A Data-Driven Framework Addressing Students' Motivation, Regulation and Strategic Approaches

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Abstract: This study employs a multi-faceted methodology integrating SPSS and eXplainable Artificial Intelligence (XAI) techniques, specifically Benefit-Risk Balance (BRB) and SP-LIME, to discern and explicate the interests and critical attributes conducive to academic success among engineering students. One of the most important tools for feature selection in order to determine the relevant student cohort is Principal Component Analysis (PCA). Furthermore, the study explores student motivation using a well-crafted series of questions that are integrated into a Google Form and make reference to previous prompts. The combination of PCA, XAI, and SPSS offers a thorough framework for identifying the distinct interests of engineering students and clarifying the essential characteristics supporting their academic success. Our study is enhanced by the incorporation of survey data obtained using Google Forms, which provides more detailed understanding of the motivational elements that influence students' success paths. This study contributes to our understanding of the motivations behind academic success and demonstrates the value of integrating survey-based methods, artificial intelligence, and statistical analysis to better understand the intricacies of student dynamics in engineering education.

Keywords: Motivation, Data-driven framework, engineering students, academics, interests, attributes, artificial intelligence.

1. Introduction

'Data-driven' describes an exercise's progression or procedure that is carried out using data instead of human labour or first-hand experience. Data-driven programming, testing, journalism, control systems, learning, companies, and security are a few examples of data-driven approaches of various kinds. A data-driven framework is one that has undergone computerized testing, wherein the software for the test is performed using computerized testing tools after the input values have been provided as a test data set (Ba et al., 2021). Databases,.xml, or.xls files are used to construct the test data set.

Since engineering relies heavily on data, it allows businesses to improve data's usefulness. Since accurate data is crucial for determining the best performance when adjusting the data development life cycle to create big data frameworks, databases, constructing infrastructure, etc. (Brunton et al., 2022). A data-driven framework aids in the identification of more precise data series for decreasing errors in tests and test outcomes in development operations when additional data must be inserted.

For instance, when we manually review an application, we must process the same scenario for several test data sets. However, this laborious procedure may be completed with the aid of a data-driven framework (Guan et al., 2020). The data-driven framework ensures that various test scenarios are appropriately implemented for various test data sets. When utilizing a data-driven framework, it is necessary to prepare multiple sets of test data that are located in different locations and are not included in the test script. It functions by allowing data to be changed without affecting the test's code, which enables it to be written once and examined several times using various processes (Heckhausen et al., 2019). Since it is much simpler to keep a large data collection and utilize it as a test script multiple times, Microsoft Excel sheets were primarily used for the data preparation. Similar to filling out a form, several data codes are present, such as name, date of birth, roll number, address, and phone number (Kilis et al., 2018). However, the form creator never prepares the form for each user individually. Typically, they prepare the form only once using a data-driven framework, which enables the form to receive various sets of data. Using Selenium, a popular set of tools for cross-browser testing in the testing community, is one of the simplest ways to build up a data-driven framework (Lu et al., 2021). It can only be used in a browser; it is not a desktop program. It is among the best sets of computerization testing tools available. The web framework that enables the execution of cross-browser tests is known as Selenium Web Driver, and it is the online version of Selenium. According to Miele et al. (2018), the Selenium web driver is typically used to automatically test web-based applications to make sure they functioned as intended.

Activities used to attract, enhance, and sustain a particular level of motivation in an individual are referred to as motivation regulation. Motivational self-regulation is a conceived process with cyclical repetition (Park et al., 2018). When a student practices self-regulation of motivation, they remain aware of oneself at all times. Determining the extent to which a learner has to work on themselves or whether they require additional motivation, is helpful. Enhanced motivational regulation has been observed to benefit students in a number of ways, including how they behave during the learning process and the results they obtain. This is because students who have higher levels of motivational regulation tend to be more determined and put forth more effort, which is what it takes to succeed (Petrović et al., 2020).

Controlling one's motivation can even help one do better in their area of interest and in the classroom. The most significant determinant of academic achievement is understood to be motivation, which requires more effort and behavior in order to achieve goals. Since the learners' cognitive abilities and past accomplishments are known to be the best indicators of academic success, it is not a single concept but rather requires a range of different sites, such as task values, motivational beliefs, working toward goals, and motive towards achieving something (Schunk et al., 2020). Incorporating the learner into the analysis is crucial when determining the impact of motivational factors on students' academic performance.

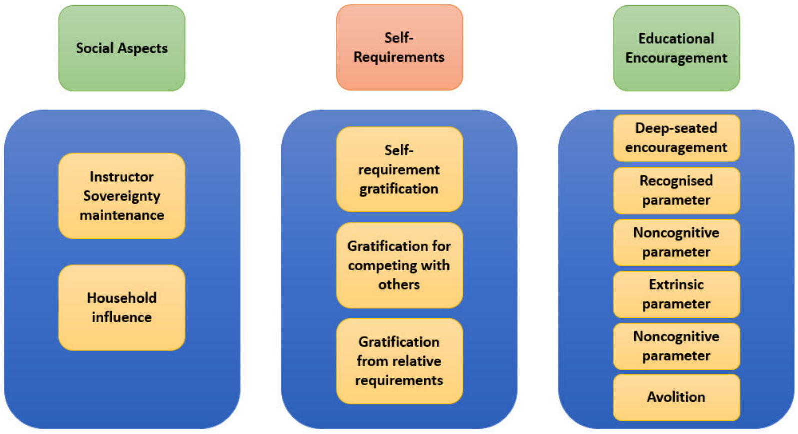

Figure1. Aspects of motivational regulation strategies

The explanation of motivational regulation strategies is presented in Figure 1 in multiple aspects. In the social domain, the emphasis is placed on critical elements like the role of the instructor, highlighting the importance of their impact on motivation. Furthermore, maintenance, sovereignty, and household upkeep become essential elements, highlighting the interdependence of social dynamics in motivational control. Turning now to self-requirements, the figure highlights the inherent desire for personal fulfillment and highlights the significance of self-requirement gratification. It also discusses the subtle motivational aspects of competition, highlighting the happiness that comes from satisfying relative needs and the satisfaction that comes from competing with others. The graphic highlights the complexity of encouragement in the context of education. It includes everything from ingrained support to the understanding of boundaries—both mental and nonmental—and the external motivators that shape conduct. The educational perspective is completed by avolition, which stands for the lack of motivation and offers a thorough analysis of motivational control techniques in a variety of settings.

It is well established that the best indicators of a learner's math and accomplishment are their interested domain-specific capability self-ideas, which are tracked by domain-specific task values. However, students do not always have access to all of the motivational concepts in the achievement domain. This is especially true for engineering students, who frequently work with large amounts of data and run the risk of making a small mistake that leads to the wrong result. As a result, these students are more likely to become demotivated when conducting experiments, but with the support of a data-driven framework, where students frequently achieve their goals and get the perfect result, they become more motivated to complete the experiments correctly (Werner et al., 2019). The social perspective casts doubt on the relationship between a learner's motivation and academic achievement. In numerous instances, there had been ups and downs in relation to the learner's motivation and academic achievement.

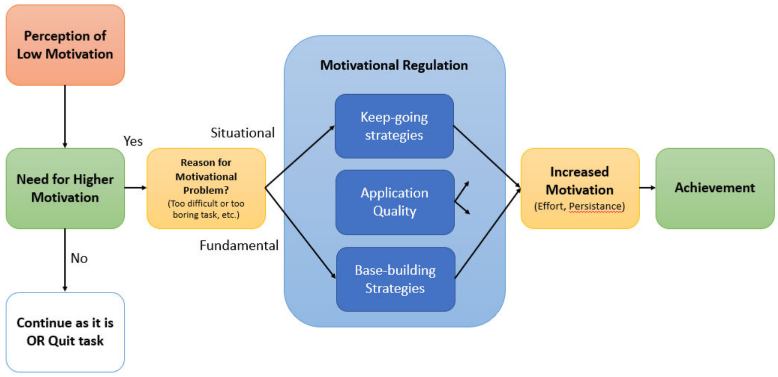

Figure2. Motivational regulation helps in the achievement

The explanation in Figure 2 focuses on motivation modulation as an achievement-promoting factor. It suggests that in situations when a student needs more motivation, recognizing and resolving any underlying motivational issues is an important first step. Teachers and mentors can apply targeted motivational restrictions that are customized to each student's needs by identifying certain motivational issues. Through the development and enhancement of motivation, this tactical method seeks to enable students to overcome challenges and meet their academic objectives. The image emphasizes the crucial role that motivation plays in the successful completion of tasks and objectives by highlighting the dynamic interplay between comprehending motivational barriers and implementing efficient regulatory actions.

Because task values in their relative organization play a significant role in their overall academic success, students are more likely to become demotivated when their self-concept of ability, goal orientations, and task values occasionally do not reach the level they wanted to. Sometimes, the exact domain of their will is not met by their domain-specific task values. The learning and performance goals also don't always line up since handling a large amount of data can be challenging in certain ways because even a small error can lead to inaccurate results (Ba et al., 2021). Additionally, the students experience demotivation after conducting the experiment with a large amount of data and receiving the incorrect conclusion.

The data-driven framework emphasizes separating the test scripts' logic and test data, enabling the creation of automated test scenarios with different sets of data. Test scripts connect to external sources like MS Excel Sheets or MS Access Tables to retrieve test data. Typically, test data is stored in Excel sheets for test execution, allowing scenarios to be run with multiple sets of data for varied test results. Using a data-driven approach is preferable over manual testing due to its time efficiency and reduced error likelihood. This framework is particularly useful when repeating the same scenario with multiple data sets. Motivational regulation comprises various strategies that individuals employ to consistently control their emotions and engage in learning activities. There are eight different motivational regulation strategies, including situational interest improvement, personal importance enhancement, self-talk control, self-cons equating, performance-tactic self-talk, goal setting in smaller divisions, performance-escaping self-talk, and environmental control.

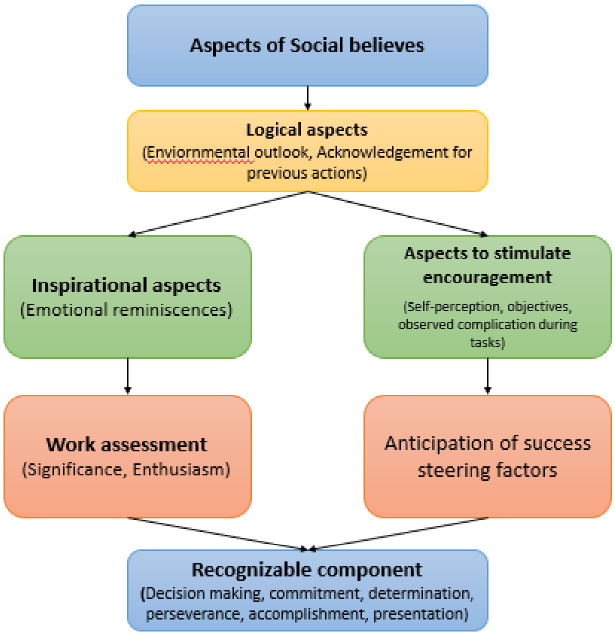

Figure 3. Motivational regulation helps in the achievement

Figure 3 illustrates the rational components of social beliefs, with particular attention to the motivating components and variables that promote support. The identifiable elements appear in this framework as important determinants that influence people's viewpoints and behaviors.

These social beliefs have several characteristics, including decision-making, commitment, determination, perseverance, accomplishment, and presentation. All of these aspects support the motivational process in a logical way. The graphic highlights how these elements are interrelated and illustrates how they affect people's perceptions and actions as a whole. Examining and comprehending these logical elements in light of social beliefs helps to build a solid foundation for decision-making and goal achievement, as well as provide insights into the complex dynamics that underpin motivation.

In the past, when technology was less advanced, handling machines and software was costly and error-prone. Testing with large data sets was challenging due to restrictions on data usage. As technology developed, processing tests with extensive data became more manageable. However, challenges like environmental concerns and language restrictions existed in earlier software and machine usage. Modifying tedious activities can make subjects more attractive, establishing a connection between study material and student interest, increasing students' goals for knowledge improvement, activating positive goals for achieving good marks, and setting rewards for goals contribute to student motivation. Breaking down goals into smaller divisions and minimizing environmental disruptions also aid in student motivation

In the technical field, technical errors may occur, processing huge data can be time-consuming, and a high level of technical knowledge is required. Data validation before and after tests, along with the presence of a developer with coding expertise, is essential. If errors occur after completing a test, the entire testing process, starting from data gathering, may need to be repeated. Despite the advantages of the data-driven framework, the overreliance on technology, especially by teenagers facing mental health issues, poses a significant drawback. Such dependency may lead to a decline in critical thinking and motivational skills, emphasizing the need for a balanced approach to technology use.

2. Constructive literature survey

In the study by [Abdurakhimova et. al. (2020)], author explores the influence of motivation on the foreign language learning process. Utilizing a qualitative approach, the researcher compiles secondary information from diverse articles. This investigation seeks to unravel the intricate dynamics of how motivation shapes and guides the acquisition of a foreign language. By delving into the motivational factors that impact language learning, the study aims to contribute valuable insights to the field, shedding light on effective strategies for fostering language acquisition and proficiency.

[Bilal Afsar et. al. (2019)] investigates the relationship between transformational leadership and innovative work behavior. The study focuses on understanding the influence of motivation to learn, task complexity, and innovation climate in this dynamic. Utilizing a survey designed for self-reporting, the researchers collected primary data through a quantitative approach. The research aims to unveil the intricate connections between transformational leadership and the innovative work behavior of individuals, considering key factors such as motivation, task complexity, and the overall climate of innovation within the workplace.

In the study titled "Explainable AI for Data-Driven Feedback and Intelligent Action Recommendations to Support Students' Self-Regulation" [Muhammad et. al. (2021)], the researchers focus on leveraging Machine Learning (ML) techniques to provide explainable AI solutions for data-driven feedback and intelligent action recommendations in the context of supporting students' self-regulation. The study employs a machine learning-based approach, utilizing primary data collected during the research process. The central objective is to enhance students' self-regulation through the integration of artificial intelligence, offering personalized and understandable feedback. The ML-based technique enables the extraction of meaningful insights from primary data, contributing to the development of a system that provides students with actionable recommendations for intelligent learning behaviors. The use of explainable AI ensures transparency in the feedback and recommendations, empowering students to comprehend and act upon the insights gained. This research represents a significant stride towards the intersection of artificial intelligence and education, aiming to foster self-regulated learning by harnessing the potential of advanced ML techniques for effective and personalized educational support. The progress in human–machine interfaces has led to the development of assistive systems for people with disabilities.

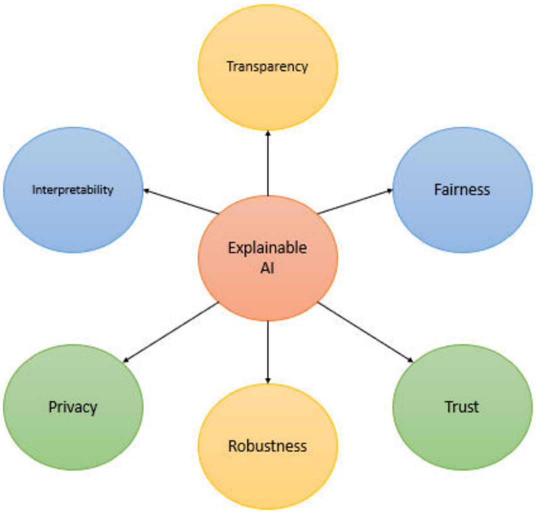

Figure 4. Functionality of Explainable AI

Figure 4 depicts Explainable Artificial Intelligence (AI) and highlights important aspects that define its capabilities. Transparency is one of the key principles that is emphasized, highlighting the openness and clarity of AI systems' decision-making processes. Another crucial component is interpretability, which highlights the understandability of AI models and helps stakeholders to accept and comprehend the results. Privacy is a crucial factor that emphasizes how crucial it is to protect sensitive data and make sure that data processing is done responsibly. Robustness is the ability of AI systems to withstand hostile attacks and unanticipated events. A key element that emphasizes the development of confidence and dependence on AI technologies is trust. The final point made is fairness, which emphasizes how AI systems must treat everyone equally and without prejudice. Collectively, these elements in Figure 4 illustrate the complex character of Explainable AI, highlighting its interpretability, privacy, robustness, reliability, and dedication to equity.

[Raghad et. al. (2018)] focused on analyzing learner behavior within Massive Open Online Courses (MOOCs) by utilizing a data-driven methodology. The study aims to understand the interplay between performance and motivation in the context of MOOCs. The researchers gathered secondary data from a diverse range of sources, including libraries and journals. This approach allowed them to draw insights from existing literature and established knowledge in the field. The quantitative methodology involved the systematic analysis of data, emphasizing statistical patterns and trends related to learners' behaviors in MOOC environments. By leveraging a data-driven approach, the study contributes to a deeper understanding of how learners engage with MOOCs, examining both their performance outcomes and motivational factors. This research has implications for the design and implementation of MOOCs, offering valuable insights into optimizing learning experiences in online educational platforms.

[Carlos et. al. (2019)], adopted a quantitative methodology. In this approach, secondary data were gathered from various sources such as libraries and journals. The research focuses on exploring the role of innovation in engineering education, examining both what it can offer to students and how students can contribute to this innovation. The quantitative methodology involves the systematic analysis of data, emphasizing statistical patterns and trends related to educational innovation in the field of engineering. The use of secondary data from diverse sources allows the researcher to leverage existing knowledge in the literature and previous research. This quantitative approach can provide key insights into how educational innovation in engineering can benefit students and how students, in turn, can contribute to the innovative process.

[Fitriana et. al. (2019)] employs a qualitative methodology, gathering information from various secondary sources such as libraries and journals. The focus of this investigation is on assessing the impact of AR on students' problem-solving skills, motivation, and learning outcomes. The researchers delve into the immersive learning experience facilitated by AR technology, aiming to understand its influence on students' cognitive abilities and motivational factors. Secondary material from diverse sources, including libraries and journals, enriches the study's foundation. This study contributes to the broader conversation on innovative pedagogical approaches, particularly in the realm of science education. By utilizing qualitative methods and drawing from a range of secondary materials, the researchers aim to provide insights into the multifaceted effects of AR on student engagement, problem-solving proficiency, and overall learning achievements.

[Mayuri et. al. (2021)] employed a qualitative methodology for the study, gathering secondary data from a variety of libraries, journals, and online sources. The research delves into the multifaceted aspects of motivation in learning, exploring factors influencing learners' engagement and enthusiasm. By utilizing qualitative methods, the study aims to provide a nuanced understanding of the motivational dynamics within the learning process.

[Sorathan et. al. (2018)] employed a quantitative methodology, gathering primary data for a case study. The focus of the research is on assessing the impact of a data-driven course planning tool on college students' academic performance, particularly their GPA. The quantitative approach involves rigorous data analysis, emphasizing statistical evidence from two field experiments.

[Daif et. al. (2020)] utilized descriptive and correlational methodologies, gathering quantitative data from primary sources. The study aims to explore variations in motivation among Saudi university students learning English. By employing quantitative methods, the researchers seek to identify patterns and relationships that contribute to a comprehensive understanding of motivational factors.

Exploring Undergraduate Students' Motivation-Regulation Strategies in Thesis Writing, [Krismalita et. al. (2020)] employed a mixed technique approach, with primary data gathering. The study explores motivation-regulation strategies among undergraduate students engaged in thesis writing.

The mixed-methods approach allows for a comprehensive examination of motivational dynamics and regulatory strategies. Suitability of Motivational Regulation Strategies for Specific Motivational Problems by [Nicole et. al. (2022)] gathered secondary data using a quantitative approach. The study investigates the appropriateness of motivational regulation strategies for addressing specific motivational challenges. The quantitative analysis provides insights into the effectiveness of different strategies in overcoming motivational issues.

[Savage et. al. (2022)] aims to explore the determinants impacting the motivation of students in technology-related fields and assess the potential for nurturing motivation. The investigation delves into the dynamics of motivational factors, considering the possibility of adjusting pedagogical interventions to enhance learning experiences. The overarching objective is to improve student satisfaction and diminish attrition rates. Additionally, the study seeks to contribute to the ongoing exploration of strategies promoting greater educational efficiency for technology students. Given the heightened financial constraints on higher education institutions, there is a critical need to focus on understanding the learning processes of students in this domain.

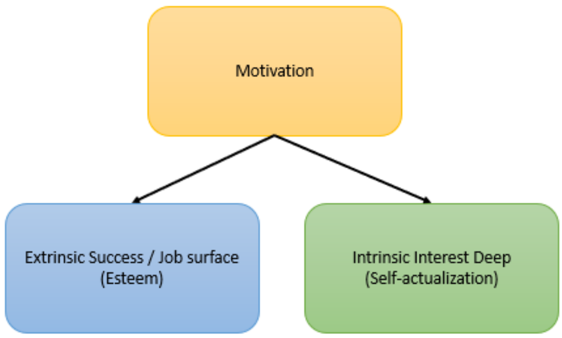

Figure 5. A framework of motivation

The motivation framework is shown in Figure 5, which presents a dualistic viewpoint that includes both intrinsic and extrinsic motivators. The graphic depicts the conflict between deep intrinsic interest, which is connected to internal fulfillment and self-actualization, and extrinsic success, or job surface, which is tied to external recognition and esteem. Extrinsic motivation is driven by outside incentives such as accolades, accomplishments, and social acceptance; it is a reflection of the desire for success in the public sphere. On the other hand, the intrinsic dimension explores the individual and ingrained passions, highlighting the satisfaction that comes from the delight and self-discovery that are inherent in the work itself. The complex interactions between these two motivational factors are captured in Figure 5, which offers a graphic depiction of the dynamic forces that propel people toward both internal and exterior fulfillment in their pursuits.

3. Review gap analysis

The provided case study highlights the pivotal role of a data-driven framework in formulating effective motivational regulation strategies for the development of engineering students. Failure to utilize data during strategy development results in weak strategies incapable of instilling motivation. Several factors must be considered in the development of these strategies, with the primary emphasis on using data as the foundation. In the past, there were limited tools and software for incorporating data into the strategy development process, and the significance of generated data was not widely recognized. Consequently, the implemented strategies lacked the strength to foster motivation among engineering students, who face numerous deadlines over the four-year duration of their courses.

In the initial years, engineering students typically possess the necessary motivation to meet deadlines effectively. However, as time progresses, this motivation tends to diminish, necessitating the implementation of strategies to reignite it. The key to effectiveness lies in collecting and analyzing data to comprehend the students' needs and expectations. While it is clear what is expected from them, understanding their expectations is crucial for developing an effective strategy. A data-driven framework plays a vital role in this process. Through this framework, input in the form of collected data is provided, and the testing phase involves an automated process, ensuring the accuracy of the analysis results. The data, representing evidence of past strategies and decisions, enhances the effectiveness of decision-making during the analysis. The ultimate goal is to develop motivational regulation strategies for engineering students, addressing observed gaps in the current approach. Our research aims to bridge these gaps by exploring how collected and analyzed data can be effectively utilized in the development of motivational regulation strategies for engineering students.

4. Technology behind the design

4.1. System Model

Statistical Package for Social Sciences (SPSS) stands out as a prominent and powerful tool for quantitative analysis, developed by IBM. With its graphical user interface and robust statistical language, SPSS caters to researchers and educators, facilitating the efficient analysis of extensive datasets. The tool's strength lies in its ability to conduct powerful data analysis swiftly and accurately. Users can navigate large datasets through equations and criteria, enabling meaningful interpretation and analysis. Moreover, SPSS empowers users to generate visual graphs and charts, enhancing data interpretation and insights. SPSS's user-friendly interface is a notable feature, making it accessible even for individuals with minimal statistical software experience. This intuitiveness ensures that users, including researchers and educators, can effectively utilize the software's features, generating meaningful data analysis for research or educational purposes.

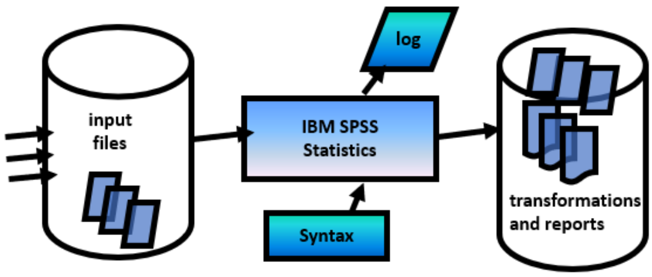

Figure 6. SPSS Statistics

The significance of SPSS extends beyond its powerful data analysis capabilities; it plays a pivotal role for businesses, researchers, and any user dealing with extensive datasets. Its speed, user-friendliness, and potency provide researchers the means to extract valuable insights, informing decision-making processes and enhancing research outcomes. IBM® SPSS® Statistics software is a crucial asset for businesses, offering powerful statistical capabilities. Figure 6 shows the working of SPSS statistics which explores data in-depth aids in making informed decisions, expanding market reach, improving research findings, ensuring legal compliance, reducing risks, and optimizing returns on investment. The tool covers the entire analytics process, from data organization to evaluation and disclosure. It utilizes linear and nonlinear regression, maximization techniques, and automated approaches to identify anomalies and handle outliers. Built-in tools simplify result delivery through diagrams and tables, allowing the classification of instances into subgroups and pinpointing target variable values based on predictor variable units.

IBM SPSS Statistics surpasses traditional tools like spreadsheets and databases, providing unparalleled proficiency in analyzing complex relationships and interrelations. Its efficiency is evident in executing data treatment and statistical operations three times faster than many non-statistical programs. Factor analysis, a data reduction approach, uncovers latent variables explaining observed variables. Various methods, including principal axis factor, maximum likelihood, generalized least squares, and unweighted least squares, can be employed for factor analysis. After extracting factors, rotations like varimax and promax can be applied, affecting the association between factors. Determining the number of factors to extract is crucial for obtaining a clear structure. Factor analysis demands a substantial amount of data, as correlations, integral to the process, take time to balance out. Comrey and Lee (1992) suggest that for efficiency, a minimum of 50 cases is insufficient, 100 cases are typical, 200 is acceptable, 300 is satisfactory, 500 is very pleasing, and over 1000 is ideal. Ensuring at least 10 observations per variable prevents algorithmic complexity

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Figure 7. SPSS modeler

Figure 7 provides information about IBM's SPSS Modeler, a program for data mining and predictive analytics. It eliminates the need for complex programming knowledge and enables users to do sophisticated analytics and create predictive models. The program makes it easier to explore data, build features, and create machine learning models for use in a variety of businesses where educated decisions are needed.

SPSS emerges as an indispensable tool, empowering users to navigate and analyze extensive datasets efficiently. Its speed, user-friendly interface, and powerful capabilities make it a preferred choice for researchers, educators, and businesses alike. Additionally, factor analysis, a vital statistical method, requires careful consideration of data size and extraction methods to yield meaningful and accurate results. Both SPSS and factor analysis contribute significantly to advancing research, decision-making, and understanding complex relationships within datasets.

5. Data driven approach on student motivation

This study offers insightful information about the structure and dependability of a dataset with 638 items and 18 parameters by delving deeply into the complexities of factor analysis and reliability testing. The dataset's integrity was revealed during the first rotation phase, when all 638 items were confirmed to be genuine and comprehensive, providing a strong basis for further analysis. Significantly, the reliability statistics table's high Cronbach's Alpha score of 0.913 highlighted the variables' general dependability and offered a solid indication of the dataset's internal consistency.

Examining the item overall statistics table's adjusted item correlation values, one interesting discovery was that none of the values were below the critical value of 0.3. This finding confirmed the validity of the dataset as a whole, indicating that no parameter required modification for the next reliability test. Moreover, the dataset's general stability was highlighted by the lack of unstable or low communality parameters—apart from V13—after the first rotation.

The second part of the study adopted a targeted strategy and looked at V13, a variable that was included in both components but wasn't specifically included in the parameters. A more nuanced knowledge of V13's impact on factor structures and data reliability was made possible by the iterative process of doing factor analysis and reliability testing without it. The process of iterative refinement yielded significant findings by emphasizing the complex interactions between variables and facilitating a more sophisticated analysis of the information.

This study highlights the significance of careful analysis, individual parameter assessment, and continuous improvement in factor analysis studies in addition to advancing our understanding of the dataset's reliability and factor structure. By adding to the analytical toolkit for analyzing complex datasets in various domains, the findings guarantee a more thorough and sophisticated approach to data analysis and interpretation.

6. Conclusion

This paper extensively explores the crucial role of a data-driven framework in the development of motivation regulation strategies for engineering students. Over time, student motivation tends to decline, necessitating strategies that involve data analysis to understand their needs. Emphasizing the importance of data-driven approaches, the study aims to address gaps in existing strategies and leverage data for effective motivation regulation. The impact of motivation regulation on engineering students' mindset and concentration is evident, allowing them to manage distractions and improve determination. Continuous monitoring through motivation regulation aids students in understanding and enhancing their performance. The paper highlights positive outcomes in students with high motivational regulation compared to those with lower degrees. Motivation regulation strategies also contribute to self-regulation, influencing the cycle of goal achievement, effort, and persistence. The paper underscores the importance of motivation in the learning process and emphasizes the need for effective regulation strategies to overcome obstacles and improve outcomes.

The paper introduces various motivation regulation strategy frameworks, stressing their implementation to help students overcome obstacles, enhance focus, and improve interest in subjects. It concludes that motivation regulation is vital for academic success, urging the adoption of effective strategies to maximize outcomes.

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