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Understanding the University Student Experience Through Big Data Analytics

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ABSTRACT

Despite best efforts, the student experience remains poorly understood. One under-explored approach to understanding the student experience is the use of big data analytics. The reported study is a work in progress aimed at exploring the value of big data methods for understanding the student experience. A big data analysis of an open dataset of student comments is being undertaken. The first and simplest use of big data analytics is for the identification of high frequency keyword groups, which, without big data analytics, would be extremely time consuming. However, the lack of context surrounding keyword groups severely limited the ability to draw meaningful conclusions and highlighted the need for human intervention in the analysis process. Future work includes sentiment analysis. This initial work is an impetus for further exploration of big data analytics methods in qualitative contexts, especially in dynamic contexts where rapid data analysis can form a basis for timely interventions.

KEYWORDS

Big Data Analytics, Category Classification, Higher Education, Keyword Analysis, Student Experience

INTRODUCTION

Understanding the student experience in higher education is important to both the institutions and the students. Positive experiences for the students during their studies are crucial as these can highly impact student motivation, engagement, learning outcomes, and even their decision to continue in the same institute for future studies or to leave (Tinto, 2017; Stanton et al., 2016). The quality of the student experience is usually evaluated based on factors such as student satisfaction, retention rates, academic progress, and post-graduation career outcomes. (Heron, 2020; Sabri, 2011). Aware of the importance of providing positive student experiences for students and institutions, universities are increasingly seeking to understand the student experience as a basis for providing learning experiences that enhance and support student well-being and satisfaction. Achieving high levels of student satisfaction positively influences student engagement and retention, consequently contributing to the timely completion of their undertaken program (Stanton et al., 2016; Shah et al., 2020; Bobe & Cooper, 2020; Raaper et al., 2022). Understanding and supporting the student experience is critical to achieving the strategic goals

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of attracting and retaining students, and remaining competitive Stanton et al., 2016). However, the student experience remains incompletely understood, despite its well-acknowledged importance, and the many efforts aimed at understanding it, usually via surveys (Shah & Pabel, 2020). This situation has motivated the authors to explore methods other than surveys to address this gap big data analytics is commonly applied in domains such as marketing to understand customer or user experience, but to date, big data methods are underexplored as a method for understanding the student experience.

In the present paper, the authors focus on the learning experience of university students and the role that big data analytics may play in helping to better understand it. The paper begins with a brief discussion of the advantages and disadvantages of commonly used traditional survey methods for collecting data about the student experience. Big data analytics is described and why big data analysis may be a useful tool for understanding the student experience is discussed. The big data analytics method used by the authors is then described. The reported study is a work in progress and preliminary results are presented.

THE STUDENT EXPERIENCE

The university experience is a complex and multidimensional journey shaped by various factors that impact students' overall satisfaction, engagement, and success. Understanding these factors is crucial for universities to create supportive and enriching educational environments. Research has identified a number of factors influencing student's experience (Gopal et al., 2021; Awidi et al., 2019; Al Kurdi et al., 2020). One of the factors is academics, which plays a pivotal role in shaping students' experiences. The quality of teaching, including pedagogical approaches, instructor-student interactions, and feedback, significantly impacts students' engagement and motivation (Chickering & Gamson, 1987). Additionally, curriculum design, including the relevance and coherence of courses, flexibility, and opportunities for experiential learning, influences students' sense of achievement and intellectual growth (Kuh et al., 2010).

Previous studies emphasize the importance of effective teaching and student engagement in shaping the student experience (Ta, Hien Thi Thu, et al., 2023; Hope, 2012). Research suggests that innovative teaching methods, interactive classroom activities, and supportive instructor-student interactions positively influence student satisfaction, motivation, and learning outcomes (McKinney et al., 2019). Engaged students tend to be more committed, involved, and satisfied with their educational experience leading to higher retention rates and academic achievement (Kahu, 2013).

Another factor contributing to the student experience is the social and environmental context in which students learn and live. Recent research (Strayhorn, 2019) emphasizes the significance of campus climate and inclusivity in promoting student engagement and success. A positive campus climate, characterized by a sense of belonging, respect for diversity, and equitable opportunities, enhances students' well-being and academic achievement (Strayhorn, 2019). Studies show that an inclusive campus climate fosters higher levels of student satisfaction, persistence, and overall success (Smith et al., 2021).

Lastly, the availability and quality of institutional support and services play a crucial role in students' experience. Adequate academic advising, mentoring, and career services contribute to students' academic and career development (Ender & Newton, 2000). Additionally, institutional policies and practices, including fairness, transparency, and responsiveness, shape students' trust and perceptions of institutional support (Hurtado et al., 2012).

The Survey-Based Approaches

While surveys offer advantages in terms of data collection and analysis, they also possess certain limitations (DeShields et al., 2005; Ferreira & Santoso 2008; Esarey & Valdes, 2020). Traditional surveys typically involve a sample population, limiting the generalisability of the findings. Moreover, traditional surveys often fail to capture the diverse range of student experiences, perspectives, and backgrounds. Students who are less inclined to participate in surveys or whose voices are marginalized may be underrepresented, resulting in a biased understanding of the overall student experience (Jackson & Gray, 2018). The exclusion of diverse perspectives can lead to an incomplete picture, hindering universities' ability to identify and address specific needs and challenges.

Another limitation of traditional surveys is their reliance on closed-ended questions, which limits the range of responses and fails to capture the nuanced and individual perceptions of students. This limitation may restrict the depth of understanding of students' experiences, as closed questions often do not allow for the expression of true perceptions, emotions, and experiences (Maguire & Delahunt, 2017). Students' complex and multifaceted experiences may not be adequately captured, potentially leading to a loss of valuable insights.

Traditional surveys provide a snapshot of the student experience at a particular moment in time, which may not reflect the dynamic and evolving nature of students' experiences throughout their academic journey. In contrast, big data analytics can continuously collect and analyze vast amounts of data from multiple sources, providing real-time insights into student behaviors, interactions, and preferences and hence may provide other avenues for gaining insights into the complex phenomenon of student experience (Siemens, 2013).

Big Data and Big Data Analytics

Big data analytics refers to a broad range of techniques used to manage complicated and large volumes of data, encompassing processes such as data capture, transfer, storage, curation, search, analysis, visualization, security, and privacy. The characteristics of big data are often referred to as the "3Vs". volume, velocity, and variety (Laney, 2001; De Mauro et al., 2019). Volume relates to the sheer amount of data generated, velocity concerns the speed at which data is generated, and variety refers to the different types of data being produced. Consequently, big data analysis methods must be capable of handling vast amounts of data, processing it quickly, and being adaptable to diverse data types (Chen & Lin, 2014). The volume of data is considered crucial as a larger dataset can yield more reliable estimations, as supported by the central limit theorem. Velocity is important because data is continuously generated through social interactions, sensor monitoring, and business activities. If the related techniques cannot process data at a pace that keeps up with its generation, a significant amount of data may go unanalyzed, resulting in missed insights. Variety is essential because valuable patterns are more easily discerned when observed from multiple perspectives (Xu & Duan, 2019). In addition to this, another "V" can be discussed which is veracity. Veracity pertains to the accuracy of the data. Data inaccuracies can arise from various reasons such as incorrect manual input, machine failures, or problematic data procedures. Incorrectly recorded raw data can lead to flawed decision-making based on that data. However, as existing techniques have become more refined in handling large-scale data and extracting value from it (Xu & Duan, 2019), the topic of big data has gained increasing prominence in recent years, particularly in emerging industries and various applications for example, in healthcare, cybersecurity, entertainment and retail trade, and especially in business, big data analytics has been transformational for how businesses compete (Manyika et al., 2011; (Maroufkhani, Tseng, Iranmanesh, Ismail, & Khalid, 2020).

Big Data and Big Data Analytics in Education

One of the more common applications of big data in education is learning analytics. Learning analytics has emerged as a rapidly developing field focused on measuring, collecting, analyzing, and reporting data about learner activity and performance. The ultimate goal of learning analytics is as a foundation for evidence-based teaching practice changes that enhance student performance and evaluate the effectiveness of curricula, programs, and educational institutions (Aldowah et al., 2019). Big data is leveraged in the education industry in other ways with personalized learning being another notable application. Through the analysis of vast amounts of data, personalized learning can be implemented to cater to the individual needs, preferences, and learning styles of students.

This enables the customization of instructional approaches and targeted support (Luan et al., 2020). Big data analytics enable personalized learning experiences tailored to individual student's needs, preferences, and learning styles. By analyzing vast amounts of data, such as students' performance records, learning behaviors, and feedback, personalized learning systems can adapt instruction and provide targeted support. Several studies (Papamitsiou & Economides, 2014; Zawacki-Richter et al., 2019; Luan et al., 2020) have discussed the use of big data analytics to personalize educational technology and improve learning outcomes. Predictive analytics can be another way of using big data in education for student success. It can help predict student success and identify at-risk students. By analyzing historical data, such as demographics, grades, attendance, and engagement, predictive analytics models can identify patterns and early warning signs of potential challenges or dropouts. Researchers have explored the use of predictive analytics in educational settings, such as identifying students at risk of failure (Arnold & Pistilli, 2012). Thirdly, big data analytics can inform curriculum design and improvement by analyzing student performance, feedback, and assessment data. Insights gained from big data can help identify areas of improvement, optimize curriculum content, and align learning outcomes with industry needs. Researchers have highlighted the benefits of using big data in curriculum design and improvement (Li et al., 2023; West, 2012).

Big data and learning analytics can enable adaptive instruction by continuously monitoring and analyzing students' progress and performance. Adaptive learning systems can provide personalized recommendations, adapt instructional strategies, and offer real-time feedback. Academic research has explored the use of big data and learning analytics in adaptive instruction and its impact on student learning outcomes (Tempelaar et al., 2017). Learning Management Systems (LMS) and online environments are increasingly being integrated into academic courses across diverse educational settings, to improve pedagogical effectiveness (Altinpulluk & Kesim, 2021). Additionally, these systems are utilized to assess teacher effectiveness, ensuring a positive experience for both students and educators. Teacher performance can be measured based on factors such as student enrolment, subject matter, behavioural classification, and other variables (Altinpulluk & Kesim, 2021). Big data can support traditional education systems by helping teachers analyse students' knowledge and determine the most effective techniques for each individual. This allows teachers to acquire new methods and approaches for their educational work. Data mining and data analytics technologies provide prompt feedback to both students and teachers regarding their academic performance. By leveraging collective and large-scale data, it becomes possible to predict which students require additional support, thereby mitigating the risk of failure or dropout. Big data opens up opportunities for new learning experiences for students, enabling them to share information with educational institutions and expand their knowledge and skills. Moreover, educational institutes and universities can utilise big data to assist and prepare their future students (Drigas & Leliopoulos, 2014).

The sources of big data in education are likely to increase. Students, parents, teachers, and school leaders now employ social media platforms for communication. Additionally, districts and state education agencies use social media to engage with stakeholders and the wider public. The increasingly pervasive use of digital devices in the educational system is anticipated (Cox & McLeod, 2014). However, the data generated from interactions on social media platforms relevant to education is currently under-utilized as a potential source of understanding of student experiences.

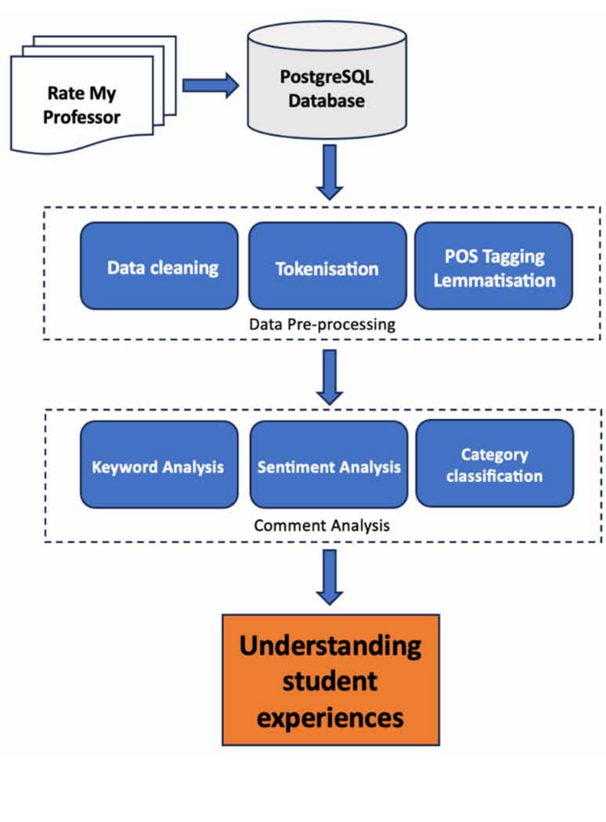
The Student Experience Analysis (SEA) System

Although there is much emphasis on learning analytics and some attention to personalised learning, big data is not well applied to properly understand the student experience. The Student Experience Analysis (SEA) system was developed for this research and used to analyse the student experience, using big data analysis and Natural Language Processing (NLP) techniques. NLP, as the name suggests, is a set of programming techniques designed to enable software to understand and generate languages naturally used by humans (Soni & Selot, 2018).

As a starting point for exploring the usefulness of big data analytics for this purpose of understanding the student experience, the authors used an open data source (https://doi.org/10.3886/E163141V1) from a website called RateMyProfessors.com. RateMyProfessors.com is a popular website that allows students to rate and review their college and university professors, providing feedback on various aspects of teaching, such as clarity, helpfulness, and overall effectiveness. (Boswell, 2020; Sperber, 2018). The website was launched in 1999 and has since grown into a large database of professor ratings and reviews. Students can search for specific professors or institutions to find ratings and comments from other students. Each professor is typically rated in categories such as overall quality, difficulty, and clarity. Additionally, students can leave written reviews detailing their personal experiences and providing additional insights (Sperber, 2018). RateMyProfessors.com aims to assist students in making informed decisions when selecting classes or professors for their courses. It allows users to gauge a professor's teaching style, difficulty level, and general reputation among students. The dataset comprises 975,860 reviews from year 1999 to year 2020. This includes written feedback from students' satisfaction ratings ranging from 1 to 5 (with 1 being the lowest and 5 being the highest), the difficulty level of the class (measured similarly to the satisfaction ratings), university names, emotions inferred from the written feedback, the word count of the feedback, and the month and year when the feedback was provided.

The SEA system uses the open dataset that was retrieved from RateMyProfessors.com, for the implementation of big data analytics as shown in figure 1. Although we have used an existing dataset, this system can be applied to collecting real-time data, such as Tweets, Facebook posts, blogs, and news articles from the Internet. The whole process begins by moving the dataset into a database.

Figure 1. The SEA system diagram composed of the raw dataset (RateMyProfessors), database, pre-processing, and comment analysis



DATA PRE-PROCESSING

Given the vast amount of data, it becomes essential to undertake a data cleaning procedure, in order to extract only pertinent information that can provide meaningful analysis. Data cleaning refers to the process of identifying and rectifying corrupt or inaccurate data within a database. This process involves identifying incomplete, incorrect, inaccurate, or irrelevant components of the data and subsequently replacing, modifying, or eliminating such flawed or coarse data. Data cleansing can be conducted interactively using data wrangling tools or through batch processing via scripting (Wikipedia, 2021).

Before conducting the comment analysis, tokenisation, and part-of-speech (POS) tagging are employed. Token refers to an instance of a sequence of characters in a text that is grouped as a meaningful element for processing, like a word, number, or punctuation mark. In NLP, tokens are the basic units of text that have been identified as significant, typically by an algorithm that segments the text. Tokenization in the context of NLP is the process of breaking down a stream of textual information into smaller units called tokens, which are often words, phrases, symbols, or other meaningful elements. This is a fundamental step in preparing text for further processing such as parsing, part of speech tagging, and semantic analysis. Tokenization is necessary because it helps in recognizing the boundaries of words and other elements within unstructured text, which computers can then process and analyse (manning et al., 2008).

POS tags are special labels assigned to each token in a text corpus, indicating its part of speech, and often including other grammatical categories such as tense, number, and case. When a text corpus is processed for POS tagging, each word, symbol, or entity that can be assigned a POS tag is considered a token (Jurafsku & Martin., 2021). These tags play a crucial role in corpus searches, text analysis tools, and algorithms. POS tagging is a widely used process in NLP that involves assigning specific labels to each word token in a text, facilitating assumptions about semantic meanings based on the characteristic structure of lexical terms within sentences or texts (Towards Data Science, 2021). POS tags enable automatic text processing tools to consider the specific part of speech associated with each word, allowing for the integration of linguistic criteria alongside statistical analysis. In languages where a single word can serve multiple parts of speech, POS tags serve the purpose of distinguishing between different instances of the word, depending on whether it is functioning as a noun or a verb, for example. Furthermore, POS tags play a vital role in searching for instances of grammatical or lexical patterns without specifying a particular word. They provide the flexibility to either search for patterns without specifying a concrete word or to combine both approaches simultaneously (Sketch Engine, 2021).

The subsequent step involves lemmatization, a linguistic process that involves grouping the various inflected forms of a word so that they can be analyzed as a single entity, represented by the word's lemma or dictionary form. For instance, words like "runs," "running," and "ran" are all different forms of the word "run," with "run" being their common lemma. Word grouping, or word clustering, can be a valuable technique in the analysis of textual data, especially when dealing with large datasets or trying to reduce dimensionality. This approach can help simplify and enhance the interpretability of the analysis results. In this research, students employed numerous similar words that can be regarded as having the same meaning for the analysis, such as 'good,' 'wonderful,' and 'excellent.'

The Comment Analysis Module

The pre-processed data is then moved into the comment analysis stage, which includes three modules: keyword analysis, sentiment analysis, and category classification. The keyword analysis involves scanning the data for occurrences of keywords or phrases in the comments. In big data analysis, keyword analysis is used to extract meaningful information, patterns, and insights from large volumes of data by identifying and analyzing specific keywords or terms that are relevant to the research or the problem being addressed. In this research, keyword analysis is employed to identify occurrences of pre-processed words, to discern the interests, preferences, and concerns of students, while also uncovering the relationships among these keywords. This analysis provides insights into the primary factors influencing satisfaction ratings and sentiment analysis.

Sentiment Analysis is a crucial aspect of comment analysis. It serves as a vital component in the original SEA system too. However, the RateMyProfessor dataset already includes pre-analysed sentiment values. In this research, we will not delve into sentiment analysis as it has already been conducted on the dataset. Also, the primary focus of this research is to introduce the entire system.

Category classification, also known as text classification or document categorization, is a fundamental task in NLP that involves automatically assigning predefined categories or labels to text documents based on their content. The goal of category classification is to develop algorithms and models that can accurately identify the most appropriate category for a given document, enabling efficient organization, retrieval, and analysis of large volumes of textual data (Jin et al., 2016; Wang et al., 2017). In this paper, the category classification reveals the main primary topics that students are interested in or discussing.

While the comment analysis module in the SEA system includes keyword analysis, sentiment analysis, and category classification, this paper will mainly focus on keyword identification and frequency in relation to satisfaction ratings.

Keyword Identification and Frequencies Related to Satisfaction Ratings

The dataset retrieved from RateMyProfessor comprises 975,860 reviews from the year 1999 to the year 2020. This includes:

- ‘Satisfaction ratings’ ranging from 1 to 5 (with 1 being the lowest and 5 being the highest),
- ‘Comments’ or ‘written feedback’ from students
- ‘Emotions’ resulting from the analysis of the written feedback

The dataset also includes other information such as university names, the word count of the feedback, and the month and year when the feedback was provided. This information is not considered in this research.

The SEA system analysed two distinct groups: the ‘satisfied’ group, represented by ratings of 4 and 5, and the ‘unsatisfied’ group, represented by ratings of 1 and 2. The frequency of a keyword might be an indicator popularity or importance of an idea. However, the frequency of keyword groups without considering the context limits the ability to derive correct results. Following commonly accepted strategies in NLP, the authors need to be partly involved in the analysis, manually tuning the keywords considering the context which is the grouping similar keywords into one keyword group. When the SEA system retrieves the most frequent keywords in the comments, it often finds multiple keywords with similar meanings, such as ‘good,’ ‘better,’ ‘nice,’ ‘excellent,’ ‘wonderful,’ etc., all indicating a positive response to the course or teaching. To extract unique keywords, the keyword analysis process incorporates a step to group similar keywords together. Table 1 illustrates a few examples of keyword grouping:

For the keyword grouping task, the SEA system utilises a thesaurus to retrieve synonyms. However, it necessitates manual revision by the researcher, as some synonyms may be irrelevant in the given context.

Top 20 Most Frequent Appeared Keyword Groups

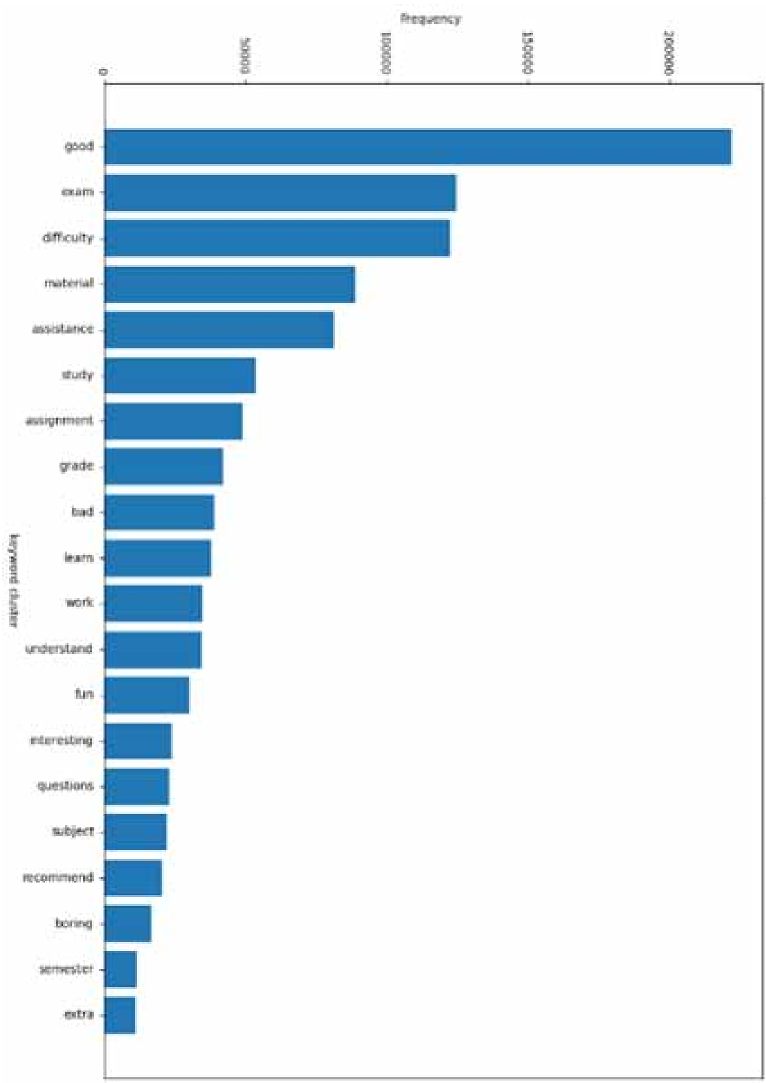
The examination of the most frequently appearing keywords in the context of the reviews helped to draw some conclusions about the various dimensions of the students’ experiences. Figure 2 shows the top 20 most frequently appearing keyword groups.

The top keyword groups indicate what is an important element for university students to consider when it comes to student perceptions and priorities within the educational environment.

Table 1. Keyword group table

Keyword Groups	Member Keywords
grade	grade, pass, fail, score, mark
assessment	test, exam, quiz, examination
assignment	project, assignment, homework
assistance	assistance, assist, help, support, care
good	nice, well, great, best, wonderful, excellent, amazing, awesome, acceptable, exceptional, favourable, marvellous, positive, satisfactory, satisfying, superb, valuable, pleasing, superior, worthy, admirable, deluxe, precious, splendid, perfect
bad	bad, worse, worst, awful, crummy, dreadful, poor, unacceptable, garbage, imperfect, inferior, junky, deficient, defective, inadequate, icky, incorrect, dissatisfactory, dissatisfaction, rude
difficulty	difficult, tough, challenging, laborious, painful, problematic, severe, backbreaker, difficile, effortful, not-easy, hard, easy

Figure 2. Top 20 most frequently appearing keyword groups



Overall, students most frequently used the keywords within the 'good' keyword group indicating a positive sentiment towards the subject matter under review.

This research randomly selected some comments associated with each keyword group and investigated the implications and related situations. The keyword groups "exam" and "difficulty" feature prominently, indicating that students pay significant attention to the nature of examinations and the associated challenges.

The presence of "material" and "assistance" indicates the weight students give to the resources and help provided during the course. Students place significant value on courses that are thoroughly supported with appropriate materials and assistance, including office hours, teaching assistants, and supplementary resources.

The appearance of "study" alongside "assignment" and "grade" gives an insight into the students' focus on performance metrics. They seem to be closely monitoring the relationship between their study efforts, assignments submitted, and the grades they receive. This could imply a keen interest in understanding how their efforts translate into tangible results.

Furthermore, the presence of keyword groups such as "learn", "work", and "understand" emphasizes the importance students place on the actual process of learning. They are not merely looking for a grade, but genuinely seek to grasp the content, work through challenges, and emerge with a better understanding of the subject matter.

On the lighter side, the inclusion of "fun" suggests that while academic rigor is essential, students also appreciate an element of enjoyment in their learning journey.

In contrast, the keyword group "bad" appearing on the list serves as a reminder that not all feedback is positive. It's crucial to delve deeper into the context surrounding this term to pinpoint areas of potential improvement.

In conclusion, this graph offers a bird's eye view of student perspectives, touching upon various facets of their learning experience. From the importance of course difficulty and available resources to the balance between work and enjoyment, the feedback provides a roadmap for educators to refine and enhance their teaching methodologies and course structures.

Top 20 Most Frequently Appearing Keyword Groups in the Satisfaction Rating Between 4-5

Figure 3 shows the top 20 most frequent keyword groups that appeared in the satisfaction rating between 4 to 5.

The total number of comments in the 4 to 5 satisfaction rating group is 481,117.

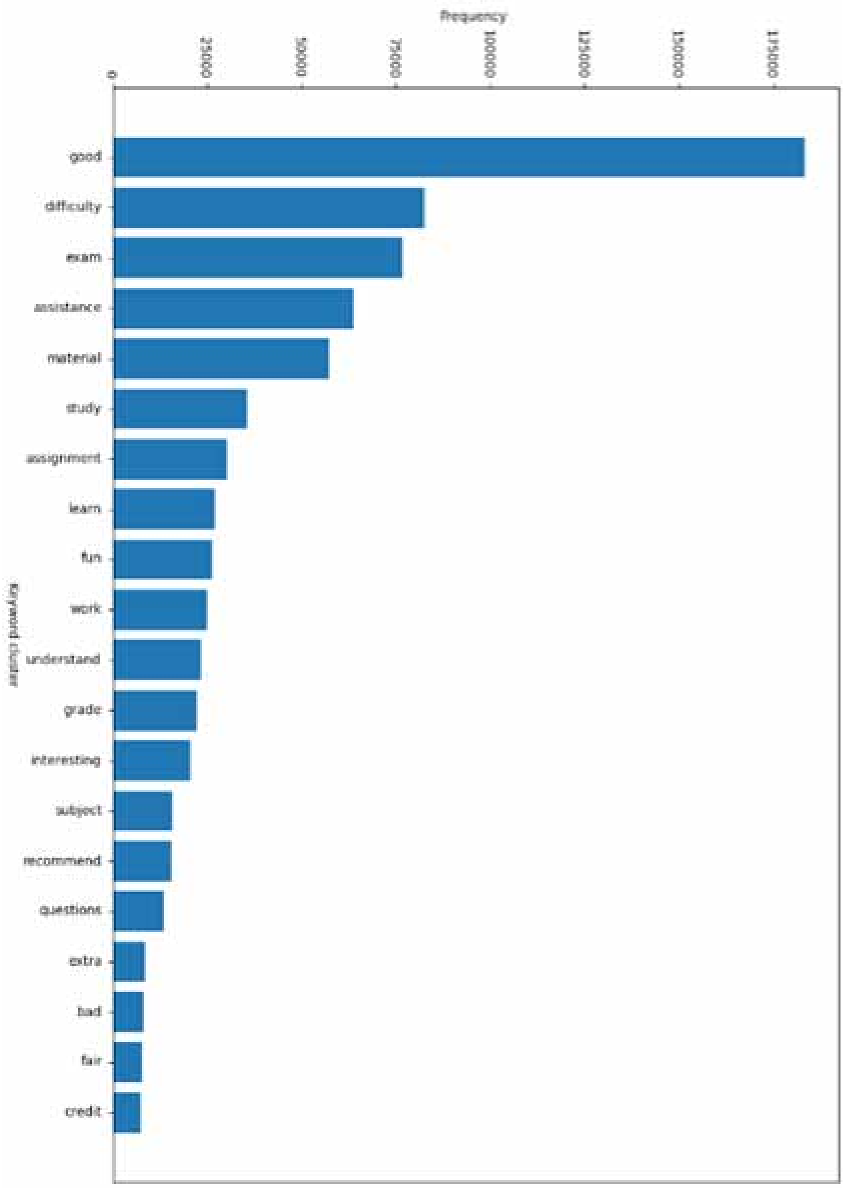
The keyword group "good" stands at the forefront, indicating students' overarching positive sentiments regarding their educational experiences. This term's prominence, when taken together with the context of the comments in the dataset (as reviewed by the human researcher), underscores that students predominantly found their academic experiences favorable. This keyword group often implies negative meaning when they are used with negative adverbs such as no, not, never, etc.

The prominence of the keyword group "difficulty" following closely indicates the significance of academic rigor and challenge in shaping student perspectives. Students, it seems, highly value a balanced curriculum that, while challenging, remains accessible and manageable, allowing them to navigate their academic pursuits successfully.

The high frequency of the keyword group "exam" is an indicator that evaluations play a central role in shaping students' satisfaction. The very mention of these words reflects that the evaluation mechanisms are not only from an academic standpoint but also in how students perceive their overall educational journey. In existing literature, it is acknowledged that assessment and its feedback mechanisms are highly significant influences on the student experience (Nicol & Macfarlane-Dick, 2006).

The keyword groups "Assistance", "material" and "assignment" were the next most frequently occurring. Taken in context this suggests that students highly value the support and resources provided

Figure 3. Top 20 most frequent appearing keyword groups in the satisfaction rating between 4-5



to them. Their frequent occurrence points towards students' appreciation for academic help, which could include both faculty guidance and supplementary resources and support in completing their assignments. This has also been acknowledged in other literature.

The keyword groups "study", "learn", and "understand" emphasize the essence of university education the process of acquiring knowledge. Their inclusion at high frequencies indicates that satisfied students find the act of learning itself fulfilling and are keenly invested in their academic growth.

Interestingly, the keyword group "fun" features on the list, suggesting that beyond the rigors of academic work, students also value elements of enjoyment in their learning journey.

Further down the list, terms like "work", "grade", and "subject" offer insights into students' perceptions of their academic endeavours, the evaluation processes, and the courses themselves. The balance between workload, performance feedback (grades), and the relevance or interest in subjects seems to play a role in student satisfaction.

The inclusion of keyword groups such as "interesting", "recommend", and "questions" indicate that students not only desire academic rigor but also seek courses that stimulate their curiosity and are worth recommending to peers. It is a testament to their desire for a comprehensive academic experience, which is both challenging and engaging.

To give a better understanding of each keyword, examples of actual written reviews from RateMyProfessor are given below with the main keywords group that occurs highly frequently within the satisfaction rating range.

The keyword group "exam", along with its associated discussions around the "quality of exam questions" and "difficulty of the exam", garnered considerable attention. Notably, there was a clear inclination towards satisfaction with the quality of exam questions. This satisfaction, contrasted with mentions of exam difficulty, perhaps indicates that participants appreciate balanced challenging questions that test their grasp but are framed with clarity and precision. The keyword groups "exam", and "assignment" also revolved around the satisfaction with the quality of questions and tasks presented. This showed a broader satisfaction with evaluative components in the curriculum, beyond just examinations.

Examples of written reviews are:

"Excellent teacher. He uses example problems to explain each concept, which ultimately makes up the tests."
"Took him for both Business law & management. I love this man! His class is not about memorizing the material, but about understanding it and being able to work with your classmates. His exams test your understanding and deciding on an answer based on what was given and being able to work with others."
"Very hard homework but easy tests. If you listen to the lectures and attend class you will do great, reading the book is mostly optional."

A recurrent theme, evident from the keyword group "assistance", revealed a significant number of reviews that underscored a positive experience when receiving help. This consistent mention of assistance adds weight to the argument that students place inherent value on effective support mechanisms within the academic framework, underscoring the importance of readily available help during their academic journey.

Examples of written reviews are:

"It's a tough course, be prepared to work and spend some time teaching yourself in the lab. He is a good teacher and does provide you with ample examples and <u>assistance</u>*.",*
"Has a style of teaching that is engaging and easy going. She brings everyday events into the class and demonstrates relevance to the material. When asked for <u>assistance</u> *she is unhurried and always free with her time. I will miss her lectures."*
"Professor is nice, helpful, and will give you extra <u>assistance</u> *in her office at the drop of a hat. Check her office regularly if you want help, because she's often in there outside of office hours working on this and that. Very nice prof."*

The keyword group "material" revealed predominantly positive sentiments, particularly regarding the quality and variety of class teaching materials. The emphasis on both "quality" and "variety" may suggest that participants value diverse learning resources that are also of a high standard. This underscores the significance of curating comprehensive teaching materials that cater to varied learning styles and preferences.

Examples of written reviews are:

"Excellent professor! He makes the material crystal clear to comprehend and uses logic and common sense more than anything. Expects the most from his students. Tests are easy if you do hw and go to his office for help. Funny guy. Not lenient with grading; what you wrote is what you get. Overall, you will know your stuff if you take him."
"Explains material well. His grading is based on exactly what you get. No rounding up if you've worked hard or have shown a lot of effort. Good guy overall."
"He's a good professor- and is also very helpful whenever you need help on the Physics homework. He explained the material *well and made the class an enjoyable learning experience."*

Finally, discussions stemming from the keyword "difficulty" mainly revolved around the themes of hard or easy and the pursuit of knowledge in relation to learning level expectations. The consistent mention of striving for knowledge to attain good grades may indicate a genuine passion for learning among the students.

Examples of written reviews are:

"This is a really hard *class. You have to go to class. You have to do the readings. You have to do well on the papers. He is a very good teacher and knows everything there is to know about Literature, but he will not give."*
"Nice teacher, but work can be hard*. He expects a lot so I suggest if you want to do well on assignments you meet with him so he can help you. Not an easy class."*
"You could pass the class if you only showed up for exam days... Everything is online. Nice guy, and easy *to talk to, sometimes his voice is annoying, but would be worse. Wants everyone to do well, and is willing to work with you."*

To summarise, the frequent occurrence of these keyword groups among students who offered a satisfaction rating between 4 and 5 shines a light on the multifaceted aspects of their positive educational journey. The results hint at an academic environment where challenges and support coexist, where students are actively engaged, and where they perceive their experiences as largely positive, nuanced by occasional areas of concern or improvement. From academic challenges and resources to the joy of learning and the broader university environment, these results can serve as a factor check for educational institutions aiming to enhance student experiences.

Top 20 Most Frequent Appearing Keyword Groups in the Satisfaction Rating Between 1-2

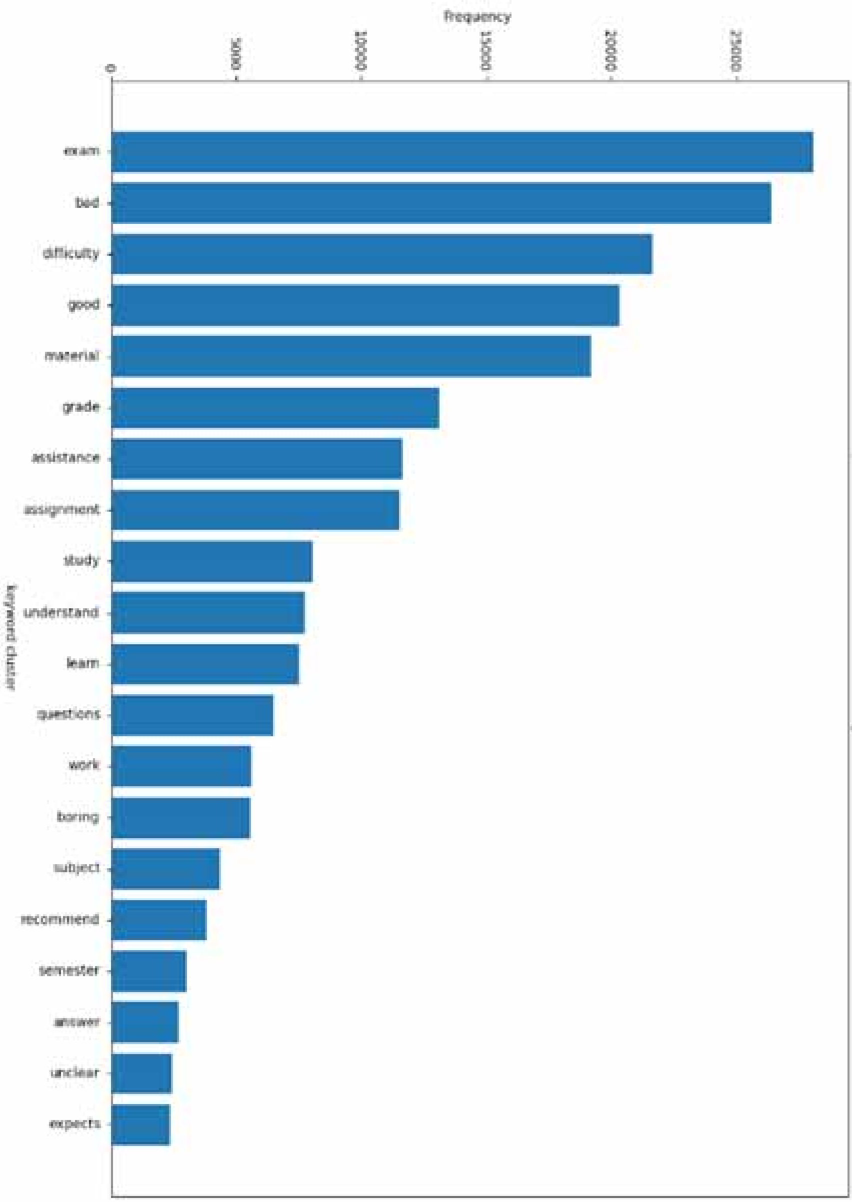
Figure 4 shows the most frequent keyword groups occurring in the student comments which rated their experience between 1 and 2.

The total number of comments in the 1 to 2 satisfaction rating group is 186,398. The keyword group "exam" stands out as the most frequently mentioned keyword group for those rating their experience between 1 and 2. This highlights the significant role that examinations and assessments play in students' discontent. The high frequency of this keyword group suggests that the structure, fairness, or content of exams might be perceived as problematic by students who report lower satisfaction.

Examples of written reviews are:

"Super hard! Homework is not relevant to exam *material and he gets annoyed if you go to clarify things during office hours. You're better off self-studying and using Slader to solve your problems. Avoid!"*

Figure 4. Top 20 most frequent appearing keyword groups in the satisfaction rating between 1-2



"She's a nice person but her teaching style is entirely based around very low info power points and she says that the tests are based on the power points but they never were. She kept changing her teaching style when it came to reviewing for <u>*exams*</u> *and it made it so you had no idea what the exam was going to be over. Talks VERY fast during lectures."*
"DO NOT TAKE HER. Worst professor I have ever had. <u>*Exams*</u> *are NOTHING like anything she teaches. She should not be a professor, plain and simple. This class is an absolute joke for a 100-level class. I am a BMS student and her class was horrible. Made me drop the nutrition emphasis. Take this class with ANYONE else."*

Following "exam", the keyword group "difficulty" features prominently, suggesting that the perceived level of challenge or rigor of the courses might be a point of contention. This could imply that some students feel overwhelmed or find the curriculum too demanding. This could even mean the course was too easy for the students and they may have perceived the course presented had no challenge or anything new to learn.

Examples of written reviews are:

"Super hard*, first midterm was somewhat by the books but the second midterm and final was terrible. Homework did not help at all."*
"The course itself covers content that is fairly straightforward and relatively easy*. The tests are not. There is no correlation whatsoever between the degree of* difficulty *of the lecture and content covered and the exams. She is terrible. She doesn't teach you. She cares about her students at only a surface level. Just terrible."*
"He seemed like a cool professor at first but the exams seemed to be based on the most random facts that were just in his head. the exams varied in difficulty *but were generally unpredictable. he played movies most days instead of teaching. don't buy the books."*

The keyword groups "good" and "bad" appearing high on the list indicate a diverse range of feedback. Even among students with low satisfaction, some aspects of their experience might be perceived positively, while others negatively. The term "bad" especially underscores the presence of negative sentiments, possibly towards course content, teaching methods, or other university facets. This can also mean that in one feedback they may have indicated what was perceived as good and bad.

Feedback keyword groups such as "material", "assistance", and "assignment" emphasize the importance of academic resources, support, and evaluative tools. Their presence in feedback with low satisfaction ratings might suggest that students feel under-supported, lack quality study materials, or find assignments unhelpful or overly demanding.

Examples of written reviews are:

"I've never been more confused in all my school years. He is very disorganized. Teaches a topic at the end that is not available online, in textbooks, or even through adequate in-class materials*. I've never seen the whole class so confused and disappointed in a teacher. You've been warned."*
"She is impossible to learn from in the online class. She grades extremely harshly for a 4-week class and gives little to no assistance *or clarification when needed. I definitely don't recommend taking her online or for a short period."*
"Very knowledgeable about his field, but he's just not good at passing that knowledge on to his students. Test averages for the class were always failing. Lab assignments *were not well written, and it was hard to figure out what he wanted you to do."*

The keyword groups "grade", "understand", and "learn" are reflective of students' primary academic goals: understanding content, learning, and receiving satisfactory grades. Their prominence in low satisfaction feedback might indicate perceived shortcomings in teaching methods, grading fairness, or the clarity of course content.

Keyword groups such as "study", "questions", and "work" further illuminate the students' academic journey. The frequency of these terms in negative feedback may suggest that students faced hurdles in their learning journey, possibly struggling to assimilate content, having their questions unanswered, or facing difficulties in their study routines.

Interestingly, the presence of "boring" provides insights into the more personal or interpersonal aspects of the student experience. Courses, lectures, or professors might be perceived as dull or uninspiring, and certain subjects or professors might be recommended to be avoided.

CONCLUSION

The preliminary analysis of the 'RateMyProfessors site using big data analytics methods has resulted in two important lessons learned.

Firstly, keyword analysis is a process cantered on the identification of recurrent words or phrases, providing insights into prevalent patterns and student perceptions. The comments contain a lot of non-important or irrelevant information, so to retrieve a unique and meaningful top-keyword set, it was imperative to undertake meticulous data cleaning and keyword grouping.

Secondly, the limitations of NLP in capturing nuanced linguistic intricacies came to the fore. Human intervention was deemed essential to gain a sense of context. Through manual inspection, we ensured the validation of NLP results, enriching the analysis by providing the much-needed contextual depth. Since the results from the automated analysis gave very limited information about the student experience, human intervention was then required. Despite the challenges, the initial analysis and results of the analysis of the comments in the dataset highlight aspects of the usefulness of big data methods for understanding the student experience. The nuances of human language mean that NLP results on their own, give limited understanding. Despite this, the method provided some high-level insights into important aspects of their experiences. The analysis reported in the present article is a preliminary outcome of a work in progress. Subsequently, the data reported centers around word frequencies. Future analysis will include sentiment analysis and correlation studies. Sentiment analysis has gained traction in fields such as marketing and other social research because of its potential to help understand opinions through the use of large, unstructured textual environments (Mills & Unsworth, 2018). It must also be acknowledged that the present work is using only one data set from one source and thus there are limitations to generalizability. A deeper exploration of the usefulness of data analytics methods will necessarily involve the application of the technique to other large qualitative data sets. The structure of the RateMyProfessor.com website cannot be ignored as potentially influencing the usefulness of the applied big data methods. The work presented in the article is the initial stages of research and can be considered a 'proof of concept' approach.

Further work also involves a systematic and deep review of existing literature. Comparing the results of analyzing student experiences with the utilization of big data analysis to the results from traditional surveys or other methods used in previous research would provide valuable insights into the usefulness of utilizing big data analysis in education.

The SEA system introduced in the present article offers the advantage of reducing some of the human effort and time required to process large volumes of qualitative data. Qualitative researchers are not unfamiliar with "big data" even before current computing power becomes available (Sarker, 2021). One example of this is the Operation War Diary project involved transcribing 1.5 million pages of unit war diaries in an attempt to compose stories of the British Army during the First World War (Greenemeier, 2014 cited in Sarker, 2021). Typically, "big data" has been associated with quantitative research methods (Sarker, 2021). Subsequently, big data analytics methods have been under-explored.

The complexity of human behavior, which is the subject of qualitative research, has to be acknowledged but manual analysis, though possible, is extremely resource-intensive. It is paramount to explore the affordances of technological innovations such as big data and find ways can make the process "simpler, easier, and faster" (Sarker, 2021). That technology can help make the process of qualitative analysis faster is not simply a matter of efficiency. The ability to analyse large volumes of qualitative data quickly opens new possibilities for understanding phenomenon dynamically. This can give a greater understanding of how various factors are influencing the nature of the phenomenon, providing a 'finger on the pulse' approach to qualitative research. Furthermore, the advent of technologies has meant that there is now a wealth of "big qualitative data" and opportunities to collect and analyse previously scarce qualitative data are growing with technological innovation. As some researchers urge “both qualitative and quantitative researchers have an important role to play in rethinking and refining how big data is collected, prepared, analysed and presented and in investigating the actual processes and consequences of using big data analytics” (Abbasi et. al 2016 cited in Sarker (2021, p. 142). It is hoped that the present work being undertaken by the authors contributes to the process of rethinking use and processes of big data in qualitative contexts.

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