40) [94] for conducting the experimentations and data analysis when compared to the large enough sample size (n=471968) we have used. It is also important to note that the comments provided by the students were given and analyzed

in Spanish. However, this study has reported and presented the results in English to cover the international audience and targeted readers of this paper.

B. EXPERIMENTAL SETUP

The authors developed a set of construct or research design it used to conduct its investigations as follows:

- For the qualitative analysis, the study applied the educational process and data mining (EPDM) model (a text mining approach) to extract the different sentiments and emotional valence (textual data quantification or polarization) expressed by the students in the comments or SET instrument, and how those varies, if any, based on the SET type (Students-to-Instructor, Student-to-Students, and overall Yes-No recommendation) and period they have completed the evaluation (2019-2021).
- For the quantitative analysis, we conducted a multivariate analysis of co-variance (MANCOVA) to determine the effect or influence that the different type of SET and periods have on the average sentiment and emotions shown by the students, and how those may vary, if any, based on the significant factors by using a multiple pairwise comparisons post-hoc test.
- Finally, we evaluated the results of both the text mining and statistical analysis, and then provide an empirical discussion of the implications of the results for practice and/or adoption of the TEL-based educational initiatives or models across the HEIs.

IV. DATA ANALYSIS AND RESULTS

The data analysis were in two phases. In the first phase which consisted of the text mining analysis (qualitative approach) of the different comments provided by the students in the SET; we applied the EPDM model [52] to extract the average sentiment and emotional valence scores for the individual comments provided by the students between 2019 to 2021, broken down by the type of SET evaluation (i.e., students-instructors, students-students, yes-no REC, respectively). This was done to determine the main thresholds (polarization or intensities) or differences upon how the students may have rated their learning experiences and outcome during those periods (2019-2021).

In the second phase of our analysis, we conducted a multivariate analysis of co-variance (MANCOVA) to determine the marginal mean of effect that the evaluation periods (2019-2021) and SET types (students-instructors, students-students, yes-no REC answer) have on the average sentiment and emotional valence scores we extracted from the comments (see Phase 1 description). Also, we used a multiple pairwise comparison post-hoc test to determine the main factors or where the significant differences may lie across the data. It is important to mention, in addition to considering the large sample size ($n = 471968$) for conducting the parametric test [94], that the study have applied the MANCOVA method considering the scale of measurement of the analyzed

variables. Whereby the independent variable and co-variate (SET type and year) are represented as categorical variables with year considered as the particular interval of time or period (categorical), and the dependent variables (average sentiment and emotional valence scores) represented as continuous scale variables.

The results of both the qualitative (text mining) and quantitative (statistical) analysis are reported in detail in the following sections (Section -IV-A and IV-B), respectively.

A. QUALITATIVE ANALYSIS (TEXT MINING)

The text mining analysis (see Section III-B) was performed using R statistics tool [95]. The study used the *sentiment_by*, *get_sentiments*, and *get_nrc_sentiment* functions in R to extract the sentiment and emotional valence scores for the different comments provided by the students in the SET. Technically, the method focused on computing (through polarization or terms quantification) the average sentiments and intensities of the different emotions expressed by the students in the data by assigning a numerical score to each term/emotion found [52]. The outcome of the method (see: Tables 1 and 2) consists of quantified or polarized values that denote the intensities of the different terms (emotions) using the positive (+), neutral (0), and negative (-) connotations to represent each relevant term it finds in each iteration [41], [52], [96]. The resultant values with positive emotional valence (+) scores represents attractive emotions, whilst the negative (-) scores signify aversive emotions. The zeros (0) represent emotions that are classified as neutral by the model.

As gathered in Table 1, the average sentiment scores for the individual comments provided by the students in each matrix of the tables we built from the dataset shows that there were differences in the overall sentiment expressed by the students across the years (2019-2021), and they differ by SET evaluation type (Table 1). It is interesting to note that both the highest (max = 1.92695) and lowest (min = −1.18511) sentiment scores (see Table 1) was observed for the Students-Instructors recommendation, particularly for the period of 2019 in comparison to the following or subsequent years (2020, 2021). The study note that a number of factors may have led to this observation which are discussed in detail in the Discussion section (see Section V).

Furthermore, the authors considered it essential to determine the polarity or intensities (emotional valence) of the different combinations of words/comments provided by the students, and how those may vary based on the different types of emotions we found (see Figs. 2, 3, and 4). This was done based on the polarization method described in Okoye et al. [52]. To do this, we obtained the valence scores, which is computed by summing up the scores (polarity) of the words or terms the model identifies that can be used to express an emotion in the texts (comments), represented as either positive (++), neutral (0) or negative (–) values. The summary of the valence scores broken down by the SET type and period of evaluation (2019-2021) is reported in Table 2.

TABLE 1. Average sentiment expressed by the students in the SET data broken down by SET type and year (2019-2021).

SET_type	evaluation_period	measure	element_id	word_count	sd	ave_sentiment
Student-to-Instructor	2019	min	1	0.00	0.00	-1.185
		mean	92702	12.60	0.04	-0.005
		max	185403	528.00	1.09	1.926
	2020	min	1	0.00	0.00	-1.041
		mean	72312	14.22	0.04	-0.005
		max	144622	514.00	0.96	1.570
	2021	min	1	0.00	0.00	-0.750
		mean	30375	14.35	0.04	-0.006
		max	60749	359.00	0.76	1.463
	Sum (2019-2021)	min	1	0.00	0.00	-1.185
		mean	195388	13.47	0.00	-0.005
		max	390774	528.00	1.10	1.926
Student-to-Student	2019	min	1	0.00	0.00	-0.707
		mean	7454	15.08	0.05	-0.011
		max	14907	548.00	0.50	0.900
	2020	min	1	0.00	0.00	-0.707
		mean	17657	18.48	0.05	-0.010
		max	35312	695.00	0.75	1.453
	2021	min	1	0.00	0.00	-0.707
		mean	8358	20.16	0.05	-0.010
		max	16715	551.00	0.70	1.060
	Sum (2019-2021)	min	1	0.00	0.00	-0.707
		mean	33468	18.14	0.05	-0.010
		max	66934	695.00	0.75	1.453
REC (Yes-No)	2019	min	1	0.00	0.00	-0.577
		mean	3261	11.61	0.04	-0.005
		max	6521	394.00	0.38	0.750
	2020	min	1	0.00	0.00	-0.707
		mean	2712	11.33	0.04	-0.004
		max	5424	392.00	0.59	0.750
	2021	min	1	0.00	0.00	-0.557
		mean	1158	13.18	0.04	-0.005
		max	2315	503.00	0.35	0.750
	Sum (2019-2021)	min	1	0.00	0.00	-0.707
		mean	7130	11.76	0.04	-0.004
		max	14260	503.00	0.59	0.750

Note: **element_id** = individual comments provided by the students, **word_count** = number of words in each comment, **sd** = standard deviation, **ave_sentiment** = average sentiment score for the individual/corresponding comments

As reported in Table 2, there were differences in the overall intensities (emotional valence) of the comments provided by the students in the SET. It is noteworthy to mention that whilst the highest and lowest average sentiment (see: Table 1) shown by the students was observed for the period of 2019 for the Students-instructor REC. In the emotional valence analysis (Table 2), we note that the most positive (max = 9.00) valence score was observed for the evaluation period of 2021 for the Students-instructors REC, with the lowest (negative valence) score (min = −5.00) reported for the Students-students REC for the period of 2020. Indeed, a number of factors may have led to the aforenoted observations, ranging from the uncertainties or anxieties that the students might have experienced as a result of the COVID-19 pandemic especially during its peak that happened in 2020, to factors that can be linked to migration issues from the routine face-to-face mode of learning to the remote learning mode or settings. However, the height of the emotions (max = 9.00) (see: Table 2) expressed by the students, that was observed for the period of 2021, could be as a result of how appreciative and reassured the students had eventually became following the technical and pedagogical support they received from their teachers and the institution, including as an indicator of the effectiveness of the MFD model that was implemented by the HEI to ensure the continuity of learning/teaching process for them during that time.

TABLE 2. Summary of emotional valence scores by the students in the SET data broken down by SET type and year (2019-2021).

SET type	evaluation_period	min	median	mean	max
Students-to-Instructors	2019	-4.00	0.000	-0.015	6.00
	2020	-3.00	0.000	-0.014	6.00
	2021	-3.00	0.000	-0.021	9.00
	Sum (2019-2021)	-4.00	0.000	-0.015	9.00
Students-to-Students	2019	-3.00	0.000	-0.047	4.00
	2020	-5.00	0.000	-0.043	4.00
	2021	-4.00	0.000	-0.051	5.00
	Sum (2019-2021)	-5.00	0.000	-0.046	5.00
REC (Yes or No)	2019	-4.00	0.000	-0.013	2.00
	2020	-3.00	0.000	-0.005	3.00
	2021	-3.00	0.000	-0.018	3.00
	Sum (2019-2021)	-4.00	0.000	-0.011	3.00
Note: Min = -5.00, Max = 9.00					

Along these lines, the study turned its attention towards determining the different categories of emotions that the students have reported or expressed in the comments, and the differences that may exist amongst them based on the type of SET evaluation they have completed and periods (2019-2021). It is also important to mention that while the majority of the comments provided by the students in the SET were classified as neutral (i.e., values or valence = 0) (see: Fig. 1), thus, no emotional terms were found in the corresponding comments. The study reported in Figs. 2, 3, and 4, the different emotions' categories that it found for the students who did so.

Emotional valence analysis (text mining method) and its implications in the different areas of its application particularly within the education domain, has been demonstrated in the literature [41], [52], [96], [97], [98], [99], [100]. As shown in this study, the EPDM model [52] was used to determine the polarity of the (textual) educational dataset (comments provided by the students in the SET). In Figs. 2, 3, and 4, the study applied the emotions' polarization or classifications of educational data as defined in Okoye et al. [52] and Litman & Forbes-Riley [96] to describe the different categories of emotions we found in the SET. This was done to establish the similarities and differences in the way the students have rated or expressed emotions in the comments, including its implications for instructional practice. It is noteworthy to mention that while the students trusts that their learning experiences were positive and are thus ''confident'' (approximately ~25%) in the instructors and their learning outcome when making the recommendations (Fig. 2). They equally, on the other hand, expressed ''concern'' (~20%) when making the recommendations to the other students (Fig. 3), including the yes-no recommendation (Figs. 4). However,

considering the SET evaluation periods (2019-2021), we note that while there was no difference in the way the students have rated the instructors (Fig. 2 (A), (B), (C)) and the students-students recommendation (Fig. 3 (A), (B), (C)). There was, on the other hand, a significant difference on how they have expressed emotions in the yes-no question or recommendation (Fig. 4 (A), (B), (C)). With emotions such as ''resentful'' (see Fig. 4 (A), (2019)), ''concerned'' (Fig. 4 (B), (2020)), and ''uncertain'' (Fig. 4 (C), (2021)) coming out top, respectively. Also noteworthy is the fact that the students' recommendations or comments for the students-instructor construct (Fig. 2 (A), (B), (C)) most significantly reflected ''confidence'' in the student' learning experiences or evaluation in comparison to the other SET types and emotions' categories we have found in the data.

B. QUANTITATIVE ANALYSIS (STATISTICAL METHOD)

In the quantitative analysis, the study turned its attention to determining the marginal means of effect or influence that the different evaluation periods (2019-2021) and SET type have on the extracted emotions and sentiment expressed by the students in the comments, and how these may differ, by making use of the quantified data (i.e., average sentiment and emotional valence scores) (see: Tables 1 and 2). To do this, we conducted a multivariate analysis of co-variance (MANCOVA) test to examine effect that the evaluation periods (2019-2021) and SET types have on the extracted average sentiment and emotional valence scores. The results of the statistical analysis are reported in Tables 3 and 4.

In the MANCOVA analysis reported in Table 3, we note by considering the ave_sentiment and emotional_valence scores, that while the SET evaluation_period and evaluation_type have a significant effect ($p \leq .05$) on the way the students
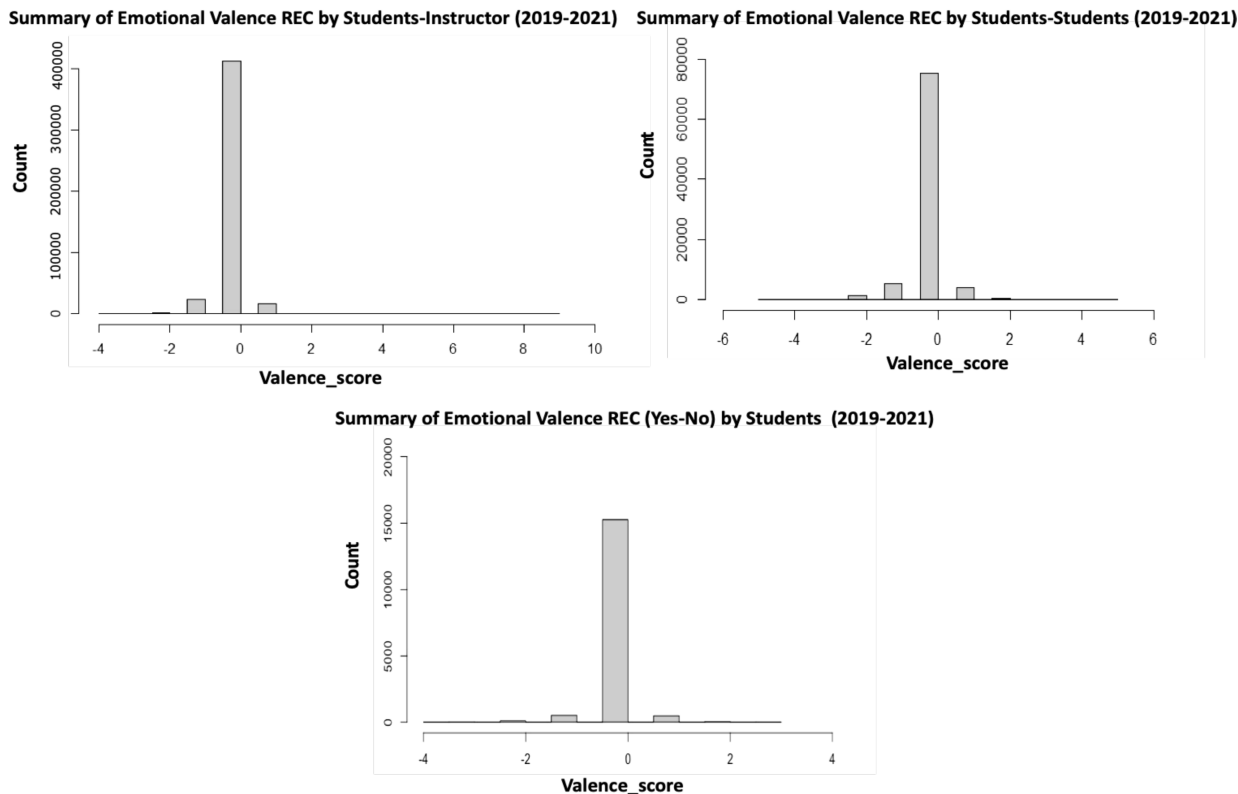
FIGURE 1. Plot showing emotional valence scores for the different SET types for the evaluation periods (2019-2021).
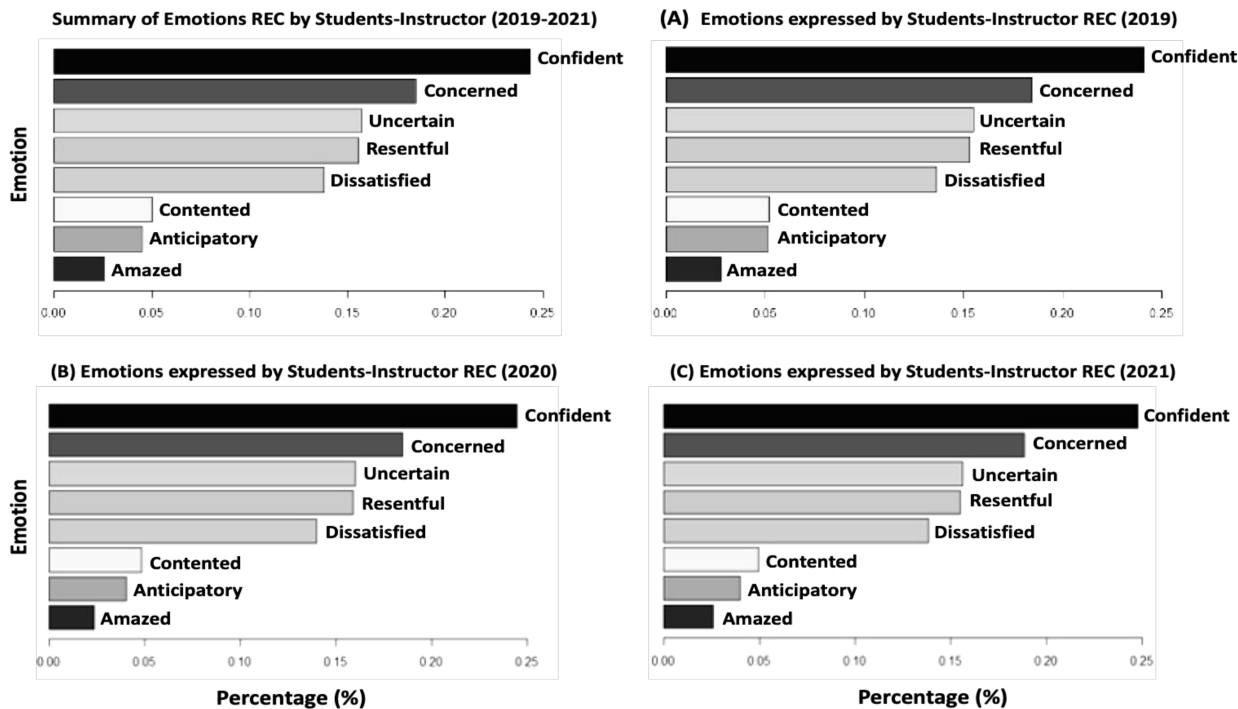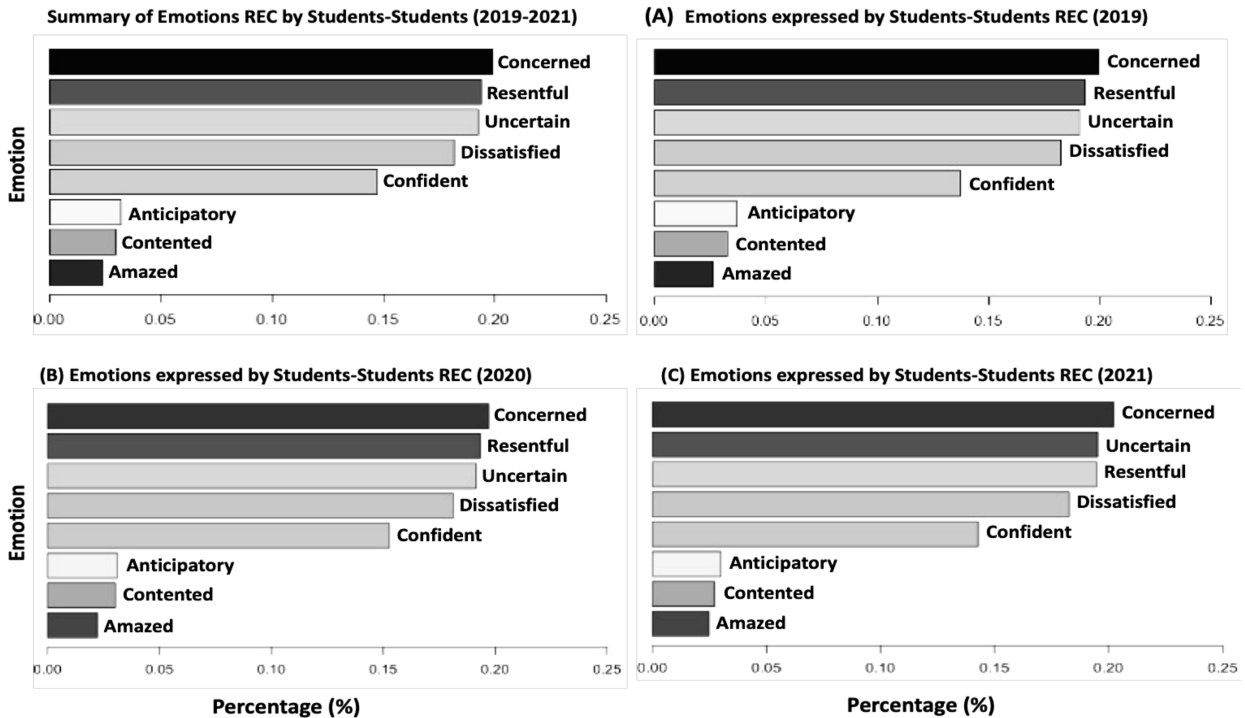

FIGURE 2. Summary of Emotions expressed by the students in Students-Instructor SET type broken down by evaluation period (2019-2021).

have rated the instructors (Students-to-Instructors) and the Students-to-Students REC (Table 3). On the other hand, they have not considered a combination of the both factors (evaluation_period*evaluation_type) when providing the comments, except for the emotional_valence that only came out significant for the Students-to-Students recommendation ($F = 4.074$, $p = .044$) (Table 3). It is also noteworthy to mention that none of the factors (evaluation_period or

FIGURE 3. Summary of Emotions expressed by the students in Students-Students SET type broken down by evaluation period (2019-2021).
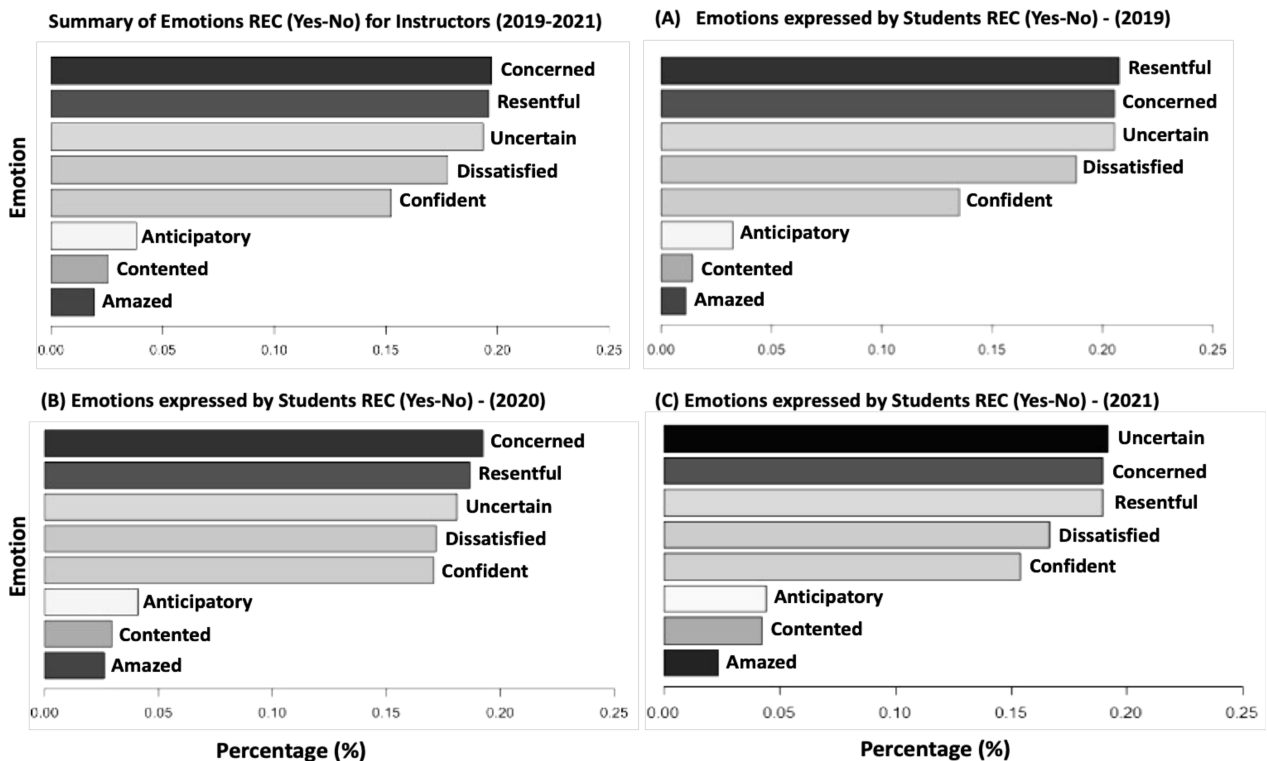
FIGURE 4. Summary of Emotions expressed by the students in Students (Yes-No) SET type broken down by evaluation period (2019-2021).

evaluation_type) had an effect on the sentiment or emotions expressed by the students for the REC yes-no question (Table 3).

Accordingly, the significant factors we have found specifically for the Students-to-Instructors and Students-to-Students

RECs were tested using a multiple pairwise comparison post-hoc test (adjusted with Bonferroni method) to determine where the significant differences lie across the data for the analyzed periods (2019-2021). The results are as shown in Table 4.

TABLE 3. Test of between-subjects effect for the ave_sentiment and emotional_valence broken down by the SET type and evaluation period (2019-2020).

SET Type	Predictor Var.	Response Var.	Sum Sq.	Mean Sq.	F	Pt. Eta. Sq.	Sig.
Students-to-Instructors	evaluation_period	ave_sentiment	.059	.029	4.205	.000	.015*
		emotional_valence	.642	.321	4.816	.000	.008*
	evaluation_type	ave_sentiment	.470	.470	67.117	.000	.000*
		emotional_valence	2.803	2.803	42.061	.000	.000*
	evaluation_period* evaluation_type	ave_sentiment	.004	.002	.283	.000	.753
		emotional_valence	.019	.009	.142	.000	.868
Students-to-Students	evaluation_period	ave_sentiment	.011	.005	.677	.001	.508*
		emotional_valence	.699	.349	2.953	.001	.052*
	evaluation_type	ave_sentiment	.292	.292	37.292	.000	.000*
		emotional_valence	6.845	6.845	57.868	.000	.000*
	evaluation_period* evaluation_type	ave_sentiment	.023	.023	2.924	.000	.087
		emotional_valence	.482	.482	4.074	.000	.044*
REC (Yes-No)	evaluation_period	ave_sentiment	.004	.002	.467	.000	.627
		emotional_valence	.016	.008	.158	.000	.853
	evaluation_type	ave_sentiment	.006	.006	1.464	.000	.226
		emotional_valence	.051	.051	1.025	.000	.311
	evaluation_period* evaluation_type	ave_sentiment	.007	.004	.936	.000	.392
		emotional_valence	.031	.016	.309	.000	.734

Significance Level: $p <= .05$

As gathered in Table 4, the main differences were found between the period of 2019 and 2020 for the Students-Instructors REC evaluation in both the ave_sentiment ($p = .030$) and emotional_valence ($p = .013$), respectively. Whereas there was only significant difference in the emotional_valence ($p = .045$) for the Students-Student REC between the period of 2020 and 2021. As previously noted also in Table 3, no significant differences were found for the yes-no REC question (Table 4).

V. DISCUSSION

The pedagogical and technological transformations witnessed today especially in higher education has been linked to the use of digital technologies to enhance the teaching-learning processes [4], [9], [37], [43], [49], [64], [68], [101], [102], [103], [104], [105], [106]. However, those advancement comes alongside with several challenges that are anticipated to be addressed or taken into consideration by the different HEIs to gain the full benefit of the resultant TEL-based educational models and innovations. A conceptual understanding of the pedagogical impact of the new and emerging teaching models, for example the SET data analysis done in this study, can be one of the promising ways to help the educators improve the didactical instructions or strategies to drive the educational process forward.

Whereas, Engen [101] note that there is a need for a greater understanding of the new (educational) technologies and their effective use by the stakeholders (teachers and students). The works of Silva et al. [102] and Raffaghelli et al. [49], have also

on the other hand, opined that the social, cultural, and technical aspects of the various users of the developed "educational technologies" toward the transformation and/or achievement of TEL-based education and initiatives must be considered, particularly as it concerns learning process management and outcomes, teaching spaces, planning, and innovative technologies that are supposedly used to support the students in their learning journey and performance [14], [15]

In those perspectives, this study shows that by analyzing the educational datasets, e.g., SET, that the educators are not only able to get a better view or conceptual understanding of the technical structure or impact of the teaching/learning models and frameworks for the teachers and students, but can also extract useful information from the readily available (educational) data which can be used to inform or support the decision-making strategies and governance for the different institutions. Our approach through the integration of the text mining and statistical methods was carried out to uncover the perceptions/perspectives of the students who are deemed the direct consumers of the different educational models and initiatives using the EPDM model for textual data quantification and quantitative analysis, grounded on the Data-structure and Descriptive decision theory [50], [51]. This was done not only to understand what the students expect, or their learning needs could be, but also, to help identify what prominent factors that affects their learning experiences and/or how they view their learning outcomes and performances.

Indeed, while the study through the qualitative (text mining) and quantitative (statistical method) analysis or lens,

TABLE 4. Multiple pairwise comparisons post-hoc test of between-subject effects for the ave_sentiment and emotional_valence broken down by SET type and Evaluation period (year).

SET Type	Dependent Var.	Evaluation period	Evaluation period	Mean Diff.	Std. Error	Sig.[b]
Students-to-Instructors	ave_sentiment	2019	2020	.001	.000	.030*
			2021	.001	.000	.106
		2020	2019	-.001	.000	.030*
			2021	.000	.000	1.00
		2021	2019	-.001	.000	.106
			2020	-.000	.000	1.00
	emotional_valence	2019	2020	-.003	.001	.013*
			2021	-.003	.001	.115
		2020	2019	.003	.001	.013*
			2021	.000	.001	1.00
		2021	2019	.003	.001	.115
			2020	-.000	.001	1.00
Students-to-Students	ave_sentiment	2019	2020	-.001	.001	.816
			2021	.000	.001	1.00
		2020	2019	.001	.001	.816
			2021	.001	.001	1.00
		2021	2019	.000	.001	1.00
			2020	-.001	.001	1.00
	emotional_valence	2019	2020	-.003	.003	1.00
			2021	.005	.004	.548
		2020	2019	.003	.003	1.00
			2021	.008	.003	.045*
		2021	2019	-.005	.004	.548
			2020	-.008	.003	.045*
REC (Yes-No)	ave_sentiment	2019	2020	-.001	.001	1.00
			2021	.001	.001	1.00
		2020	2019	.001	.001	1.00
			2021	.001	.002	1.00
		2021	2019	-.001	.001	1.00
			2020	-.001	.002	1.00
	emotional_valence	2019	2020	.000	.004	1.00
			2021	.003	.005	1.00
		2020	2019	.000	.004	1.00
			2021	.003	.006	1.00
		2021	2019	-.003	.005	1.00
			2020	-.003	.006	1.00

Significance Level: $p \leq .05$, p-values Adj. = Bonferroni Method

found that there were significant differences in the average sentiment and emotions expressed by the students when completing the SET questionnaires (see: Figs. 2, 3, 4 and Tables 3 and 4). It also, on the other hand, found that the large margin of sentiment and emotions (i.e., positive and negative) shown by the students was observed for the Students-Instructor and Students-Students SET evaluations (Tables 1 and 2) as opposed to the Yes-No recommendation question that showed the least polarity (see Tables 1 and 2). This may mean that while the Students-Instructor and Student-Students SET questionnaire was an open-ended question therein the students had autonomy to provide their individual opinion about their learning experiences and outcome. On the other hand, the Yes-No REC question which was also an open-ended question but however was in response to the reason why they would or would not recommend the teachers, and therefore, may not provide

them with the full autonomy or choice to freely express their feelings or emotions. Moreover, it is noteworthy to mention that while the students largely trust or were "confident" (~25%) (Figs. 2, 3, and 4) in their learning experiences and outcomes, they also likewise expressed "concern" (~20%) when making the recommendations, especially for the Students-Students and Yes-No REC questions (Figs. 2, 3, and 4).

Furthermore, in the text analysis (Table 2), where the study found for the evaluation periods, that the most positive emotional valence score (max = 9.00) was observed for the period of 2021, while the lowest (negative) score (min = −5.00) was found for the period of 2020. This observation can be explained to a number of factors: ranging from the uncertainty and anxieties the students may have developed as a result of the sudden shift to the remote mode of learning during the global pandemic at its peak in 2020, to technical

challenges they also may have encountered upon migrating to the new (digital) learning platforms. Moreover, the top (max = 9.00) of emotions expressed by the students during the evaluation period of 2021 (Table 2) can be explained to how appreciative and reassured the students might have eventually became in relation to the different support (technical, didactical, and emotional wellbeing) they received during the unprecedented time of learning from their instructors and institution. Besides, this results could also be an indication of the positive impact or effectiveness of the flexible digital model (MFD) applied by the HEI at that time, not only to ensure the continuity of learning for the students, but also in ensuring that they are learning effectively with the right resources and in good condition.

As example, some specific comments provided by the students in the SET data in relation to both the ''positive'' and ''negative'' emotions the study have found include, respectively:

''*First time taking the [Course], I love the [Instructor] class, such a positive and flexible environment… [Instructor] has such an extensive knowledge over the [Instructor] class, it's easy to learn and interact with what the [Instructor] teaches us. Amazing class*''

''*[Instructor] explains well and has knowledge of the subject. The problem is that it is too rigid and does not have much flexibility. If you make a small mistake that was not intentional, for example, in an activity, it gets incensed and changes the way the class is delivered….*'' *The advisory response is good, however, if you ask for a grade change, it will take until the end of the subject…. If you are going to enter with [Instructor], they will give you reading quizzes of approximately 2 hours (it depends on how long it takes to read) and those quizzes are part of your grade, [Instructor] puts them at the beginning of the class to check if you read, don't know if it was intention of the class to do that, but it does not seem like a good way to check the knowledge, because after the quick exam, it fully explains the topic of the quiz, having spent time already*''

Indeed, from the comments and observations, it can be said that ''flexibility'' of the offered courses or delivered contents was one of the top pedagogical provisions or cornerstones that the students found important in relation to their learning experiences and performance. Interestingly, HEIs are now integrating such features or element (flexibility) in the design of the several educational frameworks or learning platforms and curriculum. For instance, the MFD model [77], [87], [107] described in this paper, and the other hybrid models for learning [21], [108], [109] that didactically allows the students to choose and learn in either or both remote and in-person settings based on their learning needs and circumstances. Moreover, the flexible and digital models for learning is perceived to help tackle the problem of ''rigidity'' of the curriculums that has been identified as one of the main educational problems in both the literature and in practice [27], [30], [75], [82].

Accordingly, in the quantitative analysis (Section IV-A), therein we focused our attention on statistically determining the prominent factors that may have impacted or influenced the way the students have expressed the different sentiment and emotions in the data (see: Qualitative analysis – Section IV-B) by considering the evaluation periods (2019-2021) and SET types (Tables 3 and 4); it can be said that the SET evaluation_period and evaluation_type differed in terms of how the students have answered or rated the Students-to-Instructors and Students-to-Students questions ($p \leq .05$) (Table 3). Although, the result also showed that the students did not particularly take into account a combination of both constructs (i.e., evaluation_period*evaluation_type), except for the emotional_valence that came out significant for the Students-to-Students REC ($p = .044$) (Table 3). In the multiple pairwise comparisons post-hoc test we further conducted to determine where the significant differences lie across the data (see Table 4), we found that the difference was observed for the period of 2019 and 2020 for the Students-Instructors recommendation in both the ave_sentiment ($p = .030$) and emotional_valence ($p = .013$) factors, respectively (Table 4). The study only found significant differences in the emotional_valence ($p = .045$) for the Students-Student recommendation between the period of 2020 and 2021. Interestingly, the above results also triangulate with the results of the text mining analysis (qualitative approach) therein we have found that the most positive emotional valence score (max = 9.00) was for the evaluation period of 2021, while the lowest (negative) score (min = −5.00) was observed for the period of 2020 (Table 2), respectively.

A. IMPLICATIONS OF THIS STUDY

In education, while the pieces of evidence we drew from the literature and outcome of this study shows that the educators have invested in different innovative strategies and models to facilitate the teaching and learning processes for the teachers and students [8], [12], [18], [20], [64], [65], [74], [76], [81], [110], [111], [112]. The authors note that there still exists some issues and challenges in relation to the pedagogical transformations, hand-in-hand with the impact of the digital teaching and acceleration of the new innovative models and practices form learning, that can only be achieved through a culture of *educational innovation* and conceptual understanding of how the effectiveness of the learning processes and outcomes are assessed [18], [76], [81], [113], [114]. A lot of higher educational institutions rely exclusively on SET evaluations for assessment of the teachers' performance and learning outcomes of the students [53], [115], [116], and there are also evidence in the literature that information (educational datasets) about the teaching and learning processes (which are stored at an unprecedented rate in the databases of the different institutions) can be used to understand and drive the educational systems forward [8], [27], [49], [89], [117], [118].

In triangulation with the method and objectives of this current study, educational organizations such as The Association for Institutional Research (AIR) [119] and The Professional and Organizational Development Network in Higher Education (POD) [120] are already pioneering several themes that are focused on students/learning assessment, institutional effectiveness and use of (educational) data for informed decision-making and support of the educators or educational processes to include (i) Assessment and Evaluation initiatives that are focused on research and methods that are both externally or internally driven from the institutional perspective for planning, accreditation, amongst others, in pursuit of improved and equitable student' and institutional success (ii) Data and Technology that features the technical and ethical creation/manipulation of data and structuring through appropriate analytic tools for decision making, predictive models, and machine learning (iii) Institutional Effectiveness which constitute of student-focused paradigm that explores the roles of information retrieval (IR), information extraction (IE), and Assessment in leading institutional data strategies and strategic planning for improvement of the students' success (iv) Use of Data that proves important for improved student success with attention to institutional and student contexts, [119], [120] etc., as uncovered in this study. Indeed, The POD [120] which supports change for the improvement of higher education through faculty, instructional, and organizational development has investigated the key issues of assessment and technology particularly for faculty development across the several institutions [121], and are pioneering discussions on new or ongoing educational, professional, or organizational development research that are systematically designed by employing wide-ranging methodologies and data analysis practices, such as the two step (mixed) method and analysis applied in this study (see Sections IV-A and IV-B.

Consequentially, as one of the main contributions of this study is that it makes use of the SET data to analyze how the students perceive their learning performance and outcomes based on the comments they provided while completing the questionnaire. Our method which consisted of integration of the text mining and statistical approach, addresses one of the main themes or discourse in the current literature that suggests that the most pertinent way of determining the effectiveness of the teaching/learning processes can be combined with the students' comments to produce a more reliable and meaningful appraisal [122], [123]. Moreover, the need for "data-driven" segmentation or harvesting of data under technical archetypes, otherwise allied to the concept of "datafication" [45], [47], [124], [125], to help inform and improve the pedagogical practices of the higher institutions, as demonstrated in this study, has also been professed as one of the promising ways by which the higher education institutions can gain a better understanding or yet cross-sectional analysis of the learning needs of the students and their teachers [27], [41], [49], [82]. Although, Slade & Prinsloo [45] note that for the educators to gain an effective

"datafied-education", the stakeholders (e.g., teachers and students) should also be part or take part in defining the context, purpose, and conditions under which or for which the collected educational datasets (e.g., SET) are used and implemented. Besides, an ample analysis and conceptual understanding of the SET can offer context-appropriate solutions for effective design of the educational curriculum, models or frameworks [45], and can provide new and better ways to track, monitor, and improve the educational ecosystems at large [7], [8], [27], [49], [82], [126].

In the wider spectrum of scientific research and global education practice, particularly as it concerns the TEL-based education, the authors note that while the digital technologies should be part of any innovative strategies by the educators, and to attain an effective online teaching and self-efficacy [1], [114], [127]. On the other hand, it is important to mention the fact that these also comes with the portentous task of ensuring that the users (teachers and students) are imbued with the much-needed digital competencies, and adequate or even alternative solutions to replacing the in-person learning environments that suppositionally comprises a sizeable part of the present-day educational models and curriculum [61], [128], [129], [130], [131], [132]. The idiosyncratic or strategic tasks and action plans by the educators should also include guaranteeing proper and secured virtual learning environments or platforms for the stakeholders, to provision of uninterrupted access to the internet and network infrastructures [127], [133]. Also noteworthy is the fact that the United Nations Educational, Scientific and Cultural Organization (UNESCO) under its Global Education Coalition (GEC) initiative [111] have stipulated that never before have the educational system witnessed disruption at a global scale, and partnership amongst the concerned stakeholders is one of the only ways forward. They [111] have called for "coordinated" and "innovative" actions that are aimed at unlocking solutions that supports the teachers and their students with the teaching/learning process, and these also include methods that aim to utilize (educational) information or data stored about the users, such as the one done in this study, to inform and improve the educational process [42], [111], [134].

The recent studies that have also looked into how the transitions to the remote learning or TEL-based education have affected the students [61], [129], [135], have also discovered that both their academic and technological needs have proportionally increased, especially following the impact of crises such as the recent Covid-19 pandemic in education [61], [126], [135], [136], [137]. Some of the main challenges that have emerged as a result of the so-called transitions include: that it will be difficult to replicate the face-to-face learning experiences for the students online [130], [132] notwithstanding that the remote learning can be as good or better than in-person learning for those or students who choose it [138].

Pedagogical -wise, concerning the complementarity of the new and emerging educational technologies or TEL-based education, by comparing the synchronous and asynchronous

learning modes, it can be said that while most of the students have shown to prefer ''asynchronous'' mode of learning due to its flexibility, and the fact that they can learn at their own pace, at any time and any place [18], [81], [129], [139]. On the other hand, the students that preferred ''synchronous'' teaching style also indicated that it motivated and kept them up-to-date with learning [18], [81], [129], [139]. Moreover, it is also worth mentioning that many of the higher institutions of learning are now implementing the hybrid educational models (virtual and in-person) for teaching and learning purposes and outcomes, by allowing the students to choose the best mode of learning suitable for their learning needs and circumstances [13], [21], [23], [140].

B. LIMITATIONS AND OPPORTUNITIES FOR FUTURE RESEARCH

While this study has introduced the text mining (qualitative) and statistical (quantitative) method of analysis for a *conceptualized* outlook on the prominent factors that impacts or influences the learning experiences and performances by the students, the authors acknowledges that the study could also come with some limitations. For example, although the study has used the assimilation of the data-structure approach and descriptive decision theory to study the rationale behind the decisions that the leaners are disposed to make, there could be potentially many other ways to approach this, particularly within the education domain, or other methods that may have not been considered yet in this study. For instance, the process of identification of the learning foundations or components that can be used to aptly enable flexibility in the different learning platforms or tools, or ways to evaluate the interoperability or technical functionalities of the resultant platforms based on the individual learning settings or contexts can form another direction for future research. Also, the textual data quantification and its use for other further types of analysis such as the statistical (quantitative) analysis done in this paper, stands as a new innovation or methodological approach to analyzing the educational datasets and domain, and to the best of our knowledge, there are no studies except for the authors', currently in the literature, that have expounded on this method. Therefore, the authors note that this study represents as a methodological road map or incentives to more robust research to come particularly as it concerns the assessment of the impact of SET in education. Moreover, future studies can adopt the method described in this paper to analyze data about any given educational process or domain, or yet, transfer -ability of the method to include other components or analysis that may have not already been done in this paper.

VI. CONCLUSION

This study used SET data ($n = 471968$) collected within a higher education setting to analyze how the students evaluated the teachers and their learning performance. Qualitatively, it applied the EPDM model (a text mining approach) to extract the different sentiment and emotional valence shown by the students when completing the SET questionnaires.

Consequently, the study quantitatively analyzed the extracted information (average sentiment and emotional valence) using the MANCOVA and multiple comparisons tests to determine the marginal mean of effect that the different SET types and evaluation periods (2019-2021) have on the students' performance or views about the teaching-learning process. The pedagogical implications of the results and key findings for effective TEL-based education and practice was also discussed. Whilst the scholastic indicator from the study shows that the flexible digital models or instructional methods are effective for continuous education, innovative pedagogies, and teaching transformations. It also, on the other hand, serve as an incentive for more robust research to come that aim to explore its main implications for students' learning outcome and assessment. For instance, the results of this study should be helpful in designing questionnaires for students' satisfaction concerning the teachers' teaching, and improving of the didactical instructions or strategies. Future research can be further extended to this aspect.

REFERENCES

[1] Y.-J. Lin and H. Wang, ''Using virtual reality to facilitate learners' creative self-efficacy and intrinsic motivation in an EFL classroom,'' *Educ. Inf. Technol.*, vol. 26, pp. 4487–4505, Mar. 2021, doi: 10.1007/s10639-021-10472-9.

[2] G. Yusufu and N. Nathan, ''A novel model of smart education for the development of smart university system,'' in *Proc. Int. Conf. Math., Comput. Eng. Comput. Sci. (ICMCECS)*, Mar. 2020, pp. 1–5, doi: 10.1109/ICMCECS47690.2020.240912.

[3] F. Pettersson, ''Understanding digitalization and educational change in school by means of activity theory and the levels of learning concept,'' *Educ. Inf. Technol.*, vol. 26, no. 1, pp. 187–204, Jun. 2020, doi: 10.1007/s10639-020-10239-8.

[4] M.-S. Chiu, ''Exploring models for increasing the effects of school information and communication technology use on learning outcomes through outside-school use and socioeconomic status mediation: The ecological techno-process,'' *Educ. Technol. Res. Develop.*, vol. 68, no. 1, pp. 413–436, Feb. 2020, doi: 10.1007/s11423-019-09707-x.

[5] E. K. Zashchitina and P. V. Pavlov, ''Higher education today: Mass or individual approach,'' in *Proc. Int. Conf. Quality Manage., Transp. Inf. Secur., Inf. Technol. (IT IS)*, Sep. 2019, pp. 653–656, doi: 10.1109/ITQMIS.2019.8928325.

[6] L. Widger, M. Denny, M. Benke, M. Pajnkihar, C. Bruen, and C. Madden, ''The strategic implementation and augmentation of technology enhanced learning (TEL) in third level education: A critical lens,'' in *Proc. 10th Int. Technol., Educ. Develop. Conf. (INTED)*, Mar. 2016, pp. 1289–1297, doi: 10.21125/inted.2016.1285.

[7] UNESCO Digital Library. (2014). *Global Citizenship Education: Preparing Learners for the Challenges of the 21st Century*. Accessed: Aug. 24, 2020. [Online]. Available: https://unesdoc.unesco.org/ark:/48223/pf0000227729

[8] UNESCO. (2020). *COVID-19 Education: From Disruption to recovery. School Closures Caused by Coronavirus (COVID-19)*. Accessed: Sep. 10, 2020. [Online]. Available: https://en.unesco.org/covid19/educationresponse

[9] C.-L. Lin, Y. Q. Jin, Q. Zhao, S.-W. Yu, and Y.-S. Su, ''Factors influence Students' switching behavior to online learning under COVID-19 pandemic: A push–pull–mooring model perspective,'' *Asia-Pacific Educ. Researcher*, vol. 30, no. 3, pp. 229–245, Apr. 2021, doi: 10.1007/S40299-021-00570-0.

[10] I. Seetal, S. Gunness, and V. Teeroovengadum, "Educational disruptions during the COVID-19 crisis in small island developing states: Preparedness and efficacy of academics for online teaching," *Int. Rev. Educ.*, vol. 67, nos. 1–2, pp. 185–217, May 2021, doi: 10.1007/S11159-021-09902-0.

[11] T. Crick, C. Knight, R. Watermeyer, and J. Goodall, "The impact of COVID-19 and 'emergency remote teaching' on the U.K. computer science education community," in *Proc. United Kingdom Ireland Comput. Educ. Res. Conf.*, Sep. 2020, pp. 31–37, doi: 10.1145/3416465.3416472.

[12] UNESCO. (2021). *National Learning Platforms and Tools*. Accessed: Aug. 17, 2021. [Online]. Available: https://en.unesco.org/covid19/educationresponse/nationalresponses

[13] K. Okoye, J. A. Rodriguez-Tort, J. Escamilla, and S. Hosseini, "Technology-mediated teaching and learning process: A conceptual study of educators' response amidst the COVID-19 pandemic," *Educ. Inf. Technol.*, vol. 26, no. 6, pp. 7225–7257, Nov. 2021, doi: 10.1007/s10639-021-10527-x.

[14] O. Bälter. (2021). *Technology Enhanced Learning | KTH, Media Technology and Interaction Design*. Accessed Aug. 17, 2021. [Online]. Available: https://www.kth.se/hct/mid/research/technology-enhanced/technology-enhanced-learning-1.780656

[15] A. Sen and C. K. C. Leong, "Technology-enhanced learning," in *Encyclopedia of Education and Information Technologies*, A. Tatnall, Ed. Cham, Switzerland: Springer, 2020, pp. 1–8, doi: 10.1007/978-3-319-60013-0_72-1.

[16] G. Benabdallah, S. Bourgault, N. Peek, and J. Jacobs, "Remote learners, home makers: How digital fabrication was taught online during a pandemic," in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, May 2021, pp. 1–14, doi: 10.1145/3411764.3445450.

[17] D. E. Fatumo and S. Ngwenya, "Online learning platforms and their roles in influencing pass rate in rural communities of South Africa: Massive open online courses (MOOCs)," in *Proc. 2nd Int. Multidisciplinary Inf. Technol. Eng. Conf. (IMITEC)*, Nov. 2020, pp. 1–8, doi: 10.1109/IMITEC50163.2020.9334135.

[18] C. Diaz-Nunez, G. Sanchez-Cochachin, Y. Ricra-Chauca, and L. Andrade-Arenas, "Impact of mobile applications for a lima university in pandemic," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 2, pp. 752–758, 2021, doi: 10.14569/IJACSA.2021.0120294.

[19] O. Barabash, D. Sknarev, I. Maslova, M. Bereznyatskaya, and A. Prakhova, "Online education in new period of sustainable development after the pandemic," in *Proc. E3S Web Conf.*, vol. 244, Mar. 2021, Art. no. 11053, doi: 10.1051/E3SCONF/202124411053.

[20] R. C. Chick, G. T. Clifton, K. M. Peace, B. W. Propper, D. F. Hale, A. A. Alseidi, and T. J. Vreeland, "Using technology to maintain the education of residents during the COVID-19 pandemic," *J. Surgical Educ.*, vol. 77, no. 4, pp. 729–732, Jul. 2020, doi: 10.1016/j.jsurg.2020.03.018.

[21] TEC and Tecnológico de Monterrey. (2020). *HyFlex + Tec | The Flexible Digital Plus Model and Virtual-InPerson Learning*. Accessed: Jun. 19, 2020. [Online]. Available: https://tec.mx/es/noticias/nacional/institucion/tec-iniciara-semestre-remota-y-migrara-paulatinamente-presencial

[22] A. Rubio-Fernández, P. J. Muñoz-Merino, and C. D. Kloos, "A learning analytics tool for the support of the flipped classroom," *Comput. Appl. Eng. Educ.*, vol. 27, no. 5, pp. 1168–1185, Sep. 2019, doi: 10.1002/cae.22144.

[23] Z. Xu, H. Yuan, and Q. Liu, "Student performance prediction based on blended learning," *IEEE Trans. Educ.*, vol. 64, no. 1, pp. 66–73, Feb. 2021, doi: 10.1109/TE.2020.3008751.

[24] H. T. T. Dao and T. T. K. Le, "Transitioning from traditional learning to blended learning at some public universities in Vietnam after the COVID-19 pandemic," in *Proc. 4th Int. Conf. Adv. Artif. Intell.*, Oct. 2020, pp. 85–91, doi: 10.1145/3441417.3441429.

[25] Y. Dong, J. Ang, and Z. Sun, "Designing path of SPOC blended teaching and learning mode in post-MOOC era," in *Proc. 10th Int. Conf. Educ. Inf. Technol. (ICEIT)*, Jan. 2021, pp. 24–28, doi: 10.1109/ICEIT51700.2021.9375582.

[26] S. S. Urmi and K. A. Taher, "Integrating ICT in teaching and learning at university level focusing education 4.0," in *Proc. Int. Conf. Inf. Commun. Technol. Sustain. Develop. (ICICT4SD)*, Feb. 2021, pp. 300–304, doi: 10.1109/ICICT4SD50815.2021.9396988.

[27] LALA. (2020). *Building Capacity to use Learning Analytics to Improve Higher Education in Latin America (LALA Project)*. Accessed: Aug. 17, 2020. [Online]. Available: https://www.lalaproject.org/

[28] M. Martens, L. Hajibayova, K. Campana, G. C. Rinnert, J. Caniglia, I. G. Bakori, T. Kamiyama, L. A. Mohammed, D. M. Mupinga, and O. J. Oh, "'Being on the wrong side of the digital divide': Seeking technological interventions for education in northeast Nigeria," *Aslib J. Inf. Manage.*, vol. 72, no. 6, pp. 963–978, Nov. 2020, doi: 10.1108/AJIM-05-2020-0172.

[29] C. O'Hagan. (2020). *Startling Digital Divides in Distance Learning Emerge—UNESCO Press Service—Global Education Coalition*. Accessed: May 2, 2022. [Online]. Available: https://en.unesco.org/news/startling-digital-divides-distance-learning-emerge

[30] M. Laufer, A. Leiser, B. Deacon, P. Perrin de Brichambaut, B. Fecher, C. Kobsda, and F. Hesse, "Digital higher education: A divider or bridge builder? Leadership perspectives on edtech in a COVID-19 reality," *Int. J. Educ. Technol. Higher Educ.*, vol. 18, no. 1, pp. 1–17, Sep. 2021, doi: 10.1186/S41239-021-00287-6.

[31] E. Sánchez-Cruz, A. Masinire, and E. V. López, "The impact of COVID-19 on education provision to indigenous people in Mexico," *Revista de Administração Pública*, vol. 55, no. 1, pp. 151–164, Feb. 2021, doi: 10.1590/0034-761220200502.

[32] T. D. Oyedotun, "Sudden change of pedagogy in education driven by COVID-19: Perspectives and evaluation from a developing country," *Res. Globalization*, vol. 2, Dec. 2020, Art. no. 100029, doi: 10.1016/j.resglo.2020.100029.

[33] I. A. Cepeda-Mayorga. (2017). *Students4change INICIO*. Accessed: Jun. 25, 2020. [Online]. Available: https://www.uestudents4change.org/

[34] A. Petersoni, H. Dumontii, M. Lafuente, and N. Lawiii. (2018). *Understanding Innovative Pedagogies: Key Themes to Analyse New Approaches to Teaching and Learning*. Accessed: Jul. 6, 2021. [Online]. Available: https://www.oecd-ilibrary.org/education/understanding-innovative-pedagogies_9f843a6e-en

[35] OECD. (2020). *Regulatory Quality and COVID-19: Managing the Risks and Supporting the Recovery Note by the Secretariat in Consultation With the Chairs and Bureaus of the Regulatory Policy Committee and Network of Economic Regulators*. Accessed: May 10, 2021. [Online]. Available: https://.www.oecd.org/coronavirus/policy-responses/regulatory-quality-and-covid-19-managing-the-risks-andsupporting-the-recovery-3f752e60/

[36] *La Educación a Distancia en la Educación Superior en América Latina (Distance education in higher education in Latin America)*, OECD, Paris, France, Jun. 2017, doi: 10.1787/9789264277977-es.

[37] I. G. Ndukwe and B. K. Daniel, "Teaching analytics, value and tools for teacher data literacy: A systematic and tripartite approach," *Int. J. Educ. Technol. Higher Educ.*, vol. 17, no. 1, p. 22, Dec. 2020, doi: 10.1186/s41239-020-00201-6.

[38] F. D. Guillén-Gámez, M. J. Mayorga-Fernández, and M. Ramos, "Examining the use self-perceived by university teachers about ICT resources: Measurement and comparative analysis in a one-way ANOVA design," *Contemp. Educ. Technol.*, vol. 13, no. 1, pp. 1–13, 2021, doi: 10.30935/cedtech/8707.

[39] N. Urbancikova, N. Manakova, and B. Ganna, "Socio-economic and regional factors of digital literacy related to prosperity," *Qual. Innov. Prosperity*, vol. 21, no. 2, pp. 124–141, Jul. 2017, doi: 10.12776/QIP.V21I2.942.

[40] G. Feng, M. Fan, and C. Ao, "Exploration and visualization of learning behavior patterns from the perspective of educational process mining," *IEEE Access*, vol. 10, pp. 65271–65283, 2022, doi: 10.1109/ACCESS.2022.3184111.

[41] K. Okoye, A. Arrona-Palacios, C. Camacho-Zuñiga, J. A. G. Achem, J. Escamilla, and S. Hosseini, "Towards teaching analytics: A contextual model for analysis of students' evaluation of teaching through text mining and machine learning classification," *Educ. Inf. Technol.*, vol. 27, no. 3, pp. 3891–3933, Apr. 2022, doi: 10.1007/S10639-021-10751-5.

[42] UNESCO. (2021). *Education and Technological Transformations for Human-Centered Recovery: The Global Education Coalition in Action—ED/GEC/2021/04*. Accessed: Oct. 27, 2021. [Online]. Available: https://unesdoc.unesco.org/ark:/48223/pf0000379133

[43] C. Smith, K. Onofre-Martínez, M. F. Contrino, and J. Membrillo-Hernández, "Course design process in a technology-enhanced learning environment," *Comput. Electr. Eng.*, vol. 93, Jul. 2021, Art. no. 107263.

[44] O. Rotar, "Online student support: A framework for embedding support interventions into the online learning cycle," *Res. Pract. Technol. Enhanced Learn.*, vol. 17, no. 1, pp. 1–23, Jan. 2022, doi: 10.1186/S41039-021-00178-4.

[45] S. Slade and P. Prinsloo, "Learning analytics: Ethical issues and dilemmas," *Amer. Behav. Scientist*, vol. 57, no. 10, pp. 1510–1529, Oct. 2013, doi: 10.1177/0002764213479366.

[46] L. M. A. Zohair, "Prediction of student's performance by modelling small dataset size," *Int. J. Educ. Technol. Higher Educ.*, vol. 16, no. 1, pp. 1–18, Dec. 2019, doi: 10.1186/s41239-019-0160-3.

[47] C. Perrotta and B. Williamson, "The social life of learning analytics: Cluster analysis and the 'performance' of algorithmic education," *Learn., Media Technol.*, vol. 43, no. 1, pp. 3–16, Jan. 2018, doi: 10.1080/17439884.2016.1182927.

[48] M. A. Badri, M. Abdulla, M. A. Kamali, and H. Dodeen, "Identifying potential biasing variables in student evaluation of teaching in a newly accredited business program in the UAE," *Int. J. Educ. Manage.*, vol. 20, no. 1, pp. 43–59, Jan. 2006, doi: 10.1108/09513540610639585.

[49] J. E. Raffaghelli, S. Manca, B. Stewart, P. Prinsloo, and A. Sangrà, "Supporting the development of critical data literacies in higher education: Building blocks for fair data cultures in society," *Int. J. Educ. Technol. Higher Educ.*, vol. 17, no. 1, p. 58, Dec. 2020, doi: 10.1186/s41239-020-00235-w.

[50] M. Baucells and K. V. Katsikopoulos, "Descriptive models of decision making," in *Wiley Encyclopedia of Operations Research and Management Science*. Hoboken, NJ, USA: Wiley, 2011, doi: 10.1002/9780470400531.eorms0249.

[51] J. Chandler, "Descriptive decision theory," Stanford Encyclopedia Philosophy, Stanford Univ., Stanford, CA, USA, 2017. Accessed: Jan. 26, 2023. [Online]. Available: https://plato.stanford.edu/entries/decision-theory-descriptive/

[52] K. Okoye, A. Arrona-Palacios, C. Camacho-Zuñiga, N. Hammout, E. L. Nakamura, J. Escamilla, and S. Hosseini, "Impact of students evaluation of teaching: A text analysis of the teachers qualities by gender," *Int. J. Educ. Technol. Higher Educ.*, vol. 17, no. 1, p. 49, Dec. 2020, doi: 10.1186/s41239-020-00224-z.

[53] A. Boring, "Gender biases in student evaluations of teaching," *J. Public Econ.*, vol. 145, pp. 27–41, Jan. 2017, doi: 10.1016/j.jpubeco.2016.11.006.

[54] W. Drowling, "Why we should abolish teaching evaluations," The Daily Targum, 2020.

[55] M. Gomes and W. Ma, "Engaging expectations: Measuring helpfulness as an alternative to student evaluations of teaching," *Assessing Writing*, vol. 45, Jul. 2020, Art. no. 100464, doi: 10.1016/j.asw.2020.100464.

[56] L. F. J. Boex, "Attributes of effective economics instructors: An analysis of Student evaluations," *J. Econ. Educ.*, vol. 31, no. 3, pp. 211–227, Jan. 2000, doi: 10.1080/00220480009596780.

[57] K. Okoye, A. Arrona-Palacios, C. Camacho-Zuñiga, N. Hammout, E. L. Nakamura, J. Escamilla, and S. Hosseini, "Impact of students evaluation of teaching: A text analysis of the teachers qualities by gender," *Int. J. Educ. Technol. Higher Educ.*, vol. 17, no. 1, pp. 1–27, Dec. 2020.

[58] S. Bianchini, F. Lissoni, and M. Pezzoni, "Instructor characteristics and students' evaluation of teaching effectiveness: Evidence from an Italian engineering school," *Eur. J. Eng. Educ.*, vol. 38, no. 1, pp. 38–57, Mar. 2013, doi: 10.1080/03043797.2012.742868.

[59] W. Suarez. (2020). The stark COVID-19 challenges HE faces in Latin America. University World News. Accessed: Aug. 8, 2021. [Online]. Available: https://www.universityworldnews.com/post.php?story=20200619093615842

[60] V. Mncube, B. H. Mutongoza, and E. Olawale, "Managing higher education institutions in the context of COVID-19 stringency: Experiences of stakeholders at a rural South African university," *Perspect. Educ.*, vol. 39, no. 1, pp. 390–409, Mar. 2021, doi: 10.18820/2519593X/PIE.V39.I1.24.

[61] C. Rapanta, L. Botturi, P. Goodyear, L. Guàrdia, and M. Koole, "Online university teaching during and after the COVID-19 crisis: Refocusing teacher presence and learning activity," *Postdigit. Sci. Educ.*, vol. 2, no. 3, pp. 923–945, Oct. 2020, doi: 10.1007/s42438-020-00155-y.

[62] A. Bashir, M. Alhammadi, M. Awawdeh, and T. Faisal, "Effectiveness of using Arduino platform for the hybrid engineering education learning model," in *Proc. Adv. Sci. Eng. Technol. Int. Conf. (ASET)*, Mar. 2019, pp. 1–6, doi: 10.1109/ICASET.2019.8714438.

[63] F. Boninger, A. Molnar, and C. Saldaña. (Apr. 30, 2019). *Personalized Learning and the Digital Privatization of Curriculum and Teaching*. Accessed: Sep. 21, 2021. [Online]. Available: https://nepc.colorado.edu/publication/personalized-learning

[64] M. A. Almaiah, A. Al-Khasawneh, and A. Althunibat, "Exploring the critical challenges and factors influencing the e-learning system usage during COVID-19 pandemic," *Educ. Inf. Technol.*, vol. 25, no. 6, pp. 5261–5280, May 2020, doi: 10.1007/S10639-020-10219-Y.

[65] F. Reimers, A. Schleicher, J. Saavedra, and S. Tuominen. (2020). *Supporting the Continuation of Teaching and Learning During the COVID-19 Pandemic, Annotated Resources for Online Learning OECD*. Accessed: Aug. 23, 2020. [Online]. Available: https://www.oecd.org/education/Supporting-the-continuation-of-teaching-and-learning-during-the-COVID-19-pandemic.pdf

[66] V. Mayer-Schönberger and K. Cukier, *Learning With Big Data: The Future of Education*. New York, NY, USA: Houghton Mifflin Harcourt, 2014.

[67] P. Prinsloo, S. Slade, and F. Galpin, "Learning analytics: Challenges, paradoxes and opportunities for mega open distance learning institutions," in *Proc. 2nd Int. Conf. Learn. Anal. Knowl.*, 2012, pp. 130–133, doi: 10.1145/2330601.2330635.

[68] K. Kori, M. Pedaste, and O. Must, "The academic, social, and professional integration profiles of information technology students," *ACM Trans. Comput. Educ.*, vol. 18, no. 4, pp. 1–19, Dec. 2018, doi: 10.1145/3183343.

[69] C. Klein, J. Lester, H. Rangwala, and A. Johri, "Learning analytics tools in higher education: Adoption at the intersection of institutional commitment and individual action," *Rev. Higher Educ.*, vol. 42, no. 2, pp. 565–593, 2019, doi: 10.1353/rhe.2019.0007.

[70] Q. Zhang and Z. Yu, "A literature review on the influence of Khoot! On learning outcomes, interaction, and collaboration," *Educ. Inf. Technol.*, vol. 26, no. 4, pp. 4507–4535, Mar. 2021, doi: 10.1007/S10639-021-10459-6.

[71] A. Cantón. (2018). How Latin American universities can be drivers of change. University World News. Accessed: Aug. 8, 2021. [Online]. Available: https://www.universityworldnews.com/post.php?story=20181106095447251

[72] A. D. Takayanagui. (2017). Future of the Latin American and Caribbean University. University World News. Accessed: Aug. 8, 2021. [Online]. Available: https://www.universityworldnews.com/post.php?story=20171101094554917

[73] R. Winthrop and A. Barton. Innovation to leapfrog educational progress in Latin America. BROOKINGS, 2018. Accessed: Aug. 8, 2021. [Online]. Available: https://www.brookings.edu/research/innovation-to-leapfrog-educational-progress-in-latin-america/

[74] *Educational Reforms in Latin America: Realities and Prospects*, INEE, Mexico City, Mexico, 2019.

[75] L. Reisberg. (2019). Is innovation possible in Latin America? | The world view. INSIDE Higher ED. Accessed: Aug. 9, 2021. [Online]. Available: https://www.insidehighered.com/blogs/world-view/innovation-possible-latin-america

[76] CONECTA. (2021). *Novus Tríada—These 3 Projects Will Support Educational Innovation in Latin America | Tecnológico de Monterrey*. Accessed: Aug. 9, 2021. [Online]. Available: https://tec.mx/en/news/national/education/these-3-projects-will-support-educational-innovation-latin-america

[77] TEC and NUVE Magazine. (2020). *TEC, Flexible and Digital Model for Academic Continuity*. Accessed: Aug. 3, 2021. [Online]. Available: https://www.revistanuve.com/modelo-flexible-y-digital-para-la-continuidad-academica/

[78] R. M. Mayordomo, A. Espasa, T. Guasch, and M. Martínez-Melo, "Perception of online feedback and its impact on cognitive and emotional engagement with feedback," *Educ. Inf. Technol.*, vol. 27, no. 6, pp. 7947–7971, Feb. 2022, doi: 10.1007/S10639-022-10948-2.

[79] C. Marconi, C. Brovetto, I. Mendez, and M. Perera, "Learning through Videoconference. Research on teaching quality," in *Proc. 13th Latin Amer. Conf. Learn. Technol. (LACLO)*, Oct. 2018, pp. 37–40, doi: 10.1109/LACLO.2018.00018.

[80] A. D. Rio-Chillcce, L. Jara-Monge, and L. Andrade-Arenas, "Analysis of the use of videoconferencing in the learning process during the pandemic at a university in lima," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 5, pp. 870–878, 2021, doi: 10.14569/IJACSA.2021.01205102.

[81] A. P. Aguilera-Hermida, A. Quiroga-Garza, S. Gómez-Mendoza, C. A. D. R. Villanueva, B. A. Alecchi, and D. Avci, "Comparison of students' use and acceptance of emergency online learning due to COVID-19 in the USA, Mexico, Peru, and Turkey," *Educ. Inf. Technol.*, vol. 26, pp. 6823–6845, Apr. 2021, doi: 10.1007/S10639-021-10473-8.

[82] K. Okoye, H. Hussein, A. Arrona-Palacios, H. N. Quintero, L. O. P. Ortega, A. L. Sanchez, E. A. Ortiz, J. Escamilla, and S. Hosseini, "Impact of digital technologies upon teaching and learning in higher education in Latin America: An outlook on the reach, barriers, and bottlenecks," *Educ. Inf. Technol.*, vol. 2022, pp. 1–70, Aug. 2022, doi: 10.1007/S10639-022-11214-1.

[83] N. Altrabsheh, M. Cocea, and S. Fallahkhair, "Sentiment analysis: Towards a tool for analysing real-time students feedback," in *Proc. IEEE 26th Int. Conf. Tools Artif. Intell.*, Nov. 2014, pp. 419–423.

[84] R. W. Crues, G. M. Henricks, M. Perry, S. Bhat, C. J. Anderson, N. Shaik, and L. Angrave, "How do gender, learning goals, and forum participation predict persistence in a computer science MOOC?" *ACM Trans. Comput. Educ.*, vol. 18, no. 4, pp. 1–14, Sep. 2018, doi: 10.1145/3152892.

[85] L. M. Romero-Rodríguez, M. S. Ramírez-Montoya, and J. R. V. González, "Gamification in MOOCs: Engagement application test in energy sustainability courses," *IEEE Access*, vol. 7, pp. 32093–32101, 2019, doi: 10.1109/ACCESS.2019.2903230.

[86] J. Tondeur, R. Scherer, F. Siddiq, and E. Baran, "Enhancing pre-service teachers' technological pedagogical content knowledge (TPACK): A mixed-method study," *Educ. Technol. Res. Develop.*, vol. 68, no. 1, pp. 319–343, Feb. 2020, doi: 10.1007/s11423-019-09692-1.

[87] TEC. (2020). *Flexible and Digital Model*. Accessed: Jun. 19, 2020. [Online]. Available: https://innovacioneducativa.tec.mx/continuidad-academica-reporte/

[88] A. Sánchez-Mena, J. Martí-Parreño, and M. J. Miquel-Romero, "Higher education instructors' intention to use educational video games: An fsQCA approach," *Educ. Technol. Res. Develop.*, vol. 67, no. 6, pp. 1455–1478, Dec. 2019, doi: 10.1007/s11423-019-09656-5.

[89] C. Romero and S. Ventura, "Educational data mining and learning analytics: An updated survey," *WIREs Data Mining Knowl. Discovery*, vol. 10, no. 3, May 2020, Art. no. e1355, doi: 10.1002/widm.1355.

[90] ECOA. (2013). *Student Opinion Survey (ECOA)—(Encuesta de Opinión de Los Alumnus)*. Accessed: May 14, 2019. [Online]. Available: https://portalrep.itesm.mx/va/encuestas/1.htm

[91] P. A. Hernández, "Factores que inciden en la evaluación del desempeño docente por los alumnos de nivel superior en la universidad TecMilenio, campus ciudad Juárez," *Nóesis. Revista de Ciencias Sociales y Humanidades*, vol. 22, nos. 43–2, pp. 188–225, Jan. 2013, doi: 10.20983/NOESIS.2013.2.5.

[92] J. O. G. Salinas and G. M. F. Martínez, "Características personales y práctica docente de profesores universitarios y su Relación con la Evaluación del Desempeño," *Revista Iberoamericana de Evaluación Educativa*, vol. 11, no. 2, pp. 9–33, Oct. 2018, doi: 10.15366/RIEE2018.11.2.001.

[93] J. E. Montemayor-Gallegos, "Reliability and validity of the opinion survey carried out to the students to evaluate and provide feedback on the performance of the ITESM-single edition teachers," Instituto Tecnológico y de Estudios Superiores de Monterrey (Tecnologico de Monterrey), Monterrey, Mexico. Tech. Rep. Campol‖5‖53‖5302‖530202, 2002. Accessed: Jan. 26, 2023. [Online]. Available: http://hdl.handle.net/11285/567554

[94] J. T. Roscoe, *Fundamental Research Statistics for the Behavioral Sciences*, 2nd ed. New York, NY, USA: Holt, Rinehart, and Winston, 1975.

[95] (2020). *Rstudio*. Accessed: Apr. 19, 2020. [Online]. Available: https://rstudio.com/products/rstudio/

[96] D. J. Litman and K. Forbes-Riley, "Predicting student emotions in computer-human tutoring dialogues," in *Proc. 42nd Annu. Meeting Assoc. Comput. Linguistics*, 2004, pp. 351–358, doi: 10.3115/1218955.1219000.

[97] B. Kort, R. Reilly, and R. W. Picard, "An affective model of interplay between emotions and learning: Reengineering educational pedagogy-building a learning companion," in *Proc. IEEE Int. Conf. Adv. Learn. Technol.*, Aug. 2001, pp. 43–46, doi: 10.1109/ICALT.2001.943850.

[98] L. Shen, M. Wang, and R. Shen, "Affective e-learning: Using 'emotional' data to improve learning in pervasive learning environment," *Educ. Technol. Soc.*, vol. 12, no. 2, pp. 176–189, 2009. [Online]. Available: https://eric.ed.gov/?id=EJ836299

[99] F. Tian, Q. Zheng, and D. Zheng, "Mining patterns of e-Learner emotion communication in turn level of Chinese interactive texts: Experiments and findings," in *Proc. 14th Int. Conf. Comput. Supported Cooperat. Work Design*, Apr. 2010, pp. 664–670, doi: 10.1109/CSCWD.2010.5471892.

[100] L. Tian, C. Lai, and J. D. Moore, "Polarity and intensity: The two aspects of sentiment analysis," 2018, *arXiv:1807.01466*.

[101] B. K. Engen, "Understanding social and cultural aspects of teachers' digital competencies," *Comunicar*, vol. 27, no. 61, pp. 9–19, Oct. 2019, doi: 10.3916/C61-2019-01.

[102] J. Silva, M. Usart, and J.-L. Lázaro-Cantabrana, "Teacher's digital competence among final year pedagogy students in Chile and Uruguay," *Comunicar*, vol. 27, no. 61, pp. 33–43, Oct. 2019, doi: 10.3916/C61-2019-03.

[103] C. Herodotou, B. Rienties, A. Boroowa, Z. Zdrahal, and M. Hlosta, "A large-scale implementation of predictive learning analytics in higher education: The teachers' role and perspective," *Educ. Technol. Res. Develop.*, vol. 67, no. 5, pp. 1273–1306, Oct. 2019, doi: 10.1007/s11423-019-09685-0.

[104] L. P. Prieto, M. J. Rodríguez-Triana, R. Martínez-Maldonado, Y. Dimitriadis, and D. Gašević, "Orchestrating learning analytics (OrLA): Supporting inter-stakeholder communication about adoption of learning analytics at the classroom level," *Australas. J. Educ. Technol.*, vol. 35, no. 4, pp. 14–33, Aug. 2019.

[105] M.-J. Gallego-Arrufat, N. Torres-Hernández, and T. Pessoa, "Competence of future teachers in the digital security area," *Comunicar*, vol. 27, no. 61, pp. 57–67, Oct. 2019, doi: 10.3916/C61-2019-05.

[106] A. Gordillo, S. López-Pernas, and E. Barra, "Effectiveness of MOOCs for teachers in safe ICT use training," *Comunicar*, vol. 27, no. 61, pp. 103–112, Oct. 2019, doi: 10.3916/C61-2019-09.

[107] A. J. Carroll and M. N. Mallon, "Using digital environments to design inclusive and sustainable communities of practice in academic libraries," *J. Academic Librarianship*, vol. 47, no. 5, Sep. 2021, Art. no. 102380, doi: 10.1016/J.ACALIB.2021.102380.

[108] D. Yao and X. Deng, "An learning situation early warning method based on linear regression," in *Proc. Int. Conf. Big Data Inf. Educ. (ICBDIE)*, Apr. 2020, pp. 354–357, doi: 10.1109/ICBDIE50010.2020.00089.

[109] H. Lu, M. Ye, B. Gao, W. Guan, and Z. Gao, "Exploration and practice of hybrid teaching mode under MOOC environment: Taking 'Database system Principle' as an example," in *Proc. 9th Int. Conf. Inf. Technol. Med. Educ. (ITME)*, Oct. 2018, pp. 498–502, doi: 10.1109/ITME.2018.00117.

[110] R. K. R. Kummitha, "Smart technologies for fighting pandemics: The techno- and human- driven approaches in controlling the virus transmission," *Government Inf. Quart.*, vol. 37, no. 3, Jul. 2020, Art. no. 101481, doi: 10.1016/j.giq.2020.101481.

[111] UNESCO. (2021). *Global Education Coalition*. Accessed: Aug. 17, 2021. [Online]. Available: https://en.unesco.org/covid19/educationresponse/globalcoalition

[112] CONECTA. (2021). *Tec de Monterrey and UNAM Join Forces: Create Research Consortium*. Accessed: Aug. 18, 2021. [Online]. Available: https://tec.mx/es/noticias/nacional/institucion/se-unen-el-tec-de-monterrey-y-unam-crean-consorcio-de-investigacion

[113] X. Wei, N. Saab, and W. Admiraal, "Assessment of cognitive, behavioral, and affective learning outcomes in massive open online courses: A systematic literature review," *Comput. Educ.*, vol. 163, Apr. 2021, Art. no. 104097, doi: 10.1016/J.COMPEdu.2020.104097.

[114] K. Ma, M. Chutiyami, Y. Zhang, and S. Nicoll, "Online teaching self-efficacy during COVID-19: Changes, its associated factors and moderators," *Educ. Inf. Technol.*, vol. 26, pp. 6675–6697, Mar. 2021, doi: 10.1007/s10639-021-10486-3.

[115] W. Buser, J. Hayter, and E. C. Marshall, "Gender bias and temporal effects in standard evaluations of teaching," in *Proc. AEA Papers*, vol. 109, May 2019, pp. 261–265, doi: 10.1257/PANDP.20191104.

[116] C. W. Tseng, J. J. Chou, and Y. C. Tsai, "Text mining analysis of teaching evaluation questionnaires for the selection of outstanding teaching faculty members," *IEEE Access*, vol. 6, pp. 72870–72879, 2018, doi: 10.1109/ACCESS.2018.2878478.

[117] L. Juhaňák, J. Zounek, and L. Rohlíková, "Using process mining to analyze students' quiz-taking behavior patterns in a learning management system," *Comput. Hum. Behav.*, vol. 92, pp. 496–506, Mar. 2019, doi: 10.1016/j.chb.2017.12.015.

[118] X. Du, J. Yang, B. E. Shelton, J.-L. Hung, and M. Zhang, "A systematic meta-review and analysis of learning analytics research," *Behav. Inf. Technol.*, vol. 40, no. 1, pp. 49–62, Jan. 2021, doi: 10.1080/0144929X.2019.1669712.

[119] (2022). *Association for Institutional Research (AIR) | Call for Proposals*. Accessed: Dec. 3, 2022. [Online]. Available: https://www.airweb.org/forum/2023/information/call-for-proposals

[120] POD. (2022). *POD at a Glance—POD Network: Professional and Organizational Development Network in Higher Education*. Accessed: Dec. 4, 2022. [Online]. Available: https://podnetwork.org/about/pod-at-a-glance/

[121] K. Gillespie and D. L. Robertson. *A Guide to Faculty Development—POD Network: Professional and Organizational Development Network in Higher Education*. Accessed: Dec. 4, 2022. [Online]. Available: https://podnetwork.org/publications/guide-to-faculty-development/

[122] S. Baddam, P. Bingi, and S. Shuva, "Student evaluation of teaching in business education: Discovering student sentiments using text mining techniques," *J. Bus. Educ. Scholarship Teach.*, vol. 13, no. 3, pp. 1–13, 2019.

[123] P. B. Stark and R. Freishtat, "An evaluation of course evaluations," *ScienceOpen Res.*, pp. 1–7, Sep. 2014, doi: 10.14293/S2199-1006.1.SOR-EDU.AOFRQA.V1.

[124] P. Prinsloo and S. Slade, "An elephant in the learning analytics room: The obligation to act," in *Proc. 7th Int. Learn. Anal. Knowl. Conf.*, Mar. 2017, pp. 46–55, doi: 10.1145/3027385.3027406.

[125] P. Prinsloo, "Fleeing from Frankenstein's monster and meeting Kafka on the way: Algorithmic decision-making in higher education," *E-Learn. Digit. Media*, vol. 14, no. 3, pp. 138–163, May 2017, doi: 10.1177/2042753017731355.

[126] IITE. (2022). *New Publication of UNESCO IITE and SOU: The Analytical Report on the Use of Advanced ICT for Digital Transformation of Education—UNESCO IITE.* Accessed: Aug. 18, 2022. [Online]. Available: https://iite.unesco.org/news/unesco-iite-and-sou-analytical-report-on-the-use-of-advanced-ict-for-digital-transformation-of-education/

[127] G. D. Pietro, F. Biagi, P. Costa, Z. Karpinski, and J. Mazza, "The likely impact of COVID-19 on education: Reflections based on the existing literature and recent international datasets," Joint Res. Center, Publications Office Eur. Union, Luxembourg, U.K., 2020, doi: 10.2760/126686202.

[128] A. Mikheev, Y. Serkina, and A. Vasyaev, "Current trends in the digital transformation of higher education institutions in Russia," *Educ. Inf. Technol.*, vol. 26, pp. 4537–4551, Mar. 2021, doi: 10.1007/s10639-021-10467-6.

[129] E. Armstrong-Mensah, K. Ramsey-White, B. Yankey, and S. Self-Brown, "COVID-19 and distance learning: Effects on Georgia state university school of public health students," *Frontiers Public Health*, vol. 8, Sep. 2020, Art. no. 576227, doi: 10.3389/fpubh.2020.576227.

[130] K. R. Devkota, "Inequalities reinforced through online and distance education in the age of COVID-19: The case of higher education in Nepal," *Int. Rev. Educ.*, vol. 67, nos. 1–2, pp. 145–165, Mar. 2021, doi: 10.1007/S11159-021-09886-X.

[131] D. Almaghaslah and A. Alsayari, "The effects of the 2019 novel coronavirus disease (COVID-19) outbreak on academic staff members: A case study of a pharmacy school in Saudi Arabia," *Risk Manag. Healthcare Policy*, vol. 13, pp. 795–802, Jul. 2020, doi: 10.2147/RMHP.S260918.

[132] A. Al-Maskari, T. Al-Riyami, and S. K. Kunjumuhammed, "Students academic and social concerns during COVID-19 pandemic," *Educ. Inf. Technol.*, vol. 27, no. 1, pp. 1–21, Jan. 2022, doi: 10.1007/s10639-021-10592-2.

[133] IEEE Transmitter. (2020). *COVID-19 Made Internet Access, Broadband and Hotspots an Educational Necessity.* Accessed: Jun. 9, 2020. [Online]. Available: https://transmitter.ieee.org/covid-19-made-internet-access-broadband-and-hotspots-an-educational-necessity/

[134] UNESCO and Global Education Coalition. (2021). *International Community Rallies Behind Technological Transformations for Quality, Equitable and Inclusive Education.* Accessed: Nov. 26, 2021. [Online]. Available: https://en.unesco.org/news/international-community-rallies-behind-technological-transformations-quality-equitable-and

[135] S. Pokhrel and R. Chhetri, "A literature review on impact of COVID-19 pandemic on teaching and learning," *Higher Educ. Future*, vol. 8, no. 1, pp. 133–141, Jan. 2021, doi: 10.1177/2347631120983481.

[136] Global Education Coalition. (2022). *Transforming Education Through Innovation: The Global Education Coalition Leading in Action—UNESCO Digital Library—ED/GEC/2022/01.* Accessed: Apr. 5, 2022. [Online]. Available: https://unesdoc.unesco.org/ark:/48223/pf0000381023

[137] (2022). *UIS Releases New Data for SDG 9.5 on Research and Development | UNESCO.* Accessed: Jul. 6, 2022. [Online]. Available: http://uis.unesco.org/en/news/uis-releases-new-data-sdg-9-5-research-and-development

[138] L. Burke. (2020). *Moving Into the Long Term, Transforming Teaching & Learning.* Accessed: Mar. 10, 2021. [Online]. Available: https://www.insidehighered.com/digital-learning/article/2020/10/27/long-term-online-learning-pandemic-may-impact-students-well

[139] A. B. Hernández-Lara, A. Perera-Lluna, and E. Serradell-López, "Game learning analytics of instant messaging and online discussion forums in higher education," *Educ. Training*, vol. 63, no. 9, pp. 1288–1308, Nov. 2021, doi: 10.1108/ET-11-2020-0334.

[140] C. Müller and T. Mildenberger, "Facilitating flexible learning by replacing classroom time with an online learning environment: A systematic review of blended learning in higher education," *Educ. Res. Rev.*, vol. 34, Nov. 2021, Art. no. 100394, doi: 10.1016/J.EDUREV.2021.100394.

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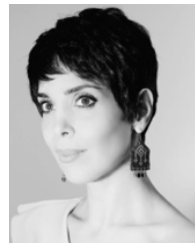
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