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Analyzing the Impact of Online Learning on Higher Education: A Text Analytics Approach

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Abstract
Amidst the relentless upheaval caused by the ongoing Covid-19 pandemic, the higher education landscape finds itself compelled to pivot towards internet-mediated learning modalities. This shift, while necessary for continuity, has engendered profound repercussions for students, educators, and administrative staff alike. Foremost among the concerns is the discernible impact on student learning outcomes and academic performance. Studies, such as those conducted by Brookings and The University of Chicago, underscore the alarming projections of learning loss and escalating failure rates within this context. Bloom, a prominent higher education institution grappling with the tumult of the pandemic, has witnessed a palpable decline in average grades since its onset. Recognizing the imperative to stem this tide and foster informed decision-making, Bloom endeavors to harness the power of text analytics. Through the systematic analysis of unstructured textual data sourced from diverse channels—ranging from social media platforms to educational websites—Bloom endeavors to unveil underlying patterns, discern actionable insights, and drive strategic interventions. This article presents a comprehensive framework delineating Bloom's foray into text analytics, elucidating the attendant challenges, proposed solutions, and anticipated implementation strategies. By delving into the nuances of managing unstructured textual data and navigating the complexities thereof, this endeavor seeks to empower Bloom with the tools and insights requisite for optimizing academic performance and mitigating the deleterious effects of the pandemic.

Keywords: Text Analytics, The Higher Education Industry, Failure rate, Unstructured textual data

1 Introduction

In this article, we will be employing analytical techniques to address the operational challenges at Bloom, an educational institution offering a diverse array of teaching and learning methodologies. Bloom maintains its own website and social media presence, including Facebook. Currently, the institution grapples with the complexities of aggregating unstructured textual data from various channels such as social media platforms, emails, and educational websites. Moreover, the prevailing pandemic has significantly impacted Bloom, necessitating the transition to online learning as traditional classes face cancellation mandates from education authorities. Consequently, a concerning trend of student attrition and diminished academic performance has emerged, posing formidable challenges to Bloom's educational mission [1]. Our objective is to conduct an analysis by gathering unstructured text data from multiple sources to elucidate the underlying issues at Bloom [2]. By facilitating better decision-making processes, we endeavor to enhance the institution's academic outcomes and bolster its overall performance.

1.1 *Text, web, social media analytics*

In this article, we will employ text analytics, social media analytics, and web analytics to analyze students' progress and behavior based on text data [1], [2]. Text analytics enables the extraction of valuable information from a corpus of text, such as students' emails, performance, grades, and more, utilizing computational techniques [3]. Additionally, text analytics can enhance search engine performance, thereby facilitating a faster user experience for students and significantly improving their academic outcomes. However, text analytics in education encounters challenges, such as handling data with incorrect spellings or syntax errors within specific sentences [1], [3].

Social media analytics and web analytics will complement text analytics in our analysis of Bloom's organizational data [4]. We will scrutinize Bloom's Facebook Page and Learning Management System (LMS) through these methodologies. The Bloom Facebook Page will yield insights into various metrics, including the geographic distribution of followers, age demographics, engagement levels, and monthly follower growth [5]. By interpreting these insights, we can gauge the page's popularity trends and identify target areas or demographics for promotion.

Similarly, the LMS will provide valuable data on student engagement, such as quiz attendance and assignment submissions. Leveraging LMS analytics, we can develop a student progression dashboard for educators, enabling a comprehensive understanding of students' academic advancement [1], [6]. This tool will empower both educators and students at Bloom to monitor and track progress throughout the semester effectively.

1.2 *Stream analytic and Geospatial analytics*

Stream analytics involves the processing of real-time data, enabling constant calculation of statistical analytics as data moves in real-time [7]. This capability significantly enhances decision-making speed and efficiency, providing organizations like Bloom with a powerful tool for making timely and informed decisions. Particularly during the Covid-19 pandemic, Bloom has shifted to online learning since 2020, necessitating innovative approaches to monitor and understand student progress and behavior. Stream analytics play a pivotal role at Bloom, offering valuable insights into students' academic journey and behavior patterns [7], [8].

One notable application of stream analytics and geospatial analysis at Bloom is through the utilization of the Learning Management System (LMS). The LMS serves as a comprehensive platform for reporting and analyzing students' progress and behavior. When students log in to the LMS, a myriad of data points including geographic location (longitude and latitude), time, duration, and various other factors are captured, contributing to a substantial volume of data [6], [8], [9].

According to Aguilar-Ruiz et al. [7], stream analytics empowers organizations to process massive volumes of data streaming into their systems with high velocity. Georeferenced data such as geographic coordinates is considered real-time data and plays a crucial role in geospatial analysis. This analytical approach involves collecting, displaying, and manipulating geographic information system (GIS) data, leveraging geographic coordinates and special identifiers such as street addresses and postal codes [8], [9].

The data collected through Bloom's LMS is instrumental in analyzing student behavior and understanding how students are influenced by their geographic environment [6], [7]. Since the pandemic, all students have been required to engage in online learning, resulting in a significant drop in Bloom's average grades. However, by incorporating geospatial analysis into the education industry, organizations like Bloom can enhance their understanding of student behavior and academic performance, ultimately improving educational outcomes and advancing both theory and research design in the field.

1.3 *Management issues of analytics*

According to Irti [10], businesses across various industries, including education, face challenges related to analytics management. Three key areas of concern identified in the report are data privacy protection (34%), data accuracy (26%), and data processing and analysis (24%). Protecting data privacy has emerged as a critical consideration, reflecting the growing emphasis on safeguarding sensitive information.

In line with this trend, companies must adhere to regulations governing the use of data by providing clear guidelines to users visiting their websites. An article by Makhova [11] emphasizes the importance of companies informing users about the data being collected and who has access to it. Similarly, Bloom must implement regulations or terms and conditions on its website to inform students about the data being collected and who can access it. By incorporating a checkbox for students to agree to these terms before their data is captured, Bloom can ensure transparency and compliance with data privacy regulations.

Moreover, addressing concerns about data accuracy and effective data processing and analysis is crucial for Bloom to derive meaningful insights from its data. By investing in robust data management systems and analytics tools, Bloom can enhance data accuracy and streamline the process of analyzing and deriving insights from its data. This will enable Bloom to make informed decisions that drive academic excellence and student success.

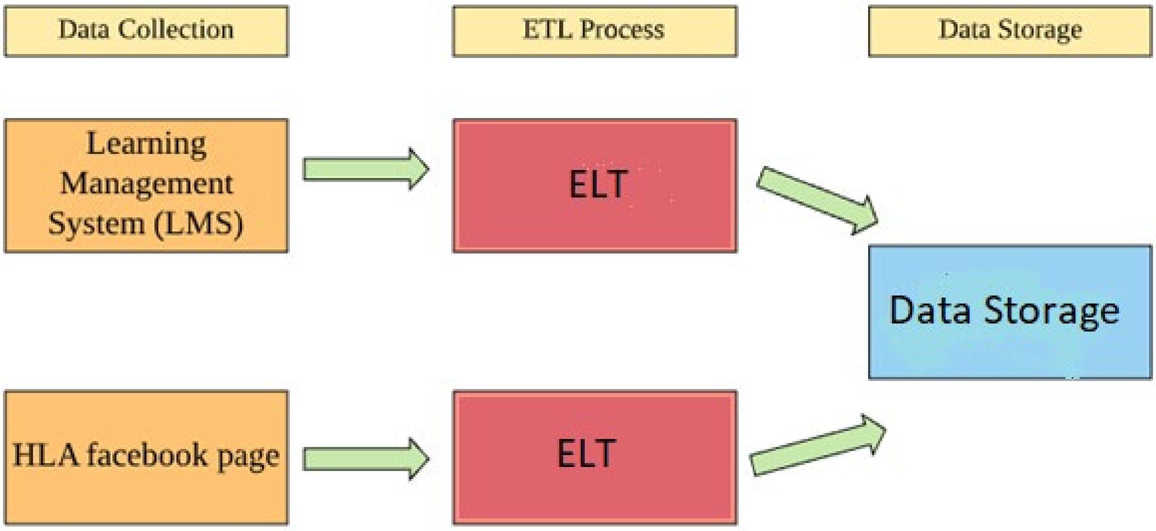

Figure 1. Initial Framework

According to Figure 1 above, Bloom will need to begin by collecting the necessary textual data. This includes obtaining students' coordinates (longitude and latitude), their progression percentage in specific subjects, as well as discussions and reviews from various platforms. This data collection process is essential for enhancing decision-making accuracy and ultimately improving Bloom's average grades. To achieve this, Bloom can gather unstructured textual data from its Facebook page and the Learning Management System (LMS).

Once collected, the data will undergo extraction, cleaning, loading, and transformation processes to convert the unstructured textual data from various sources into a structured format suitable for storage and analysis. This step is crucial in ensuring that the data is standardized and ready for analysis. By systematically organizing the data, Bloom can effectively leverage analytics tools and techniques to derive meaningful insights that inform strategic decision-making and enhance academic outcomes.

2 Problem Statement and Proposed Solution

Within Bloom, data such as students' progression, including online assessment works and time taken to complete reading certain slides from the Learning Management System, holds immense value for analyzing student performance and behavior in the education sector. These unstructured textual data streams could generate millions of data points in a second or millisecond, contributing to a substantial volume of textual data within the organization. Despite the sheer volume, this data is rich in insights and presents educators with opportunities to gain deeper insights into students' academic journey and behavior. However, the dynamic nature of this data poses a challenge. Some data may lose its relevance over time, requiring swift responses from educators to fully capitalize on its value as soon as it becomes available. Consequently, one of the primary challenges faced by Bloom is managing the large-scale influx of unstructured textual data. Handling such a vast amount of data manually would be arduous and inefficient without the proper utilization of analytical tools.

For instance, if Bloom were to post a survey on its Facebook page to gather information about students' vaccination progress, processing the data manually in the event of a large number of respondents would be challenging. Manual processing not only consumes considerable time but also increases the risk of errors and biases in decision-making. As noted by Lwin et al. [9], the sheer volume of unstructured textual data, coupled with the need to examine each word meticulously, renders certain types of unstructured analysis resource intensive. Thus, Bloom must leverage advanced analytical tools and techniques to effectively manage and analyze its large-scale unstructured textual data. By doing so, Bloom can derive actionable insights that inform strategic decision-making and drive academic excellence within the organization.

Accurate records of students are paramount for educators at Bloom to analyze their performance effectively and make informed decisions. Additionally, having correct student information is crucial for the admissions department to track prospective students throughout the enrollment and application processes. Therefore, it is imperative that errors such as misspelled words in students' names, birthplaces, student IDs, etc., are corrected during the enrollment process to ensure accurate interpretation of student records.

One of the challenges encountered within Bloom is the analysis of textual data, particularly when dealing with incorrect spelling and syntax errors in sentences. Through our research and analysis of students at Bloom, we have found that approximately 30% of students are careless when entering their personal information during the enrollment period. Students often inadvertently delete or add words or leave extra spaces within words. These errors can lead to incorrect data collection and inaccurate decision-making for the admissions, educators, and the bursary department. Therefore, addressing these errors in textual data entry is essential to ensure the integrity and accuracy of student records at Bloom.

2.1 *Text Data Retrieval Perspective*

Within Bloom, we will implement an analytics framework to delineate key analytical outputs and products at each stage of the analysis process. Initially, data will be collected from various sources including the Learning Management System (LMS) and Bloom's Facebook page. This collected data will then undergo integration, consolidating it into a more valuable form for the organization. Subsequently, textual data will be transformed and stored in the data lake, where it will serve as a foundation for multiple analytics methods such as data analytics, enabling the extraction of meaningful insights for Bloom [12].

Following data integration and storage, analytics models will be developed to facilitate predictive analytics, descriptive analytics, prescriptive analytics, and diagnostic analytics. These models will leverage the integrated data to generate actionable insights that inform decision-making processes within Bloom [13]. Finally, to visualize and communicate the outcomes of the analytics process, an analytics dashboard will be created. This dashboard will provide users with access to various types of analysis, empowering them to make informed decisions that benefit the organization. Through the implementation of this comprehensive analytics framework, Bloom will enhance its capacity for data-driven decision-making and strategic planning.

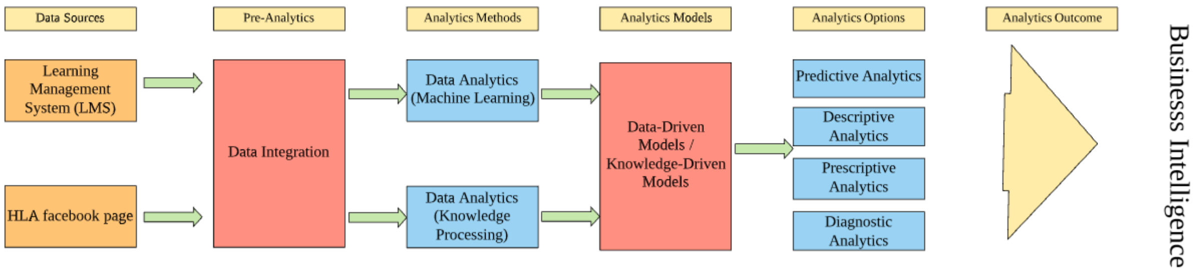

Figure 2. Proposed Framework

To address the business challenges outlined above, a solution is proposed for Bloom. This solution centers around the concept of data integration, which involves combining data from various sources into a unified structure. This process, often achieved through approaches like ELT (extract, load, transform), enables Bloom to preprocess unstructured textual data into a clean format. Managing unstructured textual data can be challenging, but employing the right techniques can simplify the process. One such technique is to consolidate all data sources into a single storage unit, allowing Bloom to integrate both static text from its Facebook page and dynamic text from the LMS. This approach reduces the complexity of managing textual data and facilitates comprehensive analysis, such as understanding student performance and behavior by combining data from Bloom's Facebook page and LMS.

Furthermore, Natural Language Processing (NLP) will be integrated into the cleaning process. NLP, a powerful tool utilized by renowned artificial intelligence systems like Alexa and Siri, enables machines to understand written text or spoken words [14]. By leveraging NLP, Bloom can address the issue of incorrect textual data by identifying misspelled words and noisy data. Additionally, Symmetric Delete Spelling Correction (SymSpell), an algorithm widely used for autocorrection of spelling errors, can be applied to rectify detected spelling errors. Following the transformation process, the cleaned data will be stored in the data lake for further analysis and utilization. This comprehensive approach to data integration and preprocessing equips Bloom with the necessary foundation to derive meaningful insights and drive informed decision-making processes.

Once the clean data has been collected through the ETL process, Bloom will leverage it to perform various data analytics methods. These structured data sets will also serve as the foundation for conducting text mining activities and developing a comprehensive dashboard to gain insights into student behavior. Through data analytics, Bloom will be able to extract valuable insights, trends, and patterns from the collected data, enabling a deeper understanding of student performance, engagement, and learning preferences. Text mining, on the other hand, will allow Bloom to analyze unstructured textual data, such as student feedback, comments, and discussions from various sources like the LMS and social media platforms [15]. By applying text mining techniques, Bloom can uncover hidden patterns and sentiments within the textual data, providing valuable insights into student sentiments, concerns, and areas of improvement [16]. Furthermore, the creation of a dashboard will offer a visual representation of the analyzed data, making it easier for educators and administrators at Bloom to interpret and understand key metrics and trends. This dashboard will provide real-time updates and visualizations, allowing stakeholders to track student progress, monitor engagement levels, and identify areas for intervention or improvement. By integrating data analytics, text mining, and dashboard creation into its processes, Bloom can enhance its ability to make data-driven decisions, improve student outcomes, and optimize educational strategies.

2.2 *Why is data analysis useful for text analytics or text data retrieval*

Data analysis plays a crucial role in text analytics and text data retrieval, as various forms of data analysis involve text-based data. Leveraging text analytics or text data retrieval allows Bloom to efficiently convert unstructured textual data from data analysis into actionable insights through the application of Natural Language Processing (NLP) and analytics techniques. For instance, Bloom can utilize text analytics to transform unstructured geospatial data, such as coordinates of a location, into more organized data, such as place names. Similarly, Bloom can employ text analytics to analyze bounce rates from the Learning Management System (LMS), which constitutes web data, to gain insights into student behavior based on the percentage of students accessing specific web pages.

Text analytics encompasses a broader concept that includes data retrieval. This involves tasks such as searching and detecting relevant documents based on a given set of keywords. By integrating text analytics into its data analysis processes, Bloom can enhance its ability to extract valuable information from unstructured textual data, thereby improving decision-making and optimizing educational strategies. Additionally, the utilization of NLP techniques further enhances Bloom's capacity to process and analyze textual data efficiently, enabling deeper insights and informed decision-making across various aspects of the organization.

2.3 *The advantages and disadvantages of using text data retrieval for the particular industry*

The challenge of overwhelming data is a prominent issue within Bloom, as previously highlighted. Utilizing text data retrieval mechanisms, akin to search engines integrated within the Learning Management System (LMS), enables students to swiftly access relevant textual information using keywords or tags. This streamlined approach significantly reduces the time required for students to extract pertinent information from textbooks and dictionaries. Moreover, unlike certain paid search engines such as LexisNexis, text data retrieval within Bloom is freely accessible to students. However, there are drawbacks associated with text data retrieval for students. For instance, search engines may lead to dead links or redundant links, consuming valuable time as students repeatedly search for the same information.

Another limitation is that text retrieval fails to account for the semantic aspects of an inquiry. Text retrieval relies solely on word matching, potentially resulting in search engines returning irrelevant information based solely on keyword matches, rather than contextual meaning. For instance, if a Bloom administrator were to search for 'How is Alex progressing?', the search engine may not yield relevant content based on meaning, but rather return content containing matching keywords. Despite these limitations, text data retrieval remains a valuable tool for Bloom students, offering quick and convenient access to a wealth of textual resources. Efforts to address these drawbacks, such as refining search algorithms to incorporate semantic understanding, could further enhance the effectiveness of text retrieval mechanisms within Bloom's educational environment.

3 Challenges in Implementation

During the data collection process, Bloom encountered several challenges in gathering information from multiple sources. The sheer volume of data for each student, sourced from various platforms such as the Learning Management System (LMS) and Bloom's Facebook page, made the collection process time-consuming. Additionally, ensuring the privacy of the collected information posed a significant challenge. Any errors during the data collection phase could potentially compromise the confidentiality of students' and their families' information, leaving it vulnerable to misuse by unauthorized individuals responsible for safeguarding such data.

Manual data entry further compounded the challenges faced by Bloom during the data collection process. Not only was it inefficient, but it also placed considerable stress on staff members tasked with entering vast amounts of information manually. Implementing a web form and data collection platform integrated with the LMS is recommended to address these challenges effectively. By doing so, Bloom can streamline the data collection process, alleviating the burden of manual data entry and ensuring the accuracy and security of collected information. This technological solution will enable Bloom to optimize its data collection efforts, freeing up staff resources for more strategic tasks and improving overall efficiency in information management.

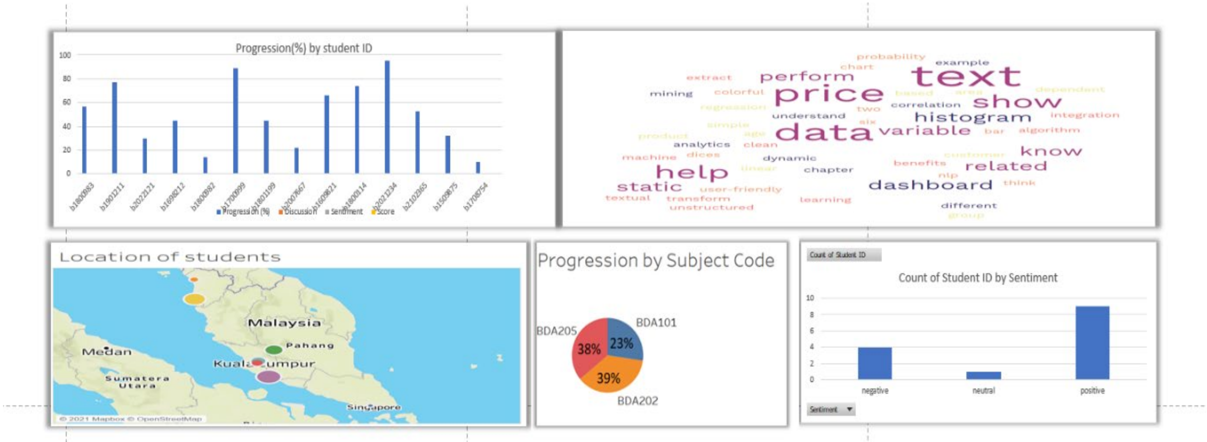

Figure 3. Analytics Dashboard

Figure 3 features various visualizations including bar charts, word clouds, pie charts, and map visualizations. Each visualization serves a specific purpose in conveying information effectively. The bar chart is utilized to illustrate the distribution of data points, providing insights into the frequency or distribution of specific variables. This visualization is particularly useful for comparing different categories or groups within the data. Similarly, the pie chart divides a circular area into proportional segments to depict the distribution of data across different categories. It offers a clear visual representation of proportions and percentages, making it easy to grasp the relative importance of each category. The word cloud, on the other hand, presents the most frequently occurring words from discussions or textual data. By visualizing word frequency, it highlights prominent themes or topics within the data, aiding in qualitative analysis and interpretation.

Lastly, map visualization utilizes geographic information to plot data points on a map. This allows for the spatial representation of data, enabling Bloom to visualize geographic patterns or distributions. It provides valuable insights into geographical trends or disparities that may exist within the data. Together, these visualizations offer Bloom a comprehensive overview of the data, facilitating data-driven decision-making and enhancing understanding of key insights and trends.

The dashboard depicted in Figure 3 presents two bar charts, each offering insights into different aspects of Bloom's student engagement and progression. The first bar chart categorizes student sentiment into negative, positive, and neutral sentiments. Upon analysis, it is evident that the majority of students exhibit a positive sentiment, with nine students reflecting this sentiment. In contrast, four students demonstrate a negative sentiment, while only 1 student falls under the neutral category. This indicates a high level of student engagement in subject discussions. However, Bloom should also prioritize attention towards the one student displaying neutral sentiment, ensuring they are equally engaged in discussions.

Moving on to the second bar chart, it depicts students' progression based on individual student IDs. The chart reveals that more than half of the students exhibit a normal progression rate, surpassing the 50% mark. Nevertheless, a significant number of students show progression below the average threshold. These students may correlate with those demonstrating less engagement in subject discussions. Therefore, addressing the needs of these students becomes crucial for Bloom in resolving the overarching issue identified.

In summary, while Bloom observes overall positive sentiment and satisfactory progression rates among students, it is imperative to identify and support those students who display lower engagement levels or progression rates. By focusing efforts on these students, Bloom can effectively address the primary challenges faced and ensure holistic student development and success within the organization.

The map visualization provided by Bloom offers valuable insights into students' locations when accessing Bloom's Learning Management System (LMS). Upon analysis of the map visualization, it becomes apparent that a significant portion of students access the LMS from Port Dickson, with Kuala Lumpur closely following suit. However, it is worth noting that there are instances where students access the LMS from locations considerably distant from the campus, particularly in the Kuala Lumpur area.

This observation raises important considerations regarding student well-being and engagement. Students accessing the LMS from remote locations may encounter challenges in developing self-motivation or fostering a sense of community due to the lack of physical proximity to their peers. As a result, Bloom can proactively address these challenges by providing facilities or resources aimed at promoting self-motivation and fostering a supportive learning environment for these students. Additionally, Bloom should pay closer attention to the behavior and academic progression of students accessing the LMS from remote areas, ensuring they receive adequate support and resources to thrive academically despite their geographical distance from campus.

By identifying and addressing the unique needs of students accessing the LMS from distant locations, Bloom can enhance student engagement, academic success, and overall well-being within the organization. This proactive approach demonstrates Bloom's commitment to providing a supportive and inclusive learning environment for all students, regardless of their geographical location.

The pie chart featured on Bloom's dashboard serves as a valuable tool for identifying subject progression percentages based on subject codes. Additionally, the word-cloud, generated through the Textmagic website, provides insights into the most frequently appearing words from subject discussion forums within Bloom's Learning Management System (LMS). Upon analysis of the word-cloud, recurring terms such as ‘Data,’ ‘Dashboard,’ ‘Perform,’ and ‘Variable’ emerge, indicating their relevance to subject-related discussions. Conversely, words unrelated to the subjects appear less frequently within the word-cloud.

In conclusion, the pie chart and word-cloud offer valuable insights into subject progression and discussion topics within Bloom's educational framework. By leveraging these visualizations, Bloom can effectively identify areas requiring intervention and tailor support strategies to enhance student engagement and academic success across various subjects within the organization.

4 Conclusion

In conclusion, within the realm of education, data integration emerges as a pivotal component. Examining it from a text data retrieval perspective reveals its efficacy in resolving encountered challenges, such as reducing data complexity and cleaning noisy data. Moreover, organizations benefit from implementing frameworks that foster consistency, comprehension, and structured classification of processes. This classification structure aids in understanding how tasks are executed and elucidates the relationships between various processes. Undoubtedly, there exists a plethora of opportunities for enhancing data gathering and analysis in education through text analytics. This approach not only facilitates Bloom's understanding of student behavior and progression in pertinent subjects but also harnesses real-time data extracted from platforms like the Bloom Facebook page and the Learning Management System (LMS). This stream of data offers Bloom a comprehensive 365-degree view, enabling more accurate decision-making and deeper insights into student dynamics.

In summation, text analytics emerges as a viable solution for Bloom to address the challenge of declining average student grades. By leveraging text analytics, Bloom can effectively navigate complexities, glean actionable insights, and propel positive educational outcomes within its institution.

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