Understanding Students' Online Reviews to Improve College Experience and Graduation Rates of STEM Programs at the Largest Post-Secondary Institution: A Learner-Centered Study

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Abstract—**This Research Category Full Paper presents an analysis of online student reviews to improve college experience. Recent studies continue to establish the efficacy of student-centered teaching strategies in increasing student satisfaction. However, with higher education programs in the Science, Technology, Engineering, and Mathematics (STEM) fields rapidly expanding in size, it is becoming increasingly more difficult not only to implement such strategies but even to identify their presence or absence. This dilemma is prevalent at the University of Central Florida, with several of its STEM programs containing more than 10,000 students. By making use of sentiment analysis and traditional statistics, we can minimize the human oversight needed to thoroughly dissect qualitative data and create a viable approach with which to tackle this issue. In this paper, we analyze massive amounts of open-ended student reviews from multiple online university review sites to gain insights on which needs students feel essential and which they feel are not being met. Through this analysis, we identify how to most efficiently realize learner-centered principles within a large institution, concurrently providing suggestions on how the university can supply their students the best possible education while also maximizing the graduation and retention rates of its STEM programs.**

Keywords—Learner-centered principles; course reviews; student success; course experience; graduation and retention rates; data analysis; student-centered learning.

I. Introduction

Higher education institutions have been using various innovative applications such as predictive analytics, data, and text mining to improve student success. Student success is one of the most widely discussed topics in the literature because of its emerging importance in university campuses across the nation to help students successfully finish college. Student success in any university is measured by the graduation and retention rates of its programs. There are various institutional factors that influence student success, and many universities have taken measures to improve it. As per the recent Edsurge report, half of the students who enter college leave without a degree [1] even though most of them are motivated to succeed in college but educational institutions lack resources to support and address students' needs. It is difficult for any educational institution to determine and prioritize student needs. This problem is prevalent in STEM programs at the University of Central Florida (UCF). UCF is one of the largest universities in the nation and its College with STEM programs is among the top five departments by enrollment. Our initial data analysis demonstrates that the transfer student population is larger than the freshmen population and that the student population consists of both international and domestic students. Additionally, some STEM programs have a high percentage of part-time enrolled students, and many students work either part-time or full-time.

There has been increasing emphasis toward understanding student expectations and requirements from a student perspective. This paradigm shift to understand institutional challenges from a student perspective may help in taking measures to improve student success. In this study, we gather 36,646 open-ended student reviews on STEM courses at UCF from four online university review sites such as RateMyProfessor.com, Unigo.com, GradReports.com, and Niche.com to gain insights on which needs students feel are essential and which they feel are not being met. In addition to the student self-reported online reviews, the program curricula were used to understand course and degree requirements on the retention and graduation rates. Based on subsequent analyses, we compare various characteristics of different STEM courses and disciplines to provide suggestions to maximize the course experience and hence graduation and retention rates of STEM programs at UCF. In more specific terms, we address the following research questions:

RQ1: *What learner-centered theories, if any, are supported by students' public, online reviews of their courses?*

RQ2: *What factors are most relevant to student satisfaction and, in turn, success?*

RQ3: *What differences, if any, exist between student perceptions of STEM and non-STEM courses?*

The major takeaways from this study are: (i) the college experience of students is influenced by both their emotional states and learning environment; (ii) student experience is less correlated with course difficulty in the case of Computer Science (CS) and; (iii) out of the American Psychological

Association (APA)'s Fourteen Learner-Centered Psychological Principles, we determined that our public course evaluations provide overwhelming support for the APA's sixth (i.e., context of learning) and seventh (i.e., motivational and emotional influences on learning) principles. Based on these results, we provide recommendations to improve STEM student experience and hence STEM student success.

II. Background

A. Learner-Centered Approach

Student-Centered learning primarily considers students' interest and acknowledges student voice as crucial to the learning experience [3]. There are various practices in higher education such as project-based learning and collaborative learning that satisfy major criteria of student-centered learning [4]. Another approach, "the hybrid approach to experiential learning," was proposed to bridge the gap between project-based learning and industry internships, and falls into a category of student-centered learning [5].

Some studies confirmed the effectiveness of student-centered approaches [6]. Student learning is most persistent if it addresses their intellects, skills, and attitudes [7]. Studies on motivation, autonomy support, individual diversity, social inclusion, and other topics have eventually framed into a set of learner-centered principles [8]. There are studies in the literature focusing on how the APA's set of fourteen Learner-Centered Principles were put into practice in a course. For example, Motschnig et al. [9] present a case study where such learner-centered principles were put into practice in one of the largest undergraduate courses on Human-Computer Interaction. Students rated this course as one of the best computer science courses at the University of Vienna. In a similar study at the Iowa State University, faculty instructors implemented learner-centered principles in one of their introductory biology courses. They observed that faculty involvement and interaction bolstered the presence of student-centered teaching in courses and positively correlated with student performance [12]. The learner-centered teacher variables such as positive relationships between teachers and students, empathy, warmth, and encouragement to learn and think show excellent associations with positive student outcomes [30]. The positive relationship between students and instructor were crucial for at-risk students who were academically weak and for children with learning difficulties, as well as children from disadvantaged economic backgrounds [30]. The instruction quality, autonomy support, and structure also influence student engagement and achievement [31].

The Learner-centered model provides an excellent framework because it considers all stakeholders including students, which is integral to continuous change and improvement [10]. A group of researchers with a focus on learner-centered principles must work with policymakers, funding sources and others to find innovative solutions to existing educational problems [10]. The collective efforts of learner-centered researchers, policymakers, teachers, students, administrators and others can advocate practices for good learner-centered relationships [30]. Most importantly, learner-centered studies are often supported by the data and proofs which can be shared with other stakeholders to take necessary measures.

B. Student Perceptions

Additionally, it is often the case that the perceptions of students and faculty differ at major scale [13]. For example, in a study to understand the views on a class titled "process of science skills," students thought the amount of time spent on that class was sufficient whereas faculty thought it was not enough [13]. Thus, what faculty thinks crucial may or may not satisfy student needs. It is important to understand student needs from their perspective. Personalized learning is one of the ways to understand student needs and create a student-centered learning environment. It is essential to incorporate technology to personalize instruction based on student needs [11]. But understanding these needs is a challenging task.

There are studies in the literature that focus on understanding needs from user (student, in this case) perspectives. For example, Ghosh et al. [27] performed thematic analysis to understand the user reviews of mobile applications to determine safety features for the design of the application that is safe for adolescent teens to use. Likewise, it is imperative to understand student needs from a student perspective. A study carried out at the University of Guelph analyzed course perceptions of both instructors and students to categorize courses according to resources and course structure [14]. Their analysis helped to change resource allocation and teaching structure.

C. Student-Centered Curriculum, Course Sequence and Personalized Course Recommendation Systems

The curriculum structure, course sequence, and course recommendations are also shown to affect student success [29]. The curriculum influences the graduation and retention rates of STEM programs [28]. Wigdahl et al. [28] represent the program curriculum in the form of a directed graph with each class as an individual node and course prerequisites as edges between them. Akbaş et al. [29] designed a course sequence planning system with the application of network analysis of program curriculum, cruciality factor, and students' historical data to improve graduation and retention rates of programs in education and training institutions. In their extended work, they designed a personalized course recommender system based on historical data and goal orientations [26]. These aforementioned course recommender systems were designed based on student needs and interests. These systems have shown a positive impact on student learning.

Studies have shown that there is a need for student-centered curriculum approach to meet the needs of the competency-based curriculum of the 21st century [33]. Student-centered curricula place students at the center of their learning. Relevance, content choice, and demonstration are three major features of student-centered curriculum [32]. Relevance refers to understanding the purpose of studying a specific subject and skills before investing time and effort [32]. Secondly, the content choice is the student's choice to select a content to focus and let their interests drive the content that teaches various skills and concepts [32]. Finally, demonstration refers to various ways that students process understanding and how a teacher can provide various options based on their knowledge of student needs and interests [32]. It is primarily important to understand student needs to implement the above mentioned three features of the student-centered curriculum.

III. Research Methodology

In order to consider learner-centered models of education, we must first understand student perspectives. To do so, we turn to online university review websites that allow students to provide open-ended assessments of not only their academic institution overall but also of specific courses. Using (R) [17], we collect such comments from GradReports.com, Niche.com, RateMyProfessors.com, and UniGo.com, subsequently performing traditional statistical as well as textual analyses to make sense of the gathered data.

Before beginning our analyses, it is important to note that the study presented in this paper analyzes online student reviews, which are unregulated student perceptions of instruction reported online. While they provide a new, unfiltered source of data with which we can analyze student satisfaction, they introduce unique challenges as well. With the review websites in question providing no form of enrollment verification, we risk including responses in our data that are not representative of the actual student experience. Similarly, due to the voluntary nature of the reviews, there is a not-insignificant possibility for biases in the demographics represented. However, online student reviews may provide some insights that could not be possible to get from institutional conducted student surveys. Furthermore, considering the large size of the data set, the exploratory nature of this study, and the intended future work, we still find it useful to continue this investigation.

A. Data Collection

The open-source (R) packages *RSelenium* [18], and *rvest* [19] allows users to write programs that can open a remote browser, navigate to any webpage, interact with a said webpage, and scrape HTML code from page sources. Using such techniques, we craft (R) scripts that navigate to the aforementioned university review websites, search for reviews of universities based on program parameters, scrape all comments, and finally save and export them to a .csv file. Directing these scripts to search for the university targeted by this research, we compile 36,646 multi-dimensional observations in total. The vast majority of these -- 25,660 of them, in particular -- come from the website RateMyProfessors.com. Throughout the remainder of this paper, we limit our inquiries to this subset of the data, as RateMyProfessors is the only site of the four surveyed to label reviews by discipline and course, and we wish to identify characteristics not just of the student experience in general, but of STEM and non-STEM departments.

B. Data Description

For comparative purposes, we gather student reviews not only from the STEM departments at UCF but also from highly-enrolled non-STEM disciplines there [20]. In total, we survey fifteen different departments: Accounting, Art, Business, Computer Science, Education, Engineering, Health Sciences, Hospitality, Information Sciences, Mathematics, Nursing, Physics, Political Science, Psychology, and Science. Each observation consists of six fields, as described in Figure I below.

FIGURE I. RateMyProfessors Data Description

Field Name	Field Description
Course.ID	The student-reported course code of the class
Overall.Rating	A discrete one-to-five rating of the course overall, with "1" representing the least satisfaction and "5", the highest
Difficulty.Rating	A discrete one-to-five rating of the course difficulty level, with "1" representing the lowest difficulty and "5", the highest
Comment	An open-ended review of the class by the student, limited to 350 characters
Would.Take.Again	A binary "yes/no" response to the question, "Would you take this class again?", stored as a Boolean variable
Department	A factor variable containing the name of the department from which the observation originates

C. Data Analysis

The first step in our analysis is to clean each comment by removing extra whitespace, punctuation, and stop words (as defined within the (R) package *tm* [21]), in addition to converting all characters to lowercase and stemming all words. With our data more fit for computational analysis, we begin pulling information from the data by calculating word frequencies; we follow with sentiment analysis. We take a dictionary-based approach to sentiment analysis, employing both the National Research Council Canada (NRC) and Finn Arup Nielsen (AFINN) lexicons. The NRC lexicon's value lay in its wide variety of sentiment labels, allowing for categorization with a total of ten sentiments: anger, anticipation, disgust, fear, joy, negativity, positivity, sadness, surprise, and trust [22]. This allows us to overcome the limiting and dichotomous nature of many other lexicons, which only utilize the sentiments of "positivity" and "negativity." The AFINN lexicon then provides a crucial complement to the NRC lexicon, allowing us to measure the intensity of sentiment, measuring words on a discrete scale from negative five to positive five, where "-5" represents extreme negativity, "0" represents complete neutrality, and "5" represents extreme positivity [23]. In the rest of this paper, we utilize a measurement derived from this lexicon -- henceforth called "sentiment intensity" -- by using the absolute values of the AFINN labels to evaluate the strength of emotion conveyed in each comment. Furthermore, using the NRC and AFINN labelings to quantify the presence of core emotions not only comment-by-comment but by discipline, we perform a Pearson correlation analysis among all gathered and derived variables -- the presence of each NRC and AFINN sentiment, the raw AFINN value score, the measured sentiment intensity, the overall class rating, and the class difficulty rating -- to identify potentially significant relationships. Finally, we utilize these same quantitative variables to introduce K-means and fuzzy C-means clustering, which are unsupervised forms of machine learning in which an algorithm iteratively classifies and reclassifies data points into groups based on their closeness. These clustering algorithms were chosen over others because of their ability to handle high-dimensional data [24].

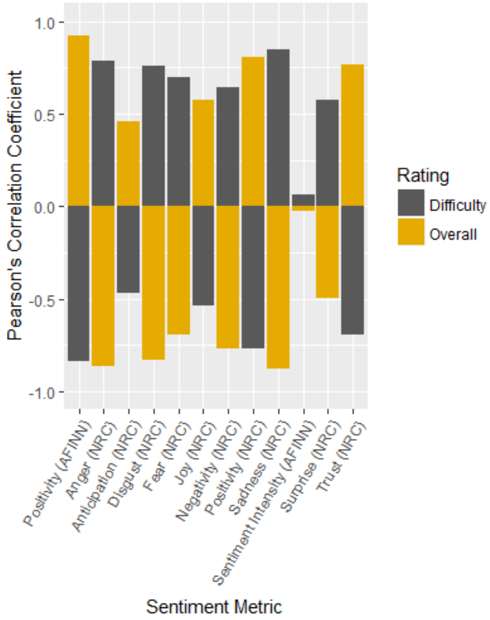
IV. Results

In this section, we describe the results of our data analysis. First, we provide a brief investigation of validity. Then we explain K-means and fuzzy C-means clustering results followed by the effects of specific sentiments. Lastly, we explain results specific to STEM courses.

A. *A Brief Investigation of Validity*

We would like to be as sure as possible that our sentiment analyses of student comments are in fact measuring trends in departmental instruction rather than linguistic differences among disciplines; that is, we want to know that the trends we infer from our data can realistically be attributed to the actual qualities of instruction rather than departmentally-influenced writing styles. Thus, we look at the measure of sentiment intensity as compared to our other variables, in order to see if the strength of word choice -- something which may be more honed in non-STEM courses -- can adequately explain any aspects of our data. We see that sentiment intensity correlates weakly with all variables; it has no Pearson correlation coefficient with any variable that has an absolute value above 0.39, and most of the said values (that is, all but those correlations with the presence of fear, surprise, and trust) fall below 0.2, which indicates a "very weak" correlation by Evans' [25] definition. Furthermore, with significance levels of these correlations surpassing 0.22 at their best and reaching an average of 0.6953, we see little -- if any -- significant relationship between the amount of emotion students use in their comments and how they rate and feel about their classes. This finding is exemplified in Figure II by the stark contrast in the small magnitude of the correlation coefficient between "Sentiment Intensity (AFINN)" and student ratings versus the much larger ones between student ratings and every other measurement. This thereby lays the groundwork for further comparisons between departments, allowing us to justifiably dismiss claims that linguistic tendencies may account for a significant portion of our observed trends.

FIGURE II. Correlation with Overall and Difficulty Ratings



B. *Clustering*

Using all aforementioned variables -- the percentage of words showing anger/anticipation/trust/etc., overall and difficulty ratings, and sentiment intensity -- we apply both K-means and fuzzy C-means clustering to identify departmental similarities and differences. Making no assumptions about the number of centers, we apply K-means clustering iteratively until the variance in our data explained by the clustering begins to plateau. Starting with one center, we find that five centers best represents the data, explaining about 91% of the variance. The groups, by department, become: Art and Physics (Phys); Accounting (Acct), Engineering (Eng), and Science (Sci); Education (Edu) and Psychology (Psych); Hospitality (Hosp), Nursing (Nurs), and Political Science (PS); and Business (Bus), Computer Science (CS), Health Science (HS), Information Science (IS), and Mathematics (Math). Fuzzy C-means applied with the same number of centers also returns this grouping, now along with membership values (a value of "0" indicates the weakest possible connection to a cluster and "1", the strongest) for each department that indicates the strength of their belonging to their cluster. We note that, while it may seem intuitive, the two computer-based disciplines CS and IS group together. In addition, we see that they are separated from most other STEM fields, with Engineering, Physics, and Science all belonging elsewhere. Finally, we further uncover that the Art and Physics departments are consistently grouped together no matter the number of centers and that their connection is quite strong, with their five-center membership values averaging at 0.746. In Figure III, these clusters are expressed visually alongside their membership values.

FIGURE III. DEPARTMENT CLUSTERS WITH MEMBERSHIP VALUE (MV)

Cluster I		Cluster II		Cluster III		Cluster IV		Cluster V	
Dept	**MV**	**Dept**	**MV**	**Dept**	**MV**	**Dept**	**MV**	**Dept**	**MV**
Art	0.93	Acct	0.94	Edu	0.96	Hosp	0.85	Bus	0.84
		Eng	0.60			Nurs	0.96	CS	0.68
Phys	0.56			Psych	0.58			HS	0.63
		Sci	0.93			PS	0.72	IS	0.61
								Math	0.91

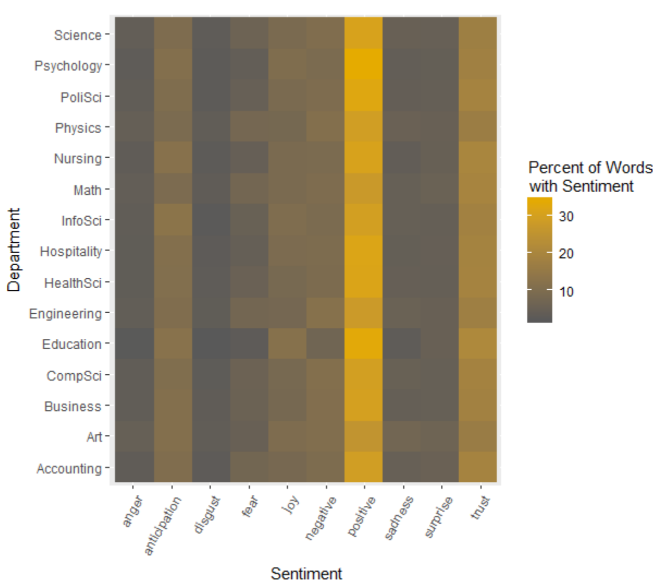
Considering the above findings, we see support for the APA's sixth Learner-Centered Principle and, thus, identify part of our answer to RQ1. The principle in question deals with the context of learning and asserts that environmental factors like technology and institutional practices are integral to the learning process. The isolation of CS and IS from almost all other surveyed STEM courses (only Mathematics is also grouped with them) tells us that something about these two disciplines differentiates them from others.

Similarly, looking at the consistent pairing of Art and Physics courses, we can infer even more support of the relevance of the learning environment to student performance. As evidenced by their K- and C-means clusterings, the Art and Physics departments elicit extremely similar emotions in students despite their very different subject material. These departments rank as the two highest when considering the presence of anger, disgust, fear, and sadness, and fall to the very bottom in terms of the presence of trust and both the NRC and AFINN measures of positivity.

C. *Effects of Specific Sentiments*

With a great deal of our analysis centering on sentiment analysis, the seventh Learner-Centered Principle identified by the APA is undoubtedly the most relevant here: concerned with motivational and affective influences on the learning process, this principle argues that both the quality and quantity of learning hinges on the individual emotional states of students. Thus, we first look at the proportion of words in student reviews exhibiting each of the ten measurable NRC sentiments, as shown in Figure IV below.

FIGURE IV. NRC SENTIMENTS IN STUDENT COMMENTS

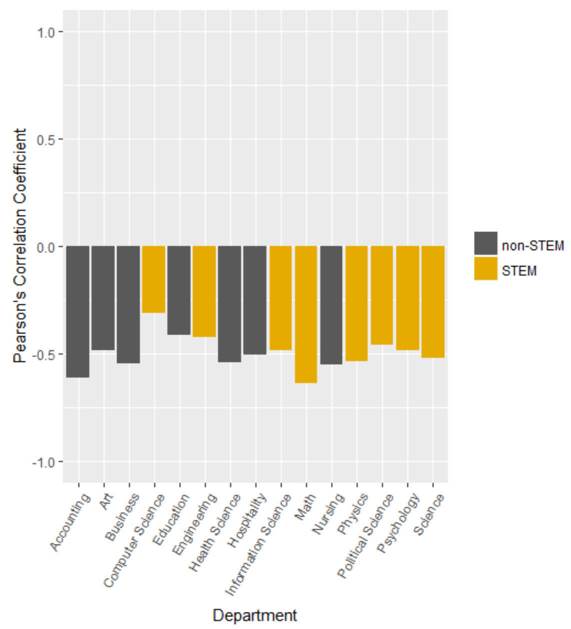


We can clearly see that positive emotions like anticipation, trust, and, of course, positivity are the most frequently expressed sentiments in general, overall departments. However, we can also note from Figure II that the more-sparse negative emotions -- anger, disgust, sadness -- have overwhelmingly stronger Pearson correlation coefficients (and corresponding significance levels) with both the Overall and Difficulty Ratings. The positive emotions show "moderate" and even some "strong" correlations with Overall Rating. The absolute values of such correlation coefficients fall between 0.461 (anticipation) and 0.765 (trust). However, they pale in comparison to the "very strong" influences of anger (Pearson's r = -0.868, p < 0.0001), disgust (r = -0.834, p = 0.0001), and sadness (r = -0.879, p < 0.0001). In other words, we find that negative experiences in courses, measured as negative sentiments in class reviews, have a strong effect on student satisfaction, and therefore success, no matter how infrequently they may occur. This fully supports the seventh Learner-Centered Principle mentioned in this section.

D. *Narrowing Focus to STEM Courses*

Examining our data, we notice that some STEM fields behave quite differently than their non-STEM counterparts. Computer Science, in particular, seems to have several unique properties. Applying a correlational analysis between the Overall and Difficulty Ratings of the departments, we find that CS -- and, to a lesser extent, Engineering -- exhibits a much weaker Pearson correlation coefficient than the other disciplines. As shown in Figure V, Pearson's r for CS is about -0.310 (a "weak" correlation according to Evans [25]) while other departments average a "moderate" correlation of about -0.512 and some, like Accounting, even reach a "strong" correlation with an r-value of -0.612. This tells us that perceived course difficulty, while significant to students in general, has much less to do with their satisfaction in CS courses.

FIGURE V. RATEMYPROFESSORS OVERALL VERSUS DIFFICULTY RATINGS



Turning our attention back to the NRC sentiment analysis, we can see that most sentiments have very similar effects on students' Overall and Difficulty Ratings both inside and outside of STEM confinements, with the changes in magnitude of the Pearson correlation coefficient after removing non-STEM data averaging at about 0.095 for Overall Rating and 0.072 for Difficulty Rating. One sentiment, however, experiences a far more extreme change: trust. The percentage of words with trust, as compared to Overall and Difficulty Ratings, attains respective Pearson *r*-values of 0.765 and -0.696 when considering all disciplines (as seen in Figure II), but drops from this "strong" correlation status to a "moderate" one (with respective *r*-values 0.513 and -0.536) upon narrowing our focus to STEM departments. We can infer from this that the general result from the previous section, that negative emotions have a stronger effect on student satisfaction than positive ones, also holds in STEM courses and is potentially even stronger there.

V. Discussion

A. *RQ1: What learner-centered theories, if any, are supported by students' public, online reviews of their courses?*

As mentioned in the previous section, this study discovers support for the APA's Learner-Centered Principles, particularly the sixth and seventh. In subsection B of section IV, we note that Computer and Information Science courses are clustered together, but apart from most other STEM disciplines. We also find through this clustering that the Art and Physics departments are perceived very similarly by students. This transcendence of classic, seemingly intuitive ideas of departmental phylogeny indicates that the structure and environment of a course can surpass subject matter in terms of its significance to students. Thus, the APA's sixth Principle, which similarly emphasizes the importance of learning environment to the student experience, remains unshaken -- and is even supported -- by the results of this study. Looking specifically at the cluster containing CS and IS, we hypothesize the overwhelming influence of technology and technologically-based environments on these computer-centric departments. Furthermore, as discussed in subsection C of the same section, we identify support for the APA's seventh Principle, that students' emotional states significantly affect their learning. We see that Overall Rating exhibits at least a moderate positive correlation with most sentiments and a negative one with negative sentiments; similarly, Difficulty Rating exhibits mostly moderate (or stronger) positive and negative correlations with negative and positive emotions, respectively. These findings are significant because they justify alternative methods for increasing student satisfaction (and thus success) that stem from the perspective of the student rather than the instructor.

B. *RQ2: What factors are most relevant to student satisfaction and, in turn, success?*

Once again referencing section IV, subsection C, we see that negative emotions tend to have stronger correlations with student course ratings than do positive ones, indicating that negative experiences are more central to a student's state of mind. However, considering the nature of the review sites used to gather the data, we must consider such conclusions with some skepticism. With submissions to all public online review websites being entirely voluntary, it is possible that only those students with particularly unfavorable experiences feel the need to post a review on such sites. If this were the case, then our findings stem from a sampling bias rather than true characteristics of the population. On the other hand, Figure V visualizes another finding that is less likely to be a result of such a demographic skew: a much weaker significance of perceived course difficulty, as compared to student sentiment, to overall course experience.

C. *RQ3: What differences, if any, exist between student perceptions of STEM and non-STEM courses?*

We find from the results of section IV, subsection D that STEM and non-STEM classes differ most considerably in terms of the effects of trust and course difficulty on the overall student satisfaction. The CS department, in particular, manifests a much weaker correlation between Difficulty and Overall Rating, and all STEM fields show a smaller relationship than their non-STEM counterparts between the presence of the sentiment "trust" and Overall Rating. These findings are most important in the light of future work, providing a narrower scope through which to apply additional investigation, as is briefly discussed in the next section.

VI. Conclusions and Future Work

In the analyses discussed above in sections IV and V, we answer both RQ1 and RQ2 in finding overwhelming support of the APA's seventh Learner-Centered Principle, that students' emotional states significantly affect their academic success and satisfaction. In particular, we see that negative emotions like sadness and fear are far more potent to the student experience than are positive ones like joy and anticipation. We thus stress the importance of accessible students' rights offices, official course evaluations that are reviewed in depth and actively used in both course-specific and institution-wide planning, and other means for identifying and remedying even the smallest of student complaints. Aligning with both this and the APA's sixth Principle, which is concerned with the relationship between learning environment and student performance, we would expect both student satisfaction and, as a result, success, to increase as student support services and student voices become more prevalent within a university.

Continuing this research in the future, we seek activity data from online classes -- like the amounts and frequencies of file uploads by professors, discussion board postings by both learners and instructors, and assignment due dates and submissions -- from the university targeted in this paper. This could potentially provide evidence for or against many hypotheses only hinted at by the analyses performed here; we could, for example, further investigate the emotions of "trust" and "surprise" by monitoring course consistency and regularity and their effects on student grades. Similarly, using the results of this study to advocate for access to university-issued course evaluations like the Student Perception of Instruction survey at UCF, we aim to facilitate our ability to hone in on specific, core classes in each department as well as inspect how well student reviews and comments reflect actual student performance. Even without new data sources, however, a great deal remains to be done here. Future implementations of natural language processing, feature extraction, thematic analyses, and other methodologies not utilized in this current research promise not only additional discoveries, but also continually-developing assessments of hypotheses and proposals from both this paper and educational psychology as a whole.

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