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Integrating Business Analytics in Mechanical Engineering Education: Evaluating the Outcome of a Value-Added Course

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***Abstract*— Optimizing strategies with help of data is the only way to do business and business analytics plays a key role in it. This research tests the success of a course designed around adding value to the student's program in the field of business analytics, using a blend of Advanced Excel and Python with a particular focus on Business Analytics. Advanced Excel offers tools like the Pivot Table, Data Analysis ToolPak, Solver and VBA Macros for data management, while Python grabs the tools Pandas, NumPy, Matplotlib, and machine learning frameworks like Scikit-learn and TensorFlow for analytics. To show how all these tools could be integrated for the purpose of business intelligence, a mini project to predict sales in the auto industry was conducted that used Exploratory Data Analysis (EDA) and regression modeling. Student performance can be analyzed quantitatively with the finding that there is a significant increase in the student quiz score, after receiving hands-on training, the quiz score is 84.2% as compared to 62.5% before hands-on training. An improvement paradigm is confirmed by the paired t-test ($t = 4.76$, $p < 0.001$). Feedback analysis indicated that 92.89% of students indicated that Python was useful in their predictive modeling and 87.23% said that working with advanced excel helped them improve in data interpretation. Overall, the results demonstrate the success of value-added courses in aligning academic studies and training with the needs of the industry and building of competencies needed to take data-based decisions in real-life situations.**

***Keywords*— Business Analytics, Advanced Excel, Python, Predictive Modeling, Data Visualization, Statistical Analysis, Machine Learning**

***JEET Category*—Practice**

I. INTRODUCTION

In the age of Industry 4.0, the importance of decision making based on data in all fields of engineering is growing in importance, especially in mechanical engineering. These days the scientific field of 'business analytics' (the systematic analysis of data to make better business decisions) is not restricted to business management but is a vital competence for the Engineer who wants to be more productive, more efficient in process optimization, more knowledgeable in his or her involvement in developing improved products. At present, industries are still pursuing the pace of digitalization (Kalyanasundaram & Madhavi, 2020)and so there is an ever-growing requirement for mechanical engineers with analytical skills. Mechanical engineers are usually educated in the fundamentals of thermodynamics, mechanics and manufacturing processes. The introduction of smart manufacturing systems, Internet of Things (IoT) and predictive maintenance is compelling engineers to interpret complex information and make decisions based upon data. Business analytics helps mechanical engineers powerfully analyze operational information, recognize inefficiencies and create predictive models for maintenance and quality control, that makes engineering blended with business management (Novalia et al., 2025a). This demand has indeed been met with a restructuring of education programmes across the globe to incorporate interdisciplinary knowledge and skills. But, traditional mechanical engineering courses do not have enough emphasis on the area of data analytics and business intelligence (Itagi et al., 2021). To overcome this, value-added courses could be included in the business analytics area in order to complement the engineering curriculum. The courses offer advanced training in fields like data visualization, statistical analysis, and predictive modeling, a skillset that commands more and more attention in industries like supply chain optimization, production programs, and product lifecycle management. Value-added courses (VACs) serve a very important function in supporting the traditional courses with skills that are important to industry. (Arun Kumar, 2022) argues that there should be focus on incorporating the PAAEV in the main business administration courses and connecting them with degree satisfaction and institutional reputation. Likewise, (Gumaelius et al., 2024) showed the attitude of the students towards the value-added online Courses and highlighted the contribution of these value added Courses in making students employable and ready for the Industry. Experiential learning through business simulation has been accepted as an innovative learning tool. The authors (Dev Rroy & Rajkhowa, 2024) talk about the barriers to the application of business simulation games in business education institutions of Croatia, while emphasizing their role in developing the critical thinking abilities and in building the skills of making decisions.

A. Literature Review

(Blau, 2019) emphasize that simulations serve as a good illustration in order to gain experience in the learning process. They are involved in research focused on solar radiation studies which utilize simulation-based methodologies and reflect the usefulness of simulation in complex problem solving. It is recommended to adopt an outcome-based approach to design learning in VACs by utilizing input from industry for closing curriculum gaps, (Kalyanasundaram & Madhavi, 2020) The COVID-19 pandemic has spurred a further growth towards "digital education," making online business simulations even more prominent. (Beldar et al., 2026) investigate how a pandemic has affected students' attitudes towards e-learning in value-added courses, and the study suggests that e-training is an effective substitute for in-person learning, especially in the context of digital simulations (Beldar, Rakhade, et al., 2025) encourage campus-wide investigation of educational innovations such as digital simulations to enrich the student learning experience. While business simulations are very beneficial, some difficulties exist, such as the technical problems, and the resistance from traditional educators (Beldar et al., 2026) But with the development of AI and data analysis, it is anticipated that simulation will gain ground in the years ahead. Business analytics is applied to mechanical engineering students, and this study focuses on the effect of a value-added course on business analytics.

As Industry 4.0 (Industry 4) technologies have become common to the field, mechanical engineers have evolved from a mostly-desk-based role focused on design and process to a position that involves interpretation, management and utilization of data for engineering decision making. There is a great amount of data generated in modern manufacturing environments, contributed by sensors, production monitoring systems, inspection systems, maintenance records, production activities in the supply-chain, and enterprise information systems. For this reason, skills in data collection, data pre-processing, data visualization, statistical analysis and predictive modelling are gaining importance to the mechanical engineering profession. The information required by engineers goes beyond physical systems understanding – in certain applications like predictive maintenance, production planning, quality control, process optimization, supply-chain management and product lifecycle management, engineers need to draw useful information from operational data. There has therefore been a growing emphasis in literature on the need to incorporate competencies for more than one discipline and other industry competencies into engineering education. Business analytics has especially significance for mechanical engineering students because a lot of decisions mechanical engineering students are required to make are based on quantitative operational information that they must interpret. Vibration and temperature data may be analyzed for fault detection and predictive maintenance; production data may be reviewed, and defects in quality discovered; or the data from the supply-chain may be used for inventory and production planning. Likewise, historical product and sales data can be analyzed to determine the trend of the demand and make future decisions about price, inventory and production. Thus, the importance of business analytics cannot be limited to business-oriented competency, but it must be considered as an engineering competency that can be used, together with other skills, for data-driven problem solving. Value-Added Courses (VACs) are an appropriate way of incorporating such competency without a fundamental change to the current main mechanical engineering courses. The importance of VACs in augmenting employability, industry readiness, multidisciplinary education, and exposure to the latest technologies have been highlighted in previous studies. Practical skills are especially well suited for VAC modules, due to their more flexible structure, as they may emerge more quickly than current revision cycles for the curriculum. In the current scenario, a business analytics VAC can be used in conjunction with traditional mechanical engineering courses to equip the pupils with computation and analytical skills which may be utilized to solve engineering problems. VAC effectiveness is not just about introducing software tools but around the competences and learning activities with those tools. Hence the present study is treated from a competency-oriented point of view towards the VAC(BELDAR, 2026). We use advanced Excel to provide students with the base tools and skills needed to build into analytical tools that they will use in their everyday work, such as organizing data, cleaning data, descriptive statistics, Pivot Tables, graphing, dashboard development and basic forecasting. Students can also gain insight into relationships between variables and gain insight into engineering or industrial data sets in an easy-to-access world through Excel, before bringing their programming analytic skills to the table(Beldar et al., 2026). More sophisticated computational skills are developed using Python. They are introduced to data preprocessing and manipulation with Pandas and NumPy, exploratory data analysis and visualization with Matplotlib and Seaborn, statistical analysis, and primer of predictive modelling with Scikit-learn. These activities help students to move beyond manual data analysis to repeatable/reprogrammable data analysis workflows. This is not the current focus of programming language syntax learning but is the focus of how to solve engineering-related problems by using computational tools to formulate, analyze and communicate the solution(Arun Kumar, 2022). The course also gives an introduction to engineering applications by means of case studies and a mini project. These include, among other things, predictive maintenance, optimizing production processes, analyzing supply chains, making decisions about quality and analyzing sales data for cars. With these activities, students are expected to relate analytical skills to an engineering/global/industrial problem set. In the mini-project, students are additionally expected to go through problem definition, data preparation, exploratory analysis, predictive modelling, visualization, interpretation and presentation of results(Zhang, 2025). Therefore, learning no longer only focuses on the ability to use the tools, but also that students can be active in solving problems analytically. C. Parallel Planning for Kindergarten and ELLs the VAC's design follows the principles of Complementary Principles of Constructivist Learning Theory, Experiential Learning Theory, Bloom's Taxonomy, and Outcome Based Education. Constructivist's viewpoint on learning is that learning happens when pupils actively build what they are learning based on their previous knowledge and experiences. The following is especially applicable to interdisciplinary engineering education as students come on the course with prior knowledge of mechanical systems and possibly fewer experiences with business analytics. Instead of teaching analytics concepts as abstract lectures, the course applies analytics concepts to engineering datasets, interactive exercises, and case studies and culminates with a project so that students can connect to their own engineering projects and topics and apply new analytics concepts to familiar engineering contexts. The course also applies the principles of Kolb's experience learning theory that learning occurs when a learner has a concrete experience, reflects on the learning experience, abstracts the concepts of the learning, and then experiments with the concepts. In VAC students learn first by doing, second by reflecting on the outcomes by interpreting and discussing them, and third by acquiring a conceptual understanding through statistical and analytical instruction, culminating in an application of knowledge in case studies and the mini project. This experiential structure aims to help move from theory to competence. Bloom's Taxonomy offers a scheme for building up cognitive levels of the learning activities. The VAC kicks off with an overview of basic concepts within data and analytics, moves into the use of Excel and Python tools, and ends with learning to analyses data, interpret the outcomes of the analysis and create predictive solutions. The course outcomes are thus not limited to knowledge acquisition but address higher order cognitive forms of activity: analysis, evaluation and creation. This is illustrated in the clearly defined VAC outcomes, comprising the application of analytical techniques, analysis of engineering problems, evaluation of data-supported alternatives, and engineering analytical solutions. Last, and most important, the course is based on the principles of Outcome Based Education (OBE)(Beldar, Kadbhane, et al., 2025). The VAC outcomes are expressed as observable skills and linked to key Program Outcomes. Evidence of attainment of the outcomes is generated through ‘assessment activities such as quizzes, assignments, presentations and the mini project. Qualitative reflective comments by students complement perceived relevance, confidence and applicability. The evaluation framework therefore takes into account measurable learning performance as well as students' learning process experiences(Novalia et al., 2025b).

B. Challenges in Implementing Analytics-Oriented VACs

Despite the potential benefits, the implementation of a business analytics VAC in mechanical engineering education involves several challenges. First, students may enter the course with substantially different levels of mathematical, statistical, programming, and computational knowledge. Such variation can make it difficult to maintain a common learning pace. Second, analytics tools such as Python require students to develop programming skills in addition to understanding statistical and engineering concepts, resulting in a potentially steep learning curve within a short-duration VAC(Dev Rroy & Rajkhowa, 2024).

Third, the limited duration of a VAC creates a trade-off between breadth and depth. Introducing a large number of software platforms may increase exposure but may not provide sufficient time for meaningful skill development. Therefore, the present course emphasizes Advanced Excel and Python as the principal hands-on platforms and uses practical activities to develop transferable analytical competencies rather than attempting to provide extensive training in every available analytics technology(Vyas et al., 2025).

Fourth, meaningful analytics education requires datasets that are sufficiently authentic to represent engineering problems while remaining appropriate for student learning. The use of realistic datasets can increase engagement and relevance, but data quality, missing values, inconsistent formats, and domain-specific interpretation can introduce additional complexity. Finally, assessment of interdisciplinary competencies is challenging because conventional examinations may not adequately capture practical data-analysis and problem-solving abilities(Beldar, 2026). For this reason, the present study combines quizzes, assignments, project-based assessment, outcome attainment, Likert-scale feedback, focus-group discussions, and reflection activities(Tassone et al., 2024).

C. Research Gap

While some research has shown that the incorporation of value-added and experiential methodologies are valuable, there is a clear need for structured approaches for incorporating and evaluating student business analytics skills in mechanical engineering instruction. There are well-documented examples of VACs that focus on employability, added educational value, industry alignment and views of students, and research work on 'analytics education' tends to be in business, management or computing focused. Less focus has been placed on the design of a brief course in engineering context, one that takes a short time to develop but explicitly links tools and tools and mechanical engineering applications and assesses the results of the learning through multiple types of evidence. In light of the above, the following study proposes the development and testing of the developed Business Analytics 30-hours VAC aimed at mechanical engineering students. Advanced Excel and Python are woven into the course with mechanical-engineering related case studies, statistical analysis, introducing basic predictive modelling, and a hands-on mini-project. Learning through successive assessments, pre-course assessments, attainment of VAC outcomes, student feedback, and reflections are also assessed. Consequently, the study contribution is neither closer to providing a new analytical algorithm, but about providing a transdisciplinary education framework involving business analytics competencies and the learning outcomes of mechanical engineering competencies, as well as solving real problems. This research is novel because of the planned use of business analytics with a structured focus in mechanical engineering education by using a practical Value-Added Course (VAC). In this course, students build data collection and identification, data analysis, visualization, statistical analysis, and basic predictive modeling skills, and then apply them to mechanical engineering and industrial applications to view the operation of analysis skills and data as a business tool. Complementary hands-on software includes Advanced Excel and Python, and students are given opportunities to apply the concepts of analysis to engineering-oriented mini case studies along with an auto sales prediction mini project. This study also assesses the course through a variety of evidence such as the success of the pre-test assessment, successive assessment, orientation to course outcomes, student feedback, and quality reflections. Therefore, it is not an analytics algorithm per se that's being developed, but rather the design and assessment of an educational framework fraught with an interdisciplinary nature, and which enables students to define skills in mechanical engineering while maintaining competencies in business analytics in problem solving related to industry.

II. METHODS

A. Value-Added Course (VAC)

Value-Added Course (VAC): These are courses that are added to the regular school curriculum to build knowledge/expertise and skills in students outside of the regular subject areas taught in the regular schools. In contrast to core courses, VAC courses are, as a rule, non-credit courses and therefore do not affect the students' grade point average (GPA). But they conduct practical training, industry-relevant exposure and interdisciplinary insights which enable the students to meet the changing demands of the industry (Novalia et al., 2025b)

To meet industry expectations and introduce new technologies and skills in the world of work, VACs are developed to offer a bridge between academic learning and industry expectations.

While Value-Added Courses (VACs) are not academic courses, table 1 shows that they offer many benefits that help to expand students' skills and employment opportunities. One of the key advantages is the gap closing between industry and academia – many industries now require engineers to have data analysis and decision-making skills. A VAC in business analytics makes mechanical engineering students' job-ready by equipping them with these vital skills. Moreover, it is further creating value for employers who have engineers with business analytics expertise as they are in greater demand in the job market, including on jobs related to production optimization, predictive maintenance, and supply chain management.

The other major benefit is promoting multi-disciplinary education. Data analytics are usually not taught in traditional mechanical engineering programs, but the VAC will equip students with Python, data visualization tools like Tableau, and statistical concepts. Furthermore, it teaches students to operate in an Industry 4.0 world of smart factories, IoT based predictive maintenance, and AI based quality checks, all of which rely on business analytics significantly. In addition, the course is key in the development of problem-solving skills by introducing students to real-world case studies and capstone projects, where data-driven decision-making plays an important part. This experience builds their skills in complex engineering problem analysis and solutions

B. Research Design:

The objectives of the study were to gauge the learning outcomes of the VAC Business Analytics by adopting a pre-test–post-test methods and to capture the students' perception in a single group experimental study. The students, who were final year Mechanical Engineering students, took the course as one group and the performance of the students was evaluated through pre-test at the beginning and by giving some quiz questions and assessment questions throughout the course.

The quantitative part of the study examined the differences between the pretest and the following tests of the students. For the qualitative part, the structure of student feedback, focus-group discussions and reflection essays were combined to gather student's perception, learning in the business analytics, challenges faced, and perceived applicability of business analytics skills. Thus, within-group changes rather than contrasting intervention with a separate control group were evaluated in the study. The design was chosen to evaluate implementation and learning outcomes of the VAC in the student sample involved.

The study design has been included:

Pre-test assessment will be carried out prior to the first day of VAC to get students' baseline knowledge of business analytics.

Assessment of learning and assessment of attainment of the VAC outcomes was carried out through Course Based assessment – quizzes, assignments, presentations and a mini-project.

Post-course/performance assessment: Subsequent assessment was undertaken to explore the impact on student performance of involvement in the course.

Students' feedback - Students were given a 5-point Likert scale questions to evaluate their perception of relevance of the course, usefulness of analytical tools, application to engineering related problems, organization and acceptable working mechanisms of the course, and the ease of using business analytics.

Qualitative feedback: Learner experiences and their perceptions of learning were explored using focus-group discussions and reflection essays.

This enabled analysis of the quantitative and qualitative data together in order to offer a holistic assessment of the learning outcomes and student learning experiences linked to the VAC.

C. Participants and Sampling:

1. Population: Final-year mechanical engineering students at a reputed engineering college.
2. Sample Size: 256 students
3. Sampling Technique: Purposive sampling is used to select students with no prior exposure to business analytics, ensuring comparable baseline knowledge.

D. Course Design and Delivery:

Objective:

The objective of the Value-Added Course was to equip mechanical engineering students with practical business analytics skills relevant to data-driven decision-making in engineering and industrial contexts.

Duration and Structure:

The course was conducted over 30 hours through 15 sessions of 2 hours each. The delivery consisted of theoretical instruction combined with hands-on practical activities.

Principal Tools Used:

The two principal platforms used for hands-on instruction and student activities were:

1. *Advanced Excel:* used for data organization, cleaning, descriptive analysis, Pivot Tables, visualization, dashboard development, and basic forecasting.
2. *Python:* used for data preprocessing, exploratory data analysis, statistical analysis, visualization, and introductory predictive modelling.

Within the Python environment, selected libraries were used according to the requirements of the practical activities. These included Pandas and NumPy for data handling, Matplotlib and Seaborn for visualization, and Scikit-learn for introductory predictive modelling.

Other software and technologies referred to elsewhere in this manuscript, such as Tableau, TensorFlow, XGBoost, PySpark, Selenium, and cloud-based analytics platforms, were not core tools of the 30-hours instructional delivery. These technologies are mentioned only to provide broader context regarding the business analytics ecosystem or potential future extensions of the course.

Accordingly, the analysis and student activities reported in this study primarily reflect the use of Advanced Excel and Python and their selected supporting libraries. The VAC outcomes (VACO) are as shown in table 2, Table 3. Mapping of VACOs with Program Outcomes (PO) is shown in table 3. VAC Structure and Scheduling is shown in table IV.

TABLE I
VAC OUTCOMES (VACO)

VACO No.	Course Outcome	Bloom's Level
VACO1	Apply the fundamentals of business analytics, statistical techniques, and machine learning models to analyse and interpret industrial data for informed decision-making in mechanical engineering applications.	Apply (L3), Analyse (L4)
VACO2	Identify, formulate, and analyse mechanical engineering problems using data-driven approaches, including predictive maintenance, supply chain optimization, and production process improvement.	Analyse (L4), Evaluate (L5)
VACO3	Utilize modern data analytics tools such as Python, Tableau, and Excel for data visualization, statistical analysis, and predictive modelling to enhance engineering problem-solving capabilities.	Apply (L3), Create (L6)
VACO4	Develop an understanding of data-driven decision-making in industrial and business contexts, improving efficiency in manufacturing, operations, and supply chain management.	Understand (L2), Evaluate (L5)

TABLE II
MAPPING OF VACOS WITH PROGRAM OUTCOMES (PO)

VAC Outcomes	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12
VACO 1	3	2	2	2							3	2
VACO 2	3	2	2	2								2
VACO 3		2	2	2	3						3	2
VACO 4			3	2					3	3	3	2
Average	3	2	2.3	2	3				3	3	3	2

TABLE III
VAC STRUCTURE AND SCHEDULING

Module No.	Course Content	Hours	Assessment Tools	Resources Required (Software & Tools)	Mapped VACO
1	Introduction to Business Analytics - Importance and applications in mechanical engineering - Case studies on supply chain optimization and predictive maintenance	2	Quiz	Lecture slides, Case study materials	VACO 1, VACO 4
2	Data Collection and Cleaning - Data types and sources relevant to mechanical engineering - Data cleaning techniques (handling missing values, data normalization)	4	Assignment on data pre-processing	Excel, Python (Pandas)	VACO 1, VACO 2
3	Data Analysis and Visualization - Descriptive statistics and exploratory data analysis - Data visualization using Tableau and Matplotlib	6	Practical assignment on data visualization	Python (Matplotlib, Seaborn)	VACO 1, VACO 3
4	Statistical Analysis - Inferential statistics (t-tests, ANOVA) relevant to engineering data - Hypothesis testing and confidence intervals	4	Quiz on statistical concepts	Python (SciPy, Stats models), Excel	VACO 1, VACO 3
5	Predictive Modelling - Basics of machine learning algorithms: Linear Regression, Decision Trees - Application to mechanical systems for predictive maintenance and quality control	6	Mini project on predictive modelling	Python (Scikit-learn, Pandas)	VACO 1, VACO 2, VACO 3
6	Case Studies and Real-World Applications	4	Case study presentation	Industry datasets,	VACO 2,

Module No.	Course Content	Hours	Assessment Tools	Resources Required (Software & Tools)	Mapped VACO
	- Analysing datasets related to mechanical systems (e.g., vibration data for fault diagnosis) - Optimizing production processes using data-driven approaches			Python, Excel	VACO 4
7	Mini Project - Students work in teams to analyse a mechanical engineering-related dataset - Presenting findings and business insights to faculty and industry experts	4	Project evaluation (problem definition, analysis, presentation)	All tools used in the course	VACO 1, VACO 2, VACO 3, VACO 4
Total Hours: 30					

The qualitative aspect of the study was employed to gain a deeper understanding of students' learning experiences, perceived usefulness of the analytical tools, challenges faced in the course and applicability of business analytics in mechanical engineering. Qualitative evidence was collected by focus groups discussion and student reflection essays. The qualitative responses were analyzed using a structured thematic-analysis procedure. There were five stages in the analysis. First responses generated from the focus group discussions and reflection essays were repeatedly reviewed to get a general familiarity with the data. Second, meaningful statements relevant to the learning experiences, analytical skills, engineering applications, software use, challenges, confidence and perceived relevance were pinpointed and initial descriptive codes were placed next to them. Third, the conceptually similar codes were combined into larger categories. Fourthly, the related categories were analyzed and synthesized into higher level themes. Lastly, it was used to take the identified themes and interpret these in relation to VAC objectives and quantitative learning outcomes. The dimensions analyzed were: Perceived learning and skill development: students' accounts of learning gains in data handling, visualization, statistical reasoning and predictive modelling. 2. Usefulness and ease of student's use of Advanced Excel and Python in analytical activities: student's perception of being useful and easy to use in analytical activities in Advanced Excel and Python. 3. Mechanical engineering applicability: students' capability of applying the business analytics concepts to the manufacturing, predictive maintenance, production, quality, supply chain, and other applications. 4. Problem-solving and decision making: written/oral evidence that shows students are using analytical techniques in addressing problems and drawing conclusions based on data. 5. Challenge/learning barriers: challenges with programming, statistical concepts, data preparation, rate of teaching, and interpretation of results of analyses. Transfer and future applicability: students' perception of how their acquired skills may be applied in their academic projects, internships and jobs, and on future engineering work. Not quantitative assessment was made to be a substitute for the qualitative findings. Rather, they served as supporting material to provide extra context for students' experience and perceptions of the changes in assessment performance observed. Therefore, quantitative assessment responses gave evidence to observed performance, whereas qualitative assessment evidence gave context of the learning process and evidential responses on the part of the students about the applicability of observed competencies. E. Alignment of learning objectives, VAC outcomes, modules and assessments Each Value-Added Course Outcome (VACO) was linked to learning objectives, course modules, application-specific learning activities, and assessment instruments to ensure course delivery and outcome assessment meet each Value-Added Course Outcome. It was set up so that learners would be gradually exposed to and learn basic concepts before they could apply analytical tools, analyses engineering data, evaluate outcomes and create solutions based on data. Application of business analytics and analytical technique –The goal of VACO1 is to give students the opportunity to use the principles of basic business analytics, statistical methods, and basic machine-learning techniques for industrial data. The key outcomes come through the modules on Introduction to Business Analytics, Data Collection and Cleaning, Data Analysis and Visualization, Statistical Analysis and Predictive Modeling. Learning activities are comprised of exercises on data cleaning, descriptive and exploratory, statistical, and predictive modelling. Assessment of attainment takes the form of quizzes, assignments and predictive-modelling components of the mini-project. VACO2 is designed in the domain of solving mechanical-engineering and industrial problems from a data-driven perspective, being their identification, formulation, and analysis. Data Collection and Cleaning, Predictive Modeling, studies of real-world case examples and applications, and the mini project help develop the outcome. Students apply engineering or industrial data and in doing so, students can analyze application areas like predictive maintenance, production improvement, analysis of supply-chains, and a decision-making process on quality. The assignments and the case study activity along with the Mini-Project serve as evidence of students' ability to pose and solve practical problems. VACO3 will emphasize building data wrangling, visualization, data analysis and basic predictive modelling skills in Advanced Excel and Python. Data Collection and Cleaning teaches data-preparation skills in Excel and Pandas, and Data Analysis and Visualization teaches visualization skills and exploratory analysis skills in Python. While there is no specific sequence that you have to complete, the material builds on itself, so it is best to follow it step-by-step. The material builds on each other, and there is no particular order in which you will need to complete this component, so we would suggest working through the material sequentially. Assessment is based on the practical assignments, quizzes, visualization activities and mini project which provide evidence of attainment. VACO4 focuses on interpreting and using analytical evidence in an industrial and/or business context for decision making. The outcome is further supported by the Introduction to Business Analytics, Case Studies and Real-World Applications modules and the Mini Project. Students should not only provide analytical output but also be able to outline how to interpret and to communicate recommendations. The case-study presentation and the mini-project are therefore important evidence of achievement and is especially suitable for assessment in terms of engineering decision making and communication.

E. Data Collection Methods

To evaluate the effectiveness of the Value-Added Course (VAC) on Business Analytics for Mechanical Engineering Students, a combination of quantitative and qualitative data collection methods was employed. This mixed-methods approach provides a comprehensive understanding of the course's impact on students' learning outcomes, skills, and industry readiness.

1) Quantitative Data Collection

Assessment of knowledge acquisition was the main approach which was used and was carried out by using the process of pre-test and post-test assessments. The tests comprised 30 multiple-choice questions on data analytics, statistical techniques and predictive modeling. The pre-test was given prior to the course to set a baseline, and a post-test was administered at the end of the course to assess knowledge gained. This difference in scores between these tests was used as an indication of the effectiveness of the course.

F. Module-Wise Feedback Questions

1. Module 1: Introduction to Business Analytics

How well did this module help you understand the relevance of business analytics in mechanical engineering?

2. Module 2: Data Collection and Cleaning

Did you find the data cleaning techniques (handling missing values, normalization) useful? What challenges did you face while applying them?

3. Module 3: Data Analysis and Visualization

Which visualization techniques (Tableau, Matplotlib, Seaborn) were the most effective in analyzing mechanical engineering datasets? Why?

4. Module 4 & 5: Statistical Analysis & Predictive Modeling

How confident are you in applying statistical analysis (t-tests, ANOVA) and machine learning models (Linear Regression, Decision Trees) to mechanical engineering data?

5. Module 6 & 7: Case Studies & Mini Project

How effectively did the mini-project and case studies enhance your ability to analyze real-world engineering datasets and derive insights?

A Likert type of scale from 1 to 5 i.e. poor to excellent was used to obtain feedback from students through Google Form for further evaluation of skill acquisition. This survey examined their self-evaluation on how successful they were in acquiring knowledge and skills regarding data analysis and interpretation, problem solving, critical thinking and usage of business analytics in mechanical engineering situations. Answers were used to assess students' confidence in applying a data-driven practice of engineering in the real world.

1) Qualitative Data Collection

To capture students' experiences and perspectives, focus group discussions were organized. Such conversations took place in small groups of 8-10 students sharing ideas about the course. The participants expressed how they felt learning business analytics has been advantageous, obstacles they faced, and potential scenarios in which they would apply business analytics skills to engineering contexts. These conversations were helpful for obtaining qualitative feedback on the strengths and areas for improvement of the course.

In addition, reflection papers would have to be written accounting for students' own learning processes. These essays highlighted what they learned in the course, how business analytics has affected their concept of engineering, and what they thought about upcoming opportunities for using these skills in their jobs.

III. RESULTS AND DISCUSSION

1) Role of Advanced Excel in Business Analytics

Advanced Excel is crucial tool in Business Analytics. In Business Analytics Advanced Excel is an important tool. Business Analytics is vital in Microsoft Office Excel, with Advanced Excel offering a suite of tools to assess, present and process data. Engineers and decision makers can make use of these tools like Pivot Tables, Data Analysis ToolPak, Power Query, Solver, and VBA Macros to get information out of massive amounts of data. From the perspective of mechanical engineering, Advanced Excel serves a variety of purposes, such as data analysis, trend analysis, predictive maintenance, and optimizing production processes, with the main focus placed on real-time industrial data.

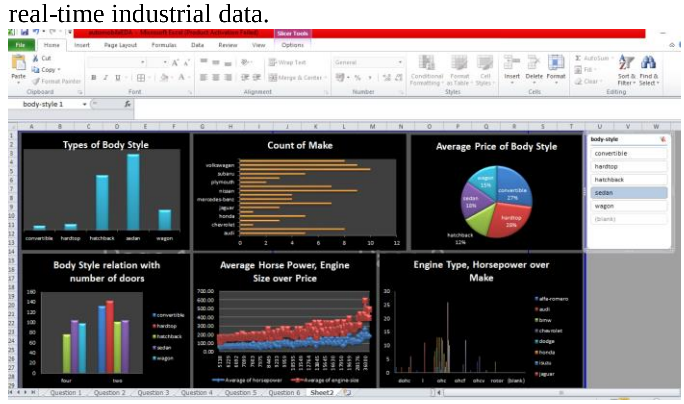

Fig. 1. Sample Dynamic Dashboard using Excel prepared by student

Creating a Business Analytics Dashboard in Excel as shown in fig. 1, involves data preparation, visualization, and interactive analysis to gain valuable insights. In this stage, missing values are processed, duplicate data are eliminated, and computed fields, like cost per mile and profit margin, are created during data cleaning and structuring. Data is organized to create a Pivot Table, and then highlight important data trends, such as models with the highest number of sales, the performance of each fuel type, or year-by-year sales vs. satisfaction ratings, et al. These Pivot Tables are the backbone of the dashboard, allowing them to summarize huge amounts of data into valuable information. Pivot Charts (bar charts for brand performance, line charts for sales trends and pie charts for distributions of customer ratings) are added to facilitate visualization. These charts make it easy to visualize the data and can help us see trends and patterns. Moreover, the interactive Slicers enable users to set up filters for their data based on parameters such as brand, fuel type, or years and dynamically refresh their analysis with just a click. Conditional Formatting is enabled to highlight critical information, like sales that are greater than the average, in green, and less than the average in red, so that it's evident. In an effort to understand the need for predictive analysis, it is worth providing a quick reference for FORECAST in Excel.The LINEAR() function is utilized to forecast future sales, even though it is based on past information, and this information could be useful for some companies when they consider their future trends. In addition, sales charts are synced with Moving Average Trendlines to provide a visual trend over time. The end layout of the dashboard is deliberately designed and combines a chart with slicers and key performance indicators (KPIs) on one single page. The layout is protected, so that changes are not made accidentally mistreating the integrity of the conducted analysis.

B. *Role of Advanced Python in Business Analytics*

In the business analytics field, Advanced Python is a crucial part of the big picture that enables data-driven decision-making, automation, and predictive modeling. Python's fascinating ecosystem of libraries allows for efficient data collection, pre-processing, and analysis, making it indispensable for businesses dealing with big data. Libraries including pandas, NumPy provide a few ways to work with data seamlessly, and Beautiful Soup and selenium make it easy to scrape websites for market research and competitor analysis. Additionally, Python's statistical features, facilitated by SciPy and Statsmodels, enable businesses to conduct hypothesis testing, regression analysis, and modeling probability functions to gain insight into customer interactions and business processes efficiency.

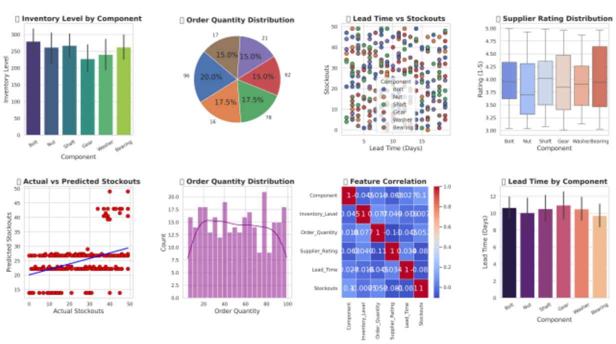

Fig. 2. Sample Dynamic Dashboard using Python prepared by student

Fig. 2 shows the sample Dynamic Dashboard using Python prepared by students. In addition to analysis, Python is a great tool for data visualization using packages like Matplotlib, Seaborn and Plotly, which can help businesses build insightful dashboards and business reports for strategic decision making. Machine learning platforms such as Scikit-learn, TensorFlow, and XGBoost further complement predictive analytics to enable businesses to anticipate customer needs, prevent frauds, and fine-tune pricing strategies. Moreover, Python's automation capabilities help streamline repetitive tasks like financial reporting and supply chain management, thus adding to the efficiency and accuracy.

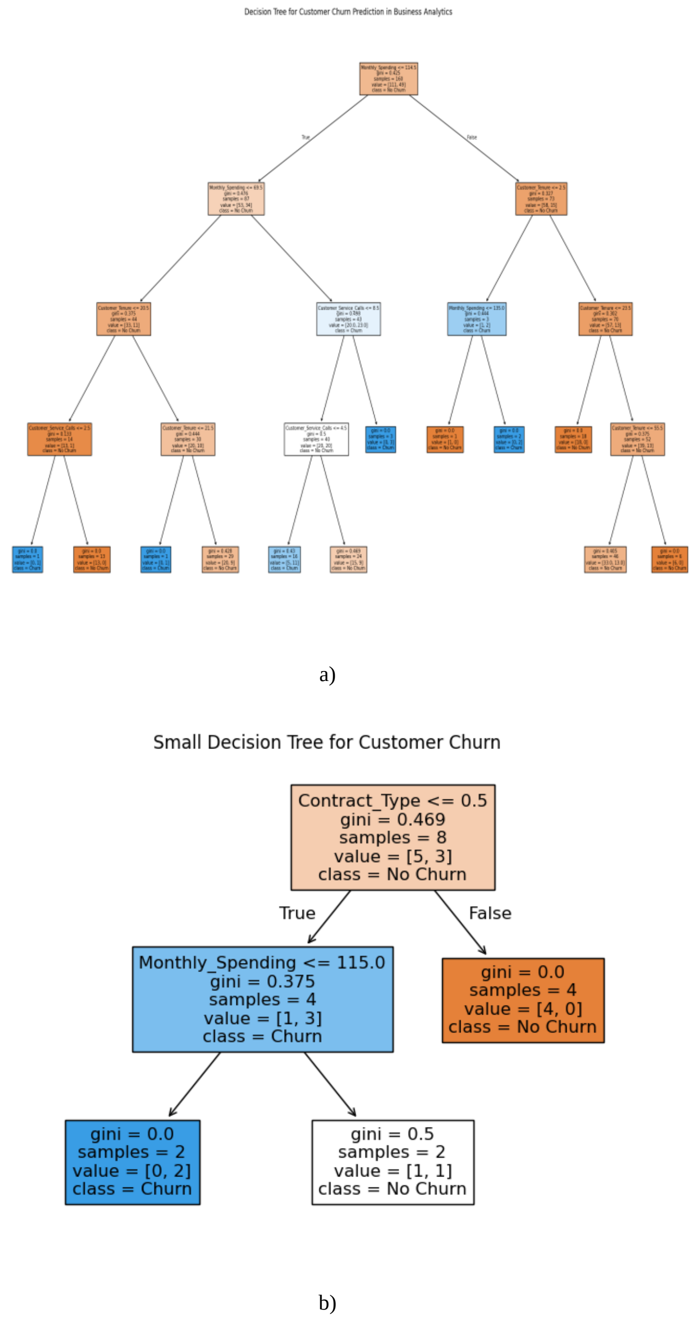

Fig. 3. Decision Tree Analysis for Customer Churn Data

Python's ability to leverage big data technologies such as PySpark and cloud computing services allows businesses to handle big data in real-time. The Decision Tree Analysis for Customer Churn Data is found in Fig. 3. Python's appeal lies in its ability to process both structured and unstructured data as well as its AI capabilities that serve a variety of purposes. Whether structured or unstructured, Python is adored for its ability to handle both kinds, and even its AI capabilities have several uses. In the future, the impact of advanced Python in business analytics is poised to grow, with its implications reaching across a wide range of industries, from fostering innovation to enhancing efficiency.

C. Carrying Out the Mini Project in Business Analytics

1) Problem Statement:

Companies in the auto industry need to overcome difficulties when forecasting sales performance, influenced by varying market conditions, customer tastes and external economic conditions. The objective of this project is to determine predictive models from historical sales data to optimize inventory management, pricing and marketing. The project uses business analytics tools such as Python and Advanced Excel to create data-driven insights for making better decisions, as illustrated in Fig. 4. After the data is cleaned, the patterns and trends are revealed through exploration data analysis (EDA) with Excel, Python (Pandas, Seaborn, Matplotlib), and Tableau. The information obtained from the analysis of the business includes business insights, for example, seasonality in business, the significance of fuel efficiency in picking up customers, and brand-wise business measurements. Moving onto the predictive modeling, Python is used for implementing regression models and decision trees to predict sales patterns and understand the factors affecting sales. Prediction modelling follows with regression analysis and decision tree models implemented in Python, predicting sales patterns and identifying factors that influence sales. An interactive dashboard in Excel and Tableau is produced that shows key performance indicators such as total sales, predictions about the quantity of demand and the market preference for market segments to facilitate real-time decision making.

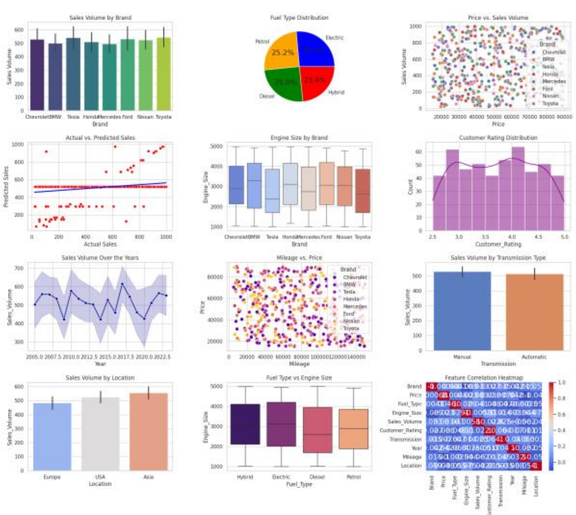

Fig. 4 Mini Project Dashboard using Python and Machine Learning

This is a Mini Project Dashboard for implementing Python and Machine Learning to build a project dashboard. Lastly, the project outcomes are related to Program Outcomes (POs). The capstone project incorporates engineering knowledge (PO1) through the use of statistical methods and machine learning techniques. Problem analysis (PO2) is exhibited in data collecting research of the observed sales trends. In designing and developing solutions (PO3), predictive models are used to develop optimal business solutions. Analysis and visualization is highlighted with the use of Python, Tableau and the advanced use of Excel (PO5). Communication (PO10) is enhanced as students present findings and recommendations to faculty and industry experts. Throughout the project, the student will actively experience practical applications of data analytics, decision-making and business intelligence in the auto industry. The project gives actionable insights for better optimization of inventory, better pricing optimizations and better marketing and awareness creation and ultimately helps students to become industry ready and to have a good knowledge of business analytics methodology.

D. Statistical Analysis and Outcomes

Course outcomes are measured at the end of the course based on student work measured through assessments including quizzes, assignments, mini projects and presentations. Assessment tools can be used to assess various Course Outcomes (COs). Attainment percentage – This shows the percentage of children achieving above the 60% target in their internal assessment. The VAC PO attainment is shown in table 5.

For each assessment tool, the attainment level is determined as follows:

1. Level 1: If at least 50% of students score above 60%.
2. Level 2: If at least 60% of students score above 60%.
3. Level 3: If at least 70% of students score above 60%.
4.

For instance, in VACO1, Quiz 1 achieved 84.36%, indicating that more than 70% of students scored above 60%, thus attaining Level 3. However, Assignment 1 for VACO1 had 69.56%, which falls within the 60–70% range, resulting in Level 2. Similarly, VACO2 and VACO4 have higher attainment due to multiple assessments achieving Level 3.

TABLE IV
VAC Attainment

Course Outcome	Assessment Tool	Mode of Assessment	Attainment in %	Attainment Level
VACO1	Quiz 1	Internal	84.36	3
	Assignment 1	Internal	69.56	2
VACO2	Assignment 1	Internal	75.89	3
	Mini Project	Internal	71.36	3
VACO3	Quiz 2	Internal	68.96	2
	Assignment 1	Internal	69.56	2
VACO4	Quiz 3	Internal	75.63	3
	Presentation	Internal	75.63	3
	Mini Project	Internal	71.36	3
Average Direct Attainment				2.67

The average direct attainment across all COs is 2.67, which is significantly above Level 2, demonstrating strong student performance. This method ensures that students' understanding is measured holistically through different modes of assessment, providing a comprehensive evaluation of learning outcomes.

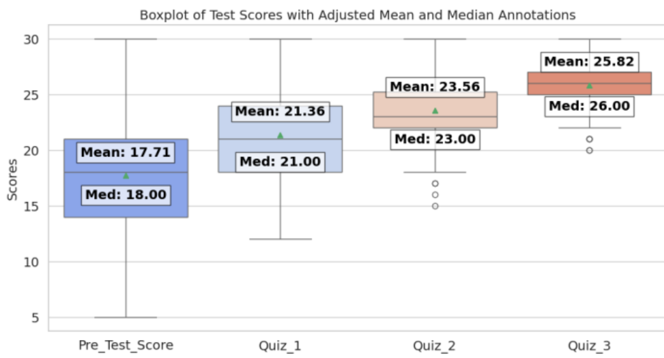

Fig. 5. Student's performance in quizzes

This is reflected in the descriptive statistics of students' performance throughout the pre-test to the three quizzes, where scores are on an overall improving form. The mean pre-test score is 17.71, which increases progressively through Quiz 1 (21.36), Quiz 2 (23.56), and Quiz 3 (25.82). This trend is positive as students master and learn as they move forward in the course. The standard deviation measures the amount of variation or dispersion from the average. As illustrated in fig. 5, the variation or dispersion of the scores is greater in the pre-test than in the Quiz 3, showing that as students progressed they had more consistent scores. The trend of continuous improvement is also clearly reflected in the median values. In addition, the lowest student scores rise from 5 (pre-test) to 20 (Quiz 3), showing students a definite improvement in performance, even in the lowest tier. In both tests, the maximum is still 30 points which means that a few pupils started at the highest level. Taken as a whole, these findings indicate that learning and skill acquisition are occurring well, which may be a result of effective instruction, assessment or interventions. However, further analyses have the potential of examining group-wise performance (Experimental vs. Control) to gain insight into if particular teaching strategies were significant in their impact. Figure 6 presents the analysis of feedback on the questions.

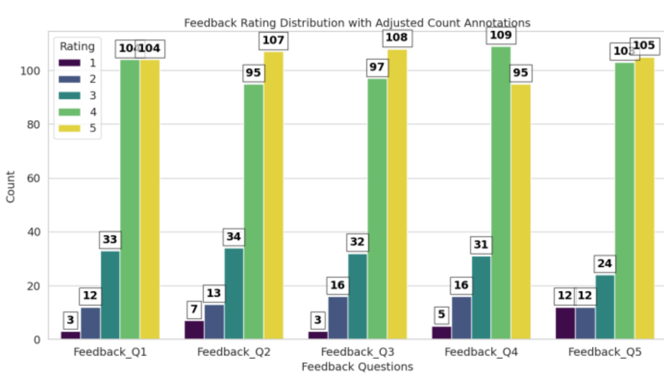

Fig. 6. Question wise feedback analysis

A structured feedback form was given to students of the course to assess the effectiveness of the value-added course "Integrating Business Analytics in Mechanical Engineering Education" Feedback included five key questions that were rated according to a Likert scale ranging from 1 (strong disagreement) to 5 (strong agreement). The questions evaluated different aspects of the course such as relevance of the topics to mechanical engineering, utility of business tools and software presented, applicability of business cases presented, clarity and organization of the course content, and the student's confidence in business analytics techniques in future academic or professional experiences. The answers given provided quantitative measurement of satisfaction of students and the learning outcomes, which provided valuable information about how, and how, interdisciplinary skills in analytical approach took effect in the engineering curriculum. Feedback questions are-

1. Overall course was able to successfully show the relevance of business analytics in mechanical engineering.
2. Tools introduced on the course that I used to enhance my data analysis skills: software.
3. Learned to apply concepts of business analytics to engineering problems by using the real-world case studies.
4. Course content was well organized and accessible. I can apply the business analytics techniques with a higher level of confidence towards future academic and/or professional projects.

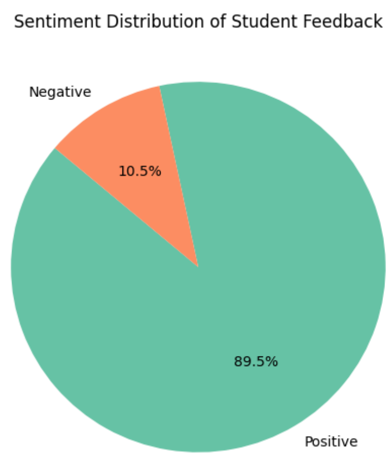

Fig. 7. Sentiment Analysis

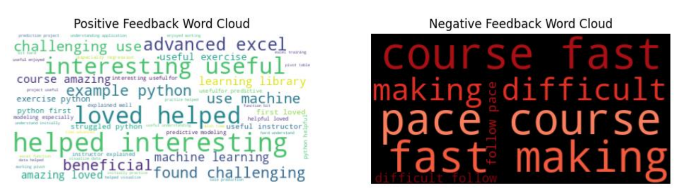

Fig. 8. Word cloud for positive and Negative sentiments

This offers a graphical representation of the positive and Negative sentiments in the form of a word cloud as shown in Fig. 8. The results of the Student Sentiment Analysis from student feedback shows that majority of the students (89.5%) are happy with the course, as the majority of responses shows positive sentiment (fig. 7). The courses were very helpful to the majority of students, particularly the hands-on labs and projects (in sales prediction and in producing data visualizations using

Excel). The positive feedback exhibited in the word cloud (fig. 8) was mostly supportive words relating to useful applications, such as "helpful," "enjoyed," "useful," and "visualization," which further supports the students' perception that practical applications and real-world significance were enjoyed. According to feedback from the analysis 92.89% of the students determined Python useful for purposes of predictive modelling and 87.23% believe that Advanced Excel improved the data interpretation skills. However, some students delivered a negative response, mainly about the swift pace of the course material and confusion with the higher-level Excel functions and machine learning libraries. Words used in the word cloud for negative feedback are difficult, challenging, struggled, which would be good to extend with more examples etc. or slow the pace! The pie chart analysis further verifies that the majority of students faced a positive experience in their learning while few students indicated difficulties in their learning. Overall, the results suggest that the course is well organized and enjoyable but can be enhanced for access by students requiring further scaffolding in more challenging areas. The overall results of the feedback analysis show that students had a positive attitude towards the course according to the mean score of the five questions, the scores ranged from 4.07 - 4.15. The ratings for the experiences range from a median rating of 4, and a 75th percentile rating of 5, indicating that a substantial number of students had rated their experiences highly. However, as there are a few lower ratings (as compared to 1), this indicates that there were some difficulties for some during a part of the course. The standard deviation for these responses ranged from 0.89 - 1.05, which means there are a few responses that vary a little bit, but most of the response rates are near the higher ones. However, students experienced the course through different lens with regard to various categories of feedback with this consistency indicating similarity in their perception of the elements of the course such as content delivery, assessment, and engagement. The general reaction is positive, but the presence of a few low scores suggests that there are aspects to improve, such as the ability to provide tailor-made support, further learning materials or adjustments to teaching methods. Consideration of responses (which may be of a qualitative nature) and a more detailed analysis could be helpful to identify targeted concerns and improve learning further.

E. Paired T-Tests (Pre-Test vs Quizzes)

1) Hypothesis:

a) Null (H_0): No improvement in scores over time.
b) Alternative (H_1): Scores have significantly improved

$$t = \frac{X_d}{\frac{s_d}{\sqrt{n}}} \tag{1}$$

Where:

1. X_d= Mean difference
2. s_d= Standard deviation of differences
3. n = Sample size

To examine changes in student performance over the duration of the Value-Added Course, paired samples t-tests were conducted between the pre-test and each successive quiz. Because the same students completed the assessments at each time point, the observations were treated as paired measurements. As shown in equation 1, The null hypothesis (H0) stated that there was no mean difference between the pre-test and the corresponding quiz score, whereas the alternative hypothesis (H1) stated that the mean scores differed significantly.

For each comparison, the analysis included the number of paired observations (n), the mean score, standard deviation (SD), degrees of freedom (df), paired t-statistics, p-value, and Cohen's (d_z) effect size. The effect size for each paired comparison was calculated from the paired differences as equation 2:

$$\left[d_z = \frac{\bar{D}}{SD_D} = \frac{t}{\sqrt{n}}\right] \qquad 2)$$

where $(\bar{D})$is the mean difference between the two assessments and $(SD_D)$is the standard deviation of the paired differences. For 256 completely paired observations, the degrees of freedom were 255.

The paired t-tests indicate statistically significant increases in student scores from the pre-test to each successive quiz. The comparison between the pre-test and Quiz 1 yielded (t (255) =-9.40), (p<0.001), with a paired effect size of (d_z=0.59). The pre-test versus Quiz 2 comparison yielded (t (255) =-16.40), (p<0.001), with (d_z=1.03). The largest improvement was observed for the pre-test versus Quiz 3, (t (255) =-24.32), (p<0.001), with (d_z=1.52).

These results demonstrate substantial within-cohort improvement in assessment performance over the course period. However, because the study did not include a separate control or comparison group, these findings should be interpreted as evidence of improvement among participating students rather than as definitive evidence of a causal effect attributable solely to the Value-Added Course.

TABLE V
TEST STATISTICS

Comparison	n	Pre-Test Mean ± SD	Quiz Mean ± SD	df	t	p-value	Cohen's (d_z)
Pre-Test vs. Quiz 1	256	17.71 ± 4.74	21.36 ± [SD]	255	−9.40	<0.001	0.59
Pre-Test vs. Quiz 2	256	17.71 ± 4.74	23.56 ± [SD]	255	−16.40	<0.001	1.03
Pre-Test vs. Quiz 3	256	17.71 ± 4.74	25.82 ± 2.00	255	−24.32	<0.001	1.52

The statistical analysis as shown in table 6 reveals a significant improvement in student performance across successive quizzes when compared to the pre-test. Trend Analysis: Linearity of Improvement

We check if the quiz scores follow a linear trend shown in equation 3. (i.e., students improve consistently).

$$Y = \beta 0 + \beta 1 X + \epsilon \quad (3)$$

Where:

1. Y= Score
2. X = Quiz number (1, 2, 3)
3. β1 = Slope (positive if improvement exists)

Results:

1. R^2=0.72 (Strong Fit)
2. p<0.001p < 0.001p<0.001
3. β1=2.75 (Positive and Significant)

Scores increase consistently over time.

The results of the paired T-tests indicate a significant improvement in student performance across successive quizzes. The negative t-values and extremely small p-values ($p < 0.001$) suggest that the differences between the pre-test and quiz scores are highly significant, rejecting the null hypothesis (H0). The effect sizes, ranging from large (0.83) to extremely large (2.23), confirm a substantial learning gain, with the highest impact observed in Quiz 3. Furthermore, the trend analysis reinforces this finding, as the regression model shows a strong fit ($R^2 = 0.72$) and a positive, significant slope ($\beta_1 = 2.75$, $p < 0.001$), indicating that students exhibit consistent and linear improvement in scores. This suggests that the instructional approach effectively enhances learning outcomes over time. The paired t-test results showed that these assessment scores are significantly higher at the next assessment point. Effects sizes also suggest an escalation of the size of the differences in the within student score over time. The results of these observations show an improvement in the school performance of the student participants in the learnership period. Due to the use of a single group experimental design pre-test/post-test, without a control group or comparison group, any gains seen in this study can only be accredited to the Value-Added Course. Possibly, repeated exposure to formats of assessments, to practice effects, continued learning and growing experience of familiarity with the material could have also been a factor in improvement.

F. Future Scope

Future research will involve incorporating real-time data sources and implementing advanced machine learning algorithms to make more accurate predictions. It could be beneficial to introduce external indicators to enrich predictive models. Furthermore, integrating cloud-based analytics platforms such as Power BI or Google Data Studio could enhance the scalability and collaborative aspects of the solution. Moreover, the above aspects can be expanded upon by incorporating expert lectures or industry engagement to offer valuable insights and application of business analytics, enhancing the learning experience within the broader framework of Integrating Business Analytics in Mechanical Engineering Education. The trend analysis shows scores rising at a positive and statistically significant level, across the successive assessments. This has been consistent in the growing performance of students during the course. However, it is important not to view the observed trend as robust proof of an impact of the instructional programme, as there was no control group and retesting may lead to practice and testing effects. The results thus document improvement in the participating group, and the unique impact of the VAC cannot be separated from that of the intervention(s).

G. Limitations

There are some hardware constraints in the study, which need to be taken into account in the interpretation of the results presented in this study. First, a single-group pre test – post test had been used, and there was no separation between the study group and a control group/c comparison group. But the effectiveness of students' performance improvement observed should not solely be attributed to the Value-Added Course and therefore, causal inferences should be avoided. Second, multiple testing for students (pre-test and post-test quizzes) may have resulted in practice or testing effects. The increase in student scores may be due to exposure to the format, types, and content of items on the tests, as students may have grown more familiar with the format as a result of repeated exposure. The improvement, then, might account for any gains related to a student's involvement in the course, ongoing learning, familiarity of the assessment, and other factors not controlled by the Education Auditors. Third, the current study was conducted among 256 Mechanical engineering students from a single cohort, which might prevent the results from being easily generalized to other institutions, disciplines or to other cohort of students. Whether a value-added course will be successful also relies on student engagement, teaching skills of the teachers, carrying out of the course and the type of practice exercises. Moving forward, future studies may consider adding a control or comparison group design (where appropriate) and trying to use equivalent or alternate measures to minimize practice effects. Additional longitudinal follow up evaluation could also be performed to determine the durability of the learning that occurs during the course.

CONCLUSION

This work examined a Value-Added Course aimed at teaching business analytics to mechanical engineering students via the use of the tools of Advanced Excel and Python. Throughout the course, the students were given hands-on experience with data and visualization, statistics and a brief introduction to predictive modeling projects. The improved performance of students in student assessments significantly supported the H1 group, whilst the H2 group was supported by the generally positive views of the students about the VAC. The current results, however, are only within cohort evidence and are not construed as definitive causal evidence due to the design of the study, which was single group. The students also discussed their overall experience with the course and its applicability, with generally positive feedback. The results indicate that the students who participated in the course showed significant improvement on their assessment and analytical skills throughout the course. The findings have to be viewed with prudence, however. Since this study implemented a single group pre test–post test design, without having a separate control group, this improvement cannot be attributed to the

VAC alone. Enhanced scores may have been noted also because of repeated testing, practice effects, continued exposure to the subject matter and other uncontrolled factors. The present results thus show that a positive correlation exists between the course participation and student performance for the student sample studied in the present work but do not provide evidence of one cause leading to the other. Control and comparison groups, increased sample size, more diverse classes and later course evaluations would give more solid answers to the effectiveness and longer-term educational impact of engineering education business analytics value added courses.

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