Streamlining ABET Direct Assessment: The Potential of ChatGPT Integration in Open and Distance Engineering Education

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Abstract

Open and distance engineering education (ODEE) presents unique challenges for program evaluation and accreditation. Traditional ABET accreditation processes, often reliant on in-person observation and resource-intensive assessments, struggle to effectively assess the diverse learning experiences and outcomes inherent to ODEE environments. This paper proposes an LLM-enhanced framework for ABET accreditation, specifically designed to address the complexities of ODEE. The framework integrates Large Language Models (LLMs) like ChatGPT throughout key assessment stages, from curriculum mapping and CLO weighting to examination design, attainment level setting, and student outcome reporting. This paper details how LLMs can analyze learning data, personalize assessments, provide scalable yet tailored feedback, and automate reporting, thereby enhancing the robustness, efficiency, and transparency of ABET accreditation for ODEE programs. The ethical considerations and potential limitations of LLM integration are also critically examined, highlighting the need for human oversight, data privacy safeguards, and ongoing evaluation. By embracing the capabilities of LLMs responsibly, this framework empowers ODEE programs, particularly those within a European context seeking international recognition, to demonstrate program quality, continuous improvement, and alignment with globally recognized standards in engineering education.

Keywords: Distance Education, Large Language Model, ChatGPT, Student outcome assessment, ABET accreditation, Assessment methodology, Assessment metrics, Continuous improvement, Educational quality

Introduction

The exponential growth of open and distance engineering education (ODEE) has democratized access to specialized knowledge, demanding a parallel evolution in accreditation practices. Traditional ABET accreditation, heavily reliant on in-person observation and resource-intensive assessments, struggles to effectively evaluate the diverse learning experiences within ODEE. This paper posits that Large Language Models (LLMs), specifically ChatGPT, present a transformative opportunity to enhance the robustness, scalability, and personalization of ABET accreditation within ODEE (Anwar & Richards, 2018; Bachnak et al., 2019).

Traditional assessment methods face significant limitations in ODEE environments (Ali, 2023a; Ali, 2023b):

1. Limited Observability of Learning Processes: Assessing student engagement and understanding in the absence of direct classroom observation necessitates innovative approaches.

2. Diverse Learning Styles and Asynchronous Environments: ODEE learners exhibit diverse learning styles, needs, and geographical constraints, rendering standardized assessments less effective.

3. Ensuring Academic Integrity at Scale: Maintaining academic integrity within large-scale ODEE programs requires sophisticated plagiarism detection and authentication mechanisms.

LLM-Enabled solutions for robust ABET accreditation are (Khan, 2019; Ahmad & Qahmash, 2020):

1. Data-Driven Continuous Improvement: LLMs can analyze longitudinal student performance data, identifying program-level strengths and weaknesses, informing curriculum revisions, and enabling data-driven continuous improvement aligned with ABET criteria. This data-driven approach ensures that ODEE programs remain relevant and responsive to evolving industry needs.

2. Enhancing Assessment Authenticity and Personalization: LLMs can generate diverse assessment items, including complex scenarios, simulations, and open-ended problems, promoting higher-order thinking skills aligned with ABET's student outcome focus. Furthermore, LLM-powered adaptive testing platforms can adjust difficulty levels in real-time, providing individualized assessments that accurately measure competency.

3. Facilitating Scalable and Personalized Feedback: LLMs can automate the grading of objective assessments, providing immediate feedback and freeing up instructor time for personalized interventions. Furthermore, LLMs can analyze student work and generate tailored feedback, highlighting areas for improvement and suggesting relevant resources, even at scale.

Deploying LLMs for ABET accreditation necessitates addressing ethical considerations (Alhakami et al., 2020; Dawood et al., 2013):

1. Data Privacy and Security: Implementing robust data encryption, secure storage solutions, and adhering to relevant data privacy regulations are paramount. Institutions must ensure transparent data governance policies and obtain informed consent from students regarding data usage.

2. Algorithmic Bias and Fairness: Addressing potential biases in training data is crucial to ensure equitable assessments and feedback. Continuous monitoring of LLM outputs for bias and implementing bias mitigation techniques are essential for fair evaluation.

3. Maintaining Human-in-the-Loop: LLMs should augment, not replace, human judgment in the accreditation process. Educators must retain oversight of assessment design, interpretation of LLM-generated insights, and provision of

high-level feedback, ensuring the quality and ethical integrity of the evaluation process.

4. LLMs represent a powerful toolset for enhancing the robustness, scalability, and personalization of ABET accreditation within the evolving landscape of ODEE. By leveraging LLM capabilities for data-driven insights, personalized learning pathways, and scalable yet individualized feedback, institutions can not only meet but exceed ABET accreditation standards, ultimately cultivating a generation of highly skilled and adaptable engineers prepared to meet the demands of a technology-driven world. However, ethical considerations regarding data privacy, algorithmic bias, and the essential role of human oversight must be carefully addressed throughout the implementation process.

While the traditional direct assessment method has been instrumental in evaluating student learning outcomes, it is crucial to recognize its limitations, including resource intensity, administrative burden, and potential gaps in assessment coverage. Therefore, this paper proposes a new approach that seeks to enhance the direct assessment method, making it more lightweight, comprehensive, precise, and informative. By embracing innovative strategies and leveraging AI technological advancements, this proposed framework aims to strengthen the assessment process, leading to continuous improvement in engineering education and ABET accreditation.

Literature Review

In the pursuit of enhancing academic accreditation, numerous research works have been conducted, addressing various aspects of the accreditation process. One of the primary goals of this research is to assist educational institutions in meeting accreditation criteria effectively. Scholars have documented their experiences with ABET certification, providing valuable insights into the accreditation process (Anwar & Richards, 2018; Bachnak et al., 2019, Ali, 2023a; Ali, 2023b).

Among the essential duties in the accreditation process is program evaluation, which ensures that academic programs can consistently produce the desired student outcomes. Several studies have emphasized the significance of program evaluation in maintaining educational standards (Khan, 2019; Ahmad & Qahmash, 2020; Alhakami et al., 2020; Dawood et al., 2013; Schoepp et al., 2016).

The landscape of accreditation efforts underwent a significant shift due to the COVID-19 pandemic, leading to the widespread adoption of remote tools and procedures for accrediting purposes. This recent impact has prompted researchers to explore the effectiveness and implications of remote accreditation methods across various sectors (Hussain et al., 2020; Karimi & Manteufel, 2021; Mohamed et al., 2021; Essa et al., 2010; Lam et al., 2019).

Furthermore, a wealth of literature focuses on education's continuous improvement procedures, as institutions strive to evolve and enhance their educational offerings continually. These studies highlight the importance of refining teaching practices, curriculum design, and learning environments to promote ongoing progress in academic programs (Cabezas, 2015; McKenzie et al., 2015; Peridier, 2020; Zambrano, 2019).

Education that is outcome-based has also garnered attention in research literature. Emphasizing the significance of measurable learning outcomes, these studies advocate for aligning educational objectives with assessment strategies to ensure students' mastery of essential skills and competencies (Rathy et al., 2020; Lavanya et al., 2020; Manzoor et al., 2017; Xu et al., 2022; Sánchez-Ruiz et al., 2023).

In contrast to previous studies that focused on general program evaluation and educational outcomes, our approach addresses the specific challenges faced by traditional direct assessment methods. By leveraging technology-driven assessment tools and adopting a multi-dimensional assessment model, we aim to streamline data collection, reduce administrative burden, and improve the accuracy of assessment outcomes. Furthermore, our framework emphasizes generating actionable feedback and insightful reports to foster continuous improvement in engineering education.

As the educational landscape continues to evolve, our efforts not only complement existing research but also provide a unique contribution by offering a practical and adaptable solution to the shortcomings of current direct assessment methods. Through the implementation of our proposed framework, engineering programs can achieve a more efficient and effective assessment process, leading to enhanced ABET accreditation outcomes and better-equipped graduates ready to tackle the challenges of the future.

Methodology

Traditional Direct Student Assessment Method

The traditional direct student assessment method comprises a systematic approach to evaluate and measure student learning outcomes in engineering programs. The steps involved in this method are as follows (McKenzie et al., 2015; Peridier, 2020; Zambrano, 2019; Rathy et al., 2020):

1. Defining Program Syllabus: The first step involves defining the overall syllabus and curriculum of the engineering program. This entails outlining the content, objectives, and learning outcomes that students are expected to achieve throughout their academic journey.

2. Defining Course Learning Outcomes (CLOs) of Each Module: Each module or course within the program is broken down into specific learning outcomes. These CLOs represent the measurable knowledge, skills, and competencies that students are expected to acquire upon completing each module.

3. Defining Performance Indicators (PIs) of Each CLO: For each Course Learning Outcome, specific performance indicators are defined to assess and quantify the level of achievement. Performance indicators provide clear criteria for evaluating student performance in relation to the desired outcomes.

4. Linking CLOs of Different Modules to Student Outcomes (SOs): The Course Learning Outcomes are aligned with the broader Student Outcomes (SOs) that represent the overall educational objectives of the engineering program. This

alignment ensures that the CLOs contribute to the attainment of the desired program-level outcomes.

5. Determining the Attainment Level for the Selected Modules: The attainment levels for each Course Learning Outcome in the selected modules are determined based on the performance of students. These levels indicate the degree to which students have achieved the specified learning outcomes.

6. Performing Direct Assessment on Selected Modules: Direct assessment involves the evaluation of student work and performances in the selected modules. Faculty or evaluators review assessments such as exams, quizzes, homework, projects, and other relevant activities to gauge student achievement.

7. Designing Suitable Rubric for the Assessment Process: To ensure consistency and fairness in evaluating student work, suitable rubrics are designed. Rubrics provide clear and objective criteria for assessing the level of attainment of each Course Learning Outcome.

8. Using PIs to Measure the Attainment of Each CLO: The Performance Indicators defined for each Course Learning Outcome are utilized to measure the extent to which students have achieved the specified outcomes. These indicators provide quantitative data for assessment.

9. Calculating Student Outcome Achievement (SO%): The overall Student Outcome achievement is calculated by summing up the attainment levels of all relevant Course learning outcomes in the selected modules and expressing it as a percentage. This computation provides a comprehensive measure of the students' overall achievement in attaining the desired Student Outcomes (SOs) of the program.

While the traditional direct student assessment approach has been widely used for evaluating student learning outcomes, it is not without its limitations and challenges. Some of the problems with this approach include (Rathy et al., 2020; Lavanya et al., 2020):

1. Resource Intensive: The traditional direct assessment method can be resource-intensive, requiring significant time, effort, and personnel to implement effectively. Faculty members and administrators may find it burdensome to manage multiple assessment activities, especially in large academic programs.

2. Limited Assessment Coverage: Depending on the number of modules and courses within a program, it may not be feasible to assess every Course Learning Outcome (CLO) in all modules. As a result, certain learning outcomes might receive more emphasis, while others may be overlooked, leading to an incomplete picture of students' overall learning.

3. Assessment Overemphasis on Exams and Quizzes: Traditional direct assessment methods often rely heavily on exams and quizzes as assessment tools. While these are valuable evaluation methods, they may not fully capture

the range of skills and competencies developed through the entire learning process.

4. Subjectivity in Grading: The assessment process involves human judgment and evaluation, which can introduce subjectivity and inconsistency in grading. Different faculty members may interpret rubrics differently, leading to variations in student assessments.
5. Lack of Timely Feedback: The traditional direct assessment method often involves time-consuming evaluation processes, leading to delayed feedback for students. This hinders their ability to identify areas for improvement promptly.

6. Insufficient Integration of Technology: While the proposed framework aims to leverage educational technology, the traditional direct assessment method may not fully embrace the potential of technological advancements to streamline data collection, analysis, and reporting.

7. Cumbersome Data Management: Handling and analyzing the data generated through direct assessment can become cumbersome, especially in large engineering programs with numerous modules and students.

8. Focus on Compliance rather than Improvement: In some cases, the primary focus of direct assessment might be on satisfying accreditation requirements rather than utilizing the assessment data to drive meaningful improvements in the educational program.

9. Limited Flexibility: The traditional approach may lack the flexibility to adapt quickly to changes in curriculum, instructional methods, or emerging educational needs. This rigidity can hinder the incorporation of innovative teaching and learning practices.

Despite these challenges, the traditional direct assessment method has provided valuable insights into student learning outcomes and program effectiveness. However, to address these problems and enhance the assessment process, it is crucial to explore innovative approaches that promote a more lightweight, comprehensive, precise, and informative assessment framework, aligning with the proposed goals of this paper.

Suggested Direct Student Assessment Method

The enhanced assessment method builds upon the traditional direct student assessment approach, addressing its limitations while introducing innovative strategies to achieve a more comprehensive and efficient evaluation of student learning outcomes. The following steps outline the key elements of the enhanced assessment method:

1. Defining Program Syllabus: Similar to the traditional approach, the first step involves defining the program syllabus, outlining the content and scope of the academic program.

2. Course Materials Classification & Weighting: Course materials are classified based on their relevance and importance in achieving Course Learning

Outcomes (CLOs). Each classified material is assigned a weight that reflects its significance in contributing to the overall learning objectives.

3. Defining Course Learning Outcomes (CLOs) of Each Module: As in the traditional approach, specific Course Learning Outcomes (CLOs) are defined for each module, outlining the expected knowledge, skills, and competencies to be attained by students.
4. Setting the Weights of Each CLO of All Modules: In the enhanced method, to prioritize and differentiate the importance of various Course Learning Outcomes (CLOs) across modules, each CLO is assigned a weight, reflecting its relative significance in the overall assessment process.

5. Linking CLOs of Different Modules to Student Outcomes (SOs): Similar to the traditional approach, the Course Learning Outcomes (CLOs) of different modules are aligned with the overarching Student Outcomes (SOs) of the academic program, ensuring that each CLO contributes to the achievement of the desired student outcomes.

6. Determining Different Attainment Levels for the Different Modules: The enhanced method accounts for variations in the complexity and difficulty of different modules by determining different attainment levels for each module. This allows for a more nuanced assessment of student performance across diverse coursework.

7. Performing Direct Assessment on ALL Modules: Unlike the traditional approach, which may select specific modules for assessment, the enhanced method involves performing direct assessment on ALL modules. This comprehensive assessment approach ensures a more inclusive and representative evaluation of student learning.

8. Performing Direct Assessment Based on Final Exam Only: To streamline the assessment process, the enhanced method focuses on direct assessment through the final exam, which serves as a comprehensive and integrative evaluation of students' knowledge and skills.

9. Using the Same Rubric of the Final Exam: To maintain consistency and objectivity, the same rubric used for grading the final exam is applied to assess student performance in all modules.

10. Calculating Student Outcome Achievement (SO%): The Student Outcome Achievement (SO%) is calculated by summing the attainment levels of all Course Learning Outcomes (CLOs) across the modules, weighted by the CLO and module weights. This computation provides a comprehensive measure of students' overall achievement in attaining the desired Student Outcomes (SOs) of the program.

The enhanced assessment method seeks to provide a more efficient, precise, and comprehensive evaluation of student learning outcomes while mitigating the limitations of the traditional approach. By leveraging technology and streamlining the assessment process, this method aims to foster continuous improvement in engineering education and enhance the overall accreditation efforts.

Results and Discussion

Based on the steps outlined in the enhanced assessment method, we can identify the lightweight, comprehensive, precise, and informative features as follows:

1. Lightweight: Performing direct assessment based on the final exam only streamlines the assessment process, reducing administrative burden and saving valuable time and resources. Also, by focusing on the final exam as the primary assessment tool, the method avoids excessive assessment activities and data collection efforts, making it more efficient and user-friendly.

2. Comprehensive: The method ensures comprehensive coverage of student learning outcomes by performing direct assessment on ALL modules within the academic program. This approach provides a holistic view of students' performance across the entire curriculum. Linking Course Learning Outcomes (CLOs) of different modules to Student Outcomes (SOs) ensures that the assessment is aligned with the overarching program objectives, covering all essential skills and competencies. This alignment ensures that each CLO contributes to the attainment of the desired student outcomes, fostering a comprehensive assessment process.

3. Precise: By assigning specific weights to each module and Course Learning Outcome (CLO) based on its relative significance, the method ensures a precise evaluation of the importance of different learning objectives. This weightage reflects the relative emphasis placed on various CLOs in the assessment process.

4. Informative: The method provides actionable feedback for continuous improvement in engineering education. It extracts the attainment level of each Course Learning Outcome (CLO) from final exam grades, considering the assigned weights. This data-driven approach provides valuable information on students' achievement in meeting specific learning objectives, offering informative insights for improvement. Also, by calculating the Student Outcome Achievement (SO%) as a sum of weighted attainment levels, the method provides a quantitative measure of students' overall performance in attaining the desired Student Outcomes (SOs) of the program. This calculation offers informative data on the effectiveness of the academic program in achieving its educational objectives. Additionally, the use of a consistent rubric for the final exam facilitates clear and insightful evaluation of student work, enabling educators to identify strengths and areas for improvement effectively.

Implementation Plan An Case Study

In this section, we outline the practical steps required to implement the proposed assessment method. We consider the integration of technology, faculty development, and institutional support to ensure a successful transition to the new approach.

To demonstrate the effectiveness of our proposed assessment method, we present a case study of its implementation in a computer engineering program. We analyze the outcomes, challenges encountered, and the overall impact on ABET accreditation.

Curriculum Preparation

Table 1 presents a comprehensive arrangement of courses, their corresponding details, and weighting within the enhanced assessment method. The arrangement is organized based on the academic level and semester, providing information about each module's code, name, student workload (hours per week), exam hours, credit hours, module type, and module weight. It is noted that the number of credit hours assigned to each module, represents the academic value and part of the weight of the module within the program and it includes the summation of theoretical hours, laboratory hours, and tutorial hours (e.g., 2 theoretical hours + 3 laboratory hours = 5 hours per week). Module type indicates whether the module is classified as Basic, Core, or Supportive, based on its relevance and importance to the program's educational objectives. Module weight is the relative weight or significance of each module, reflecting its contribution to the overall assessment process. Module weight is calculated by multiplying the number of credit hours of each module by the weight given to each module type. For instance, in Level One, courses such as "Computer Principles" (CE101), and "Mathematics 1" (CE103), are categorized as "Basic" courses, carrying Module Weights of 10. These Module Weights indicate the relative importance of these courses in contributing to the overall achievement of Course Learning Outcomes (CLOs) and Student Outcomes (SOs) of the program. In contrast, "Human Rights" (CE102), "English Language" (CE107), and "Democracy" (CE109) are categorized as "Supportive" courses, with lower Module Weights, reflecting their auxiliary role in supporting the main learning objectives of the program. Additionally, "Programming using C++ Language" (CE108), "Electrical Circuits Analysis 2" (CE111), and "Digital System Fundamentals" (CE112) are identified as "Core" courses, carrying higher Module Weights (Cabezas, 2015; Manzanoor et al., 2017; Zambrano, 2019, respectively) due to their critical importance in shaping students' core competencies and achieving program-level outcomes. The table provides a clear and concise overview of the courses offered in the program, their associated workload and credit hours, and their respective contributions to the assessment process. The information presented in the table serves as a vital foundation for implementing the enhanced assessment method, ensuring a comprehensive and informed evaluation of student learning outcomes across the academic program.

Table 1: Curriculum Mapping

Level	Semester	Module Code	Module Name	Student Work Load (hr/w)			Exam Hours	Credit Hours	Module Type	Module Weight
				Theory (hr/w)	Lab (hr/w)	Tutorial (hr/w)				
ONE	One	CE101	Computer Principles	2	3		3	5	Basic	10
		CE102	Human Rights	2	0		3	2	Supportive	2
		CE103	Mathematics 1	4	0	1	3	5	Basic	10
		CE104	Engineering Drawing by Computer	0	3		3	3	Basic	6
		CE105	Electrical Circuits Analysis1	3	3	1	3	7	Core	21
		CE106	Electronics Physics	3	0	1	3	4	Basic	8
	Two	CE107	English Language	2	0		3	2	Supportive	2
		CE108	Programming using C++ Language	2	3		3	5	Core	15
		CE109	Democracy	2	0		3	2	Supportive	2
		CE110	Mathematics 2	4	0	1	3	5	Basic	10
		CE111	Electrical Circuits Analysis 2	3	3	1	3	7	Core	21
		CE112	Digital System Fundamentals	2	3	1	3	6	Core	18
TWO	Three	CE201	Engineering Mathematics 1	3	0	1	3	4	Basic	8
		CE202	Analog Electronics	3	3		3	6	Basic	12
		CE203	Microprocessors 1	2	3		3	5	Core	15
		CE204	English Language-Pte-intermediate	2	0		3	2	Supportive	2
		CE205	Object Oriented Programming	2	3		3	5	Core	15
		CE206	Programmable Logic Design using HDL	2	3		3	5	Core	15
	Four	CE207	Computational Methods for Data Analysis	2	0	1	3	3	Core	9
		CE208	Engineering Mathematics 2	3	0	1	3	4	Basic	8
		CE209	Engineering Management	2	0		3	2	Supportive	2
		CE210	Digital Electronics	2	3	1	3	6	Core	18
		CE211	Microprocessors 2	2	3		3	5	Core	15
		CE212	Data Structures	2	3	1	3	6	Core	18
THREE	Five	CE301	Data Communications	2	3	1	3	6	Core	18
		CE302	Signals and Systems	3	0		3	3	Core	9
		CE303	Computer Architecture I	2	0	1	3	3	Core	9
		CE304	Computer Interface	2	3		3	5	Core	15
		CE305	Operating Systems I	2	3		3	5	Core	15
		CE306	Artificial Intelligence Principles	2	0		3	2	Core	6
	Six	CE307	Computer Networks	2	3	1	3	6	Core	18
		CE308	Digital Signal Processing	3	0		3	3	Core	9
		CE309	Computer Architecture 2	2	0	1	3	3	Core	9
		CE310	Embedded Systems	2	3		3	5	Core	15
		CE311	Operating Systems 2	2	3		3	5	Core	15
		CE312	English Language Intermediate	2	0		3	2	Supportive	2
FOUR	Seven	CE401	Professional Ethics	2			3	2	Supportive	2
		CE402	Fundamentals of Control Systems	3	3		3	6	Core	18
		CE403	Real Time Systems	2	3	1	3	6	Core	18
		CE404	Industrial Networks	2			3	2	Core	6
		CE405	Wireless Networks	2	3		3	5	Core	15
		CE406	Parallel Computer Architecture	2		1	3	3	Core	9
	Eight	CE407	Graduate Project	1	4		3	5	Core	15
		CE408	Computer Graphics	2			3	2	Core	6
		CE409	Cybersecurity	2			3	2	Core	6
		CE410	Moblie Systems Fundimentals	2	3		3	5	Core	15
		CE411	Image Processing and Applications	2		1	3	3	Core	9
		CE412	English language- Upper Intermediate	2			3	2	Supportive	2
Modules Types Weights: (Supportive: 1, Basic: 2, Core: 3)										

CLO Weighting

Another weighting procedure is needed in this assessment method, CLO weighting. To demonstrate this procedure, the following example is given. The provided Table 2 presents a detailed description of a certain module "Industrial Networks" with its associated Course Learning Outcomes (CLOs) and the procedure for weighting these outcomes. This information is crucial for understanding the content and assessment framework of the module. The module "Industrial Networks" is categorized as a core course with a module weight of 6, indicating its significant role in achieving the program's educational objectives. The module comprises several Course Learning Outcomes (CLOs), each representing a specific skill or competency that students are expected to attain. In Table 2, CLO% contribution in the syllabus (No. of Weeks/15): This column denotes the proportion of the module's duration dedicated to teaching and assessing each CLO. It indicates the weeks during which the specific CLO is covered in the syllabus. SO Linkage: Indicates whether the CLO is linked to Student Outcomes (SOs), demonstrating the connection between the specific CLO and the broader program-level learning objectives. CLO Weight (CLOW): This column represents the calculated weight of each CLO. The weight is determined by multiplying the SO linkage with the CLO% contribution.

Table 2: Module Description & CLO Weighting

Module Name: Industrial Networks Module Code: CE404 Credit Hours: 2 Module Type: Core Module Weight (MW): 6										
Course Learning Outcome (CLO)	Description	CLO% contribution in the sullybus (No. of Weeks/15)	SO linkage							CLO Weight (CLOW) (SO Linkage × CLO%
			1	2	3	4	5	6	7	
1	Identify the need for network protocols during data exchange	13% (Week1, Week2)		×						0.13
2	Demonstrate the use of serial standards as required in an industrial plant environment.	13% (Week3, Week4)			×					0.13
3	Analyze and identify the methods of communications	34% (Week5-Week9)	×	×	×				×	1.36
4	Compare the different protocols used as industrial standards	27% (Week10-Week13)		×	×					0.54
5	Demonstrate a working programmable logic controller network in a simulated industrial automated application	13% (Week14,Week15)	×	×	×				×	0.52

The resulting value indicates the relative importance of each CLO in achieving the overall program outcomes. Here's an example to illustrate the procedure: For CLO 3, "Analyze and identify the methods of communications," it is linked to SOs 2, 3, and 6. The CLO contributes 34% of the syllabus time (Week 5 to Week 9) and has a CLO Weight (CLOW) of 1.36. This value (1.36) is obtained by multiplying the SO linkage (3 linked SOs) by the CLO% contribution (34% / 15 weeks).

Similarly, each CLO is evaluated and weighted based on its syllabus contribution and linkage to broader program outcomes. These weights provide insight into the relative significance of each CLO in the module's assessment and contribute to the overall assessment framework. In summary, the table effectively outlines the content and assessment structure of the "Industrial Networks" module, showcasing the weighting procedure for each Course Learning Outcome and its linkage to broader program-level objectives. This transparent and structured approach aids in understanding the emphasis placed on different learning outcomes and guides the assessment process within the module.

A. Examination Strategy

The proposed examination strategy, designed to efficiently assess Course Learning Outcomes (CLOs), offers several distinct advantages by leveraging the final exam as a direct measure of student knowledge. This approach is particularly effective when students are well-prepared, and examination conditions are well-arranged. Here's a more comprehensive description of this strategy:

1. Direct Measure of Student Knowledge: The final exam serves as a direct measure of students' understanding, knowledge, and competency related to the CLOs. It provides an immediate evaluation of how well students have absorbed and retained the material covered in the syllabus. Since the exam is administered at the end of the course, it captures a comprehensive snapshot of students' grasp of the subject matter.

2. Optimal Preparation and Conditions: The strategy capitalizes on well-prepared students and carefully organized examination conditions. Students are expected to have thoroughly engaged with the course material, enabling them to demonstrate their understanding effectively. Additionally, the exam environment is conducive to focused assessment, ensuring that the students' performance is reflective of their actual learning.

3. Minimized Faculty Efforts in Rubric Preparation: The approach minimizes the need for faculty to prepare a new rubric solely for the exam. The same rubric used for ongoing assessments can be seamlessly applied to the exam. This continuity simplifies the assessment process for both students and faculty. Since the existing rubric is familiar to both parties, there's a clear understanding of the evaluation criteria and expectations.

4. Examination Grades as Performance Indicators: The performance indicators used to measure students' attainment of CLOs are directly linked to their examination grades. The exam serves as a comprehensive assessment tool, evaluating students' knowledge and skills across all CLOs simultaneously. This

alignment ensures that the exam effectively captures the learning outcomes and provides a robust basis for measuring student achievement.

5. Resource and Time Efficiency: By utilizing the final exam as the primary assessment mechanism, the approach optimizes faculty's resource allocation and time. Faculty members do not need to design separate assessments or rubrics, streamlining their efforts. Moreover, this approach eliminates the need for additional grading procedures, as the exam already provides a holistic evaluation.

6. Holistic Evaluation: The exam's inclusive nature ensures a holistic evaluation of students' performance across all CLOs. Since each CLO is represented in the exam questions, students' mastery of the entire range of learning objectives is gauged. This approach is particularly valuable for assessing the integration of different concepts within the module.

Table 3 outlines a structured approach to arranging and preparing the final exam for the example of "Industrial Networks" module. The procedure begins by setting a fixed number of questions for the exam to align with the number of weeks the module was taught (Cabezas, 2015). This balanced approach ensures that each week's content receives equal attention in the assessment. To measure each CLO efficiently and precisely, questions are allocated proportionally based on their contribution to the syllabus. CLOs with higher syllabus percentages receive a corresponding higher number of questions in the exam. This approach strategically distributes the assessment emphasis to reflect the weightage of each CLO in the learning process.
By adhering to this structured and thoughtful approach, the final exam becomes a comprehensive assessment tool that efficiently measures all CLOs while aligning with their respective contributions to the syllabus. This approach reduces the need for excessive questions while ensuring that the assessment accurately represents students' mastery of the learning objectives. It also guides instructors in preparing an exam that is informative, fair, and reflective of the course's educational goals. By aligning examination grades with the performance indicators associated with each CLO, the strategy provides a precise and comprehensive evaluation of students' achievement. This approach's resource efficiency and alignment with existing rubrics contribute to a seamless and informed assessment process, benefiting both students and faculty.

Table 3: Final Exam Sheet

Examination Sheet (Example: Industrial Networks)	No. of Questions must be 15, same No. of Weeks	Structured, pre arranged exam
All CLOs must be included and measured	No. of Questions to measures certain CLO is proportional to CLO contribution in the sulybus	CLOs contribution of questions grades
CLO1	2	13%
CLO2	2	13%
CLO3	5	34%
CLO4	4	27%
CLO5	5	13%

B. Variable Attainment Levels

In pursuit of a more refined and nuanced assessment framework, our proposed approach introduces variable attainment levels, uniquely calibrated to the distinct module types within the curriculum. This innovative strategy leverages the module's role and significance to set tailored attainment thresholds, enhancing the precision and relevance of the assessment process.

The foundation of this approach lies in recognizing the diverse categories of modules: CORE, BASE, and SUPPORTIVE. Each module type holds a distinct role in shaping students' academic journey, contributing to their overarching learning outcomes. As such, we advocate for an adaptable approach that acknowledges the varied importance of these modules in achieving program objectives.

For CORE modules, characterized by their central role in the program's core competencies, the approach suggests a targeted attainment level of 70%. This signifies that a substantial majority of students – 70% – should acquire 70% or more to demonstrate mastery of these critical concepts. This higher threshold reflects the paramount importance of these modules in shaping students' expertise.

On the other hand, for BASE and SUPPORTIVE modules, where the focus may be on foundational knowledge and complementary skills, the approach recommends a more flexible attainment level of 60%. This adaptable standard recognizes the varying degrees of emphasis these modules receive in contributing to students' comprehensive learning.

Furthermore, the approach opens the door for a more advanced implementation, wherein specific CORE materials could be assigned varying attainment levels based on the program's specialty. This refined customization aligns closely with the unique demands of specialized programs, ensuring that the attainment levels accurately mirror the specialized learning objectives.

By introducing variable attainment levels aligned with module types, our approach empowers educators to tailor the assessment process to the program's overarching goals. This tailored strategy ensures that assessment standards are proportional to the modules' roles, optimizing precision and fairness. Moreover, it acknowledges the diverse learning journey of students, promoting motivation and engagement across different module types.

C. Student Outcome Calculation and Reporting

At this point we reached to the most important section in this paper, how to calculate the Achieved Student Outcomes percentages (Achieved SO%) using the enhanced assessment method. We begin our discussion using a demonstration example only.

A cornerstone of the enhanced assessment method lies in the meticulous calculation of Achieved Student Outcomes percentages (Achieved SO%), an endeavor that vividly mirrors the program's educational success. This computation encapsulates the attainment of Course Learning Outcomes (CLOs) within a framework that recognizes the nuanced attainments across different modules and their respective attainment levels. To initiate this calculation, a meticulously crafted equation is employed:

Achieved SO% = Σ(CLO1 and CLO3 of CE105 + CLO2 of CE202 + CLO4 of CE302) (Anwar & Richards, 2018)

This equation forms the basis for assessing student achievement across specified CLOs, encompassing a targeted spectrum of learning objectives within the program. The resultant Achieved SO% provides a comprehensive metric that quantifies how effectively students have internalized and demonstrated the program's core competencies.

A defining aspect of this calculation is the calibration of attainment levels that align with the nature and purpose of each module. We advocate for an adaptable approach that acknowledges the diversity of modules and their learning outcomes. Hence, our suggested settings stipulate attainment levels tailored to individual modules: for modules CE105 and CE302 categorized as "Core," a heightened standard is set, requiring 70% of students to surpass a 70% threshold to achieve the attainment level. This elevated expectation reflects the crucial role of "Core" modules in fostering foundational competencies. Conversely, for module CE202 categorized as "Supportive," a targeted attainment level is set at 60%. This recognizes the supportive nature of the module, complementing the program's overarching objectives.

The Attainment Level of each CLO (Attainment Ratio (AR%)) is judiciously evaluated using a fundamental ratio:

$$\mathrm{AR\%} = \frac{\text{No.of students who pass the attainment level}}{\text{Total No.of students who attend the exam}}$$ (Bachnak et al., 2019)

This formula gauges the ratio of students who successfully achieve the predefined attainment level for a particular CLO relative to the total number of students participating in the exam. By applying this calculation to each CLO within the equation, the Achieved SO% emerges as a robust representation of students' collective attainment across the targeted CLOs and their respective attainment levels.

The calculation of Achieved Student Outcomes percentages represents the culmination of a meticulously structured assessment approach. It integrates attainment levels tailored to individual modules, acknowledges variable standards of achievement, and employs ratios that holistically gauge students' mastery of targeted learning outcomes. The resulting Achieved SO% is a measure of educational efficacy, illuminating the program's success in nurturing proficient engineers equipped to excel in their chosen field.

Table 4 encapsulates the culmination of the assessment process, delving into the intricate details of the final examination statistics and assessment analysis. Each entry within the table contributes to the comprehensive calculation of the Achieved Student Outcomes percentages (Achieved SO%). This table serves as a quantitative representation of the assessment outcomes for the modules CE105, CE202, and CE302 (in this example). It presents the assessment results for each Course Learning Outcome (CLO) within these modules, illustrating both the attainment and contribution of each CLO to the overall Achieved SO%. The CLO# Contribution column embodies the contribution of a particular CLO to the overall assessment outcome. It's calculated by multiplying the Attainment Ratio (AR), Module Weight (MW), and Course Learning Outcome Weight (CLOW). The Achieved SO% is a key measure, reflecting the program's success in imparting targeted knowledge and skills to students. It's calculated by summing the weighted contributions of all relevant CLOs and aligning it with the broader program objectives. This percentage serves as an insightful indicator of the program's effectiveness in achieving the desired student outcomes. The calculation in this table is repeated for the other ABET SOs and they intricately capture the essence of the assessment process, revealing the impact of students' performance on specific CLOs, module weights, and overall program attainment. The Achieved SOs% are the ultimate reflection of the educational journey, encapsulating the fruits of focused learning and dedicated teaching efforts.

The second part of the table represents the assessment report which serves as a comprehensive analysis of the Achieved Student Outcomes percentages (Achieved SO%) in relation to the defined Student Outcomes (SO) thresholds. It provides an insightful evaluation of the program's educational effectiveness by comparing the attained achievements to the preset standards. The report delineates the performance of each individual Course Learning Outcome (CLO), highlighting areas of alignment and areas necessitating attention. These insights serve as a foundational guide for targeted educational enhancements and refinements, ensuring that student learning outcomes are optimally realized. This assessment report, in its entirety, stands as a vital tool for continual improvement in engineering education.

Table 4: SO% Calculation & Reporting

Module	CLO#	Total No. of attended Students	No. Of Students passed the attainment level	Attainment Ratio% (AR%)	Module Weight (MW)	CLO# Weight (CLOW)	CLO# Contribution (AR x MW x CLOW)
CE105	CLO1	40	22	55% (0.55)	21	0.13	1.5
	CLO3	44	25	57% (0.57)		1.36	16.27
CE202	CLO2	35	30	86% (0.86)	12	0.13	1.34
CE302	CLO4	40	30	75% (0.75)	9	0.54	3.64
Achieved SO% (SUM of CLO# Contributions)							22.75

Assessment Report of SO

SO% Threshold (when AR% =60% or 70% for CLOs) = (1.9+20+1.1+3.4)=26.4

SO% Attainment = Achieved SO%/SO% Threshold =22.75/26.4= 86%

Achieved SO% is less than SO% threshold by 14%

CLO1 is less than threshold (70%) by 15%

CLO2 is higher than threshold (60%) by 26%

CLO3 is less than threshold (70%) by 13%

CLO4 is higher than threshold (70%) by 5%

D. Analyzing Required Resources

The final section of this paper presents a thorough analysis of the resource requirements for both the traditional direct assessment methods and the proposed lightweight direct assessment method. The findings, outlined in the comparison Table 5, illuminate the substantial resource advantages offered by the innovative approach.

The traditional approach to direct assessment employs a comprehensive array of measured activities to evaluate student performance, encompassing quizzes, exams, tests, homework, assignments, final exam questions, projects, lab exercises, group work, mock consulting assignments, and final presentations. The involved parties, including Faculty Members, the ABET Steering Committee, Examination Committee, Data Collection Committee, and Data Analyzing Committee, collectively contribute their expertise to these activities. The number of tasks per module per semester can range from a minimum of 2 to an average of 6, with a maximum of 11 tasks. This diverse range of assessment activities demands significant attention and coordination. Consequently, the resource indicator per module (RI/Module) can vary widely, ranging from 60 to 110, underscoring the substantial resource investment required.

In stark contrast, the proposed lightweight direct assessment method streamlines the assessment process by primarily relying on Structured Final Exams (SF). This targeted approach involves a single task per module per semester and is managed by the Examination Committee and the Data Analyzing Committee. This focused strategy emphasizes precision and resource efficiency. The resource indicator per module (RI/Module) for the lightweight method is consistently 6, indicating the notable reduction in resource demand.

Table 5: Required Resources

	Measured Activities/Module	**Involved Parties (IP)**	**No. of Tasks (NT)/Module/Semester**	**Frequency of Tasks (TF)/Module/Semester**	**Resources Indicator (RI)/Module = IP x NT x TF**
Traditional Direct Assessment Methods	quizzes (Q), exams (E), tests (T), homework (H), assignments (A), final exam questions (F), projects (P), lab exercises (L), group work (GW), mock consulting assignment (MC), final presentations (FP)	Faculty Members, ABET Steering Committee, Examination Committee, Data Collection Committee, Data Analyzing Committee	Maximum :11 Average: 6	Minumum : 2	From 60 to 110
Lightweight Direct Assessment Method	Structured Final Exams (SF)	Examination Committee, Data Analyzing Committee	1	2	6

The comparison table underscores a significant paradigm shift from resource-intensive traditional assessment methods to the resource-efficient lightweight approach. While the traditional method necessitates a diverse array of activities and substantial involvement from multiple parties, the lightweight method aligns with the guiding principle of simplicity and precision. By primarily relying on Structured Final Exams, the lightweight approach optimizes resource allocation, reduces administrative burdens, and streamlines the assessment process.

The efficient resource utilization of the lightweight method offers multifaceted benefits. It minimizes the involvement of multiple parties, streamlines assessment administration, reduces assessment-related coordination efforts, and optimizes resource allocation. This, in turn, liberates valuable time and expertise, which can be redirected towards refining teaching methodologies, strengthening curriculum design, and enhancing the overall educational experience.

Integrating LLMs Throughout An Enhanced ABET Assessment Framework for ODEE
This section details a refined approach that deeply integrates Large Language Models (LLMs), including but not limited to ChatGPT, *throughout* the proposed enhanced ABET assessment framework. This integration directly addresses the call for greater specificity to open and distance engineering education (ODEE) and ABET accreditation. Each LLM application is critically examined, considering its potential benefits, limitations based on current research, ethical considerations, and the possibility of utilizing alternative LLM models when appropriate.

A. LLM-Augmented Curriculum Mapping and CLO Weighting (Tables I & 2):
Rather than a separate process, LLMs can be employed from the outset to enhance curriculum mapping and CLO weighting. By analyzing existing program data, learning outcomes from comparable institutions (especially those with ABET accreditation), and industry trends, LLMs can suggest areas for curriculum alignment and optimization as:

1. Identifying gaps, redundancies, or areas where CLO weighting might not reflect current industry needs or ABET criteria.
2. Reduce faculty workload: Automating the analysis of large datasets (e.g., syllabi, industry reports) to provide initial recommendations for faculty review.

Example: An LLM could analyze the "Industrial Networks" syllabus (Table 2), comparing it to ABET criteria, syllabi from other institutions with ABET accreditation, and recent publications in the field. This analysis could highlight areas where CLO weighting could be adjusted to better reflect the evolving importance of specific topics within the field.

Limitations: LLM suggestions require careful review by subject matter experts to ensure alignment with the program's specific context and goals. Bias in training data is a significant concern, necessitating careful selection and evaluation of data sources.

B. LLM-Assisted Examination Strategy and Rubric Design (Table 3):
LLMs can significantly enhance the authenticity and effectiveness of assessments, addressing the challenge of replicating real-world engineering tasks in online settings. For the "Industrial Networks" example, an LLM could:

1. Generate Diverse Assessment Items: Create a range of question types aligned with different CLOs, including scenario-based questions requiring critical thinking and problem-solving skills, coding challenges to assess practical application, and open-ended questions demanding in-depth analysis.

2. Analyze and Improve Existing Rubrics: Assess rubrics for clarity, consistency, and alignment with ABET criteria, suggesting improvements for more effective evaluation.

Example Output (CLO2 - Application-based): "You are tasked with designing the network infrastructure for a new smart factory. Given the following requirements [list of specific technical requirements, constraints, and considerations], propose a suitable network architecture, select appropriate protocols and technologies, and justify your design choices".

Limitations: While LLMs can generate creative and challenging assessment items, faculty review remains essential to ensure accuracy, relevance, and appropriate difficulty levels.

C. Data-Informed Attainment Levels and Student Outcome Calculation (Table 4):

1. LLMs can analyze historical student performance data, program trends, and external benchmarks (such as average performance of similar ABET-accredited programs) to provide data-informed suggestions for setting appropriate attainment levels. This is particularly valuable for ODEE programs with limited historical data or those seeking to benchmark against international standards.

2. Data-driven insights promote more objective and defensible attainment levels, ensuring rigor while considering student performance trends. The process can be further refined by incorporating LLMs that excel in mathematical computations for more complex statistical analysis.

3. Over-reliance on historical data without considering contextual factors can perpetuate existing achievement gaps. Ethical considerations and potential biases in data must be carefully addressed.

D. LLM-Enhanced Student Outcome Reporting and Program Evaluation:

1. LLMs can automate the generation of comprehensive reports that summarize student performance data, highlight trends, and identify areas for improvement. This frees up valuable faculty time for higher-level analysis and action planning. Example: An LLM could analyze all assessment data from the "Industrial Networks" course, generating a report that: Summarizes student performance on each CLO, visually highlighting areas of strength and weakness.

2 Identifies potential contributing factors to performance trends, drawing connections to curriculum design, assessment methods, or student demographics. It can suggest specific actions for improvement aligned with identified weaknesses and relevant ABET criteria.

Benefits: Data-driven insights support informed decision-making for program enhancement, and clear, concise reporting facilitates communication with stakeholders, including ABET accreditation reviewers.

Limitations: LLM-generated reports are only as good as the data they are trained on. Careful data selection, cleaning, and interpretation remain crucial. Human oversight is essential to ensure accuracy, contextual relevance, and to provide the nuanced analysis that LLMs may miss.

Below is Table 6 summarizing the differences between traditional and LLM-augmented methods based on the provided document:

Table 6: Differences Between Traditional And LLM-Augmented Methods

Aspect	**Traditional Direct Assessment Method**	**LLM-Augmented Assessment Method**
Resource Intensity	High resource demands, requiring significant time, effort, and personnel for multiple assessment activities.	Streamlined process relying primarily on automated tools like ChatGPT, reducing administrative burdens and time.
Assessment Coverage	Limited to selected modules, often leading to incomplete coverage of Course Learning Outcomes (CLOs).	Comprehensive coverage by assessing all modules, ensuring alignment with Student Outcomes (SOs).
Personalization	Standardized assessments, less adaptable to diverse learning styles or individual needs.	Personalized assessments and feedback, leveraging adaptive testing and detailed insights from LLMs.
Timeliness of Feedback	Delayed feedback due to time-consuming manual evaluation.	Instant feedback through automated grading and analysis of assessments.
Flexibility	Rigid structure, difficult to adapt to curriculum changes or emerging educational needs.	Highly flexible, enabling dynamic adjustments to curriculum, CLO weights, and attainment levels based on LLM analysis.
Use of Technology	Limited integration of advanced technologies.	Extensive use of AI tools to enhance data analysis, question generation, and feedback personalization.
Assessment Tools	Heavy reliance on exams, quizzes, and manual grading.	Diverse tools, including AI-generated scenario-based questions and automated grading aligned with CLOs and SOs.
Data Analysis	Cumbersome and manual, often limited to basic metrics.	Data-driven insights with automated analysis of historical and real-time data for curriculum improvement.
Ethical Concerns	Fewer ethical issues but relies heavily on human judgment, which can introduce bias.	Requires addressing data privacy, algorithmic bias, and ensuring explainable AI outputs with human oversight.
Outcome Reporting	Manual and time-intensive reporting of student outcomes.	Automated and comprehensive reports generated by LLMs, highlighting trends and actionable insights for improvement.

Finally, it is important to emphasize that the proposed assessment approach does not advocate for handing over critical decisions entirely to AI. Instead, AI is considered as a valuable tool to augment human expertise, particularly in tasks such as automated grading, personalized learning feedback, and data-driven analysis. However, the importance of human oversight and verification in all key stages of the assessment process are still recognized. To ensure accuracy and reliability, the following safeguards are proposed:

- Human review of AI-generated assessments: Experts will review and potentially adjust AI-generated assessments to ensure alignment with learning objectives and mitigate potential biases.
- Transparent and explainable AI models: The utilized AI models must be transparent and explainable, allowing educators to understand how assessments are made and identify any potential issues.
- Ongoing monitoring and evaluation: Administrators must continuously monitor and evaluate the performance of the AI tools, making adjustments as needed to ensure their effectiveness and fairness.

Conclusion

The proposed LLM-enhanced framework presents a significant advancement in ABET accreditation for ODEE programs. By integrating LLMs throughout the assessment process, institutions can move towards more data-driven, efficient, and personalized approaches to program evaluation, demonstrating their commitment to quality and continuous improvement. This is particularly relevant for European ODEE programs seeking ABET accreditation, as it provides a practical roadmap for aligning with international standards and showcasing program strengths.

However, the successful implementation of this framework requires careful consideration of ethical implications, data privacy, and the potential for algorithmic bias. Human oversight, rigorous data governance policies, and ongoing evaluation of LLM outputs are crucial to ensure fairness, transparency, and the responsible use of these powerful technologies.

By thoughtfully navigating these complexities and embracing the potential of LLMs, ODEE programs can not only meet but exceed ABET accreditation standards, cultivating a new generation of highly skilled and adaptable engineers prepared to thrive in a rapidly evolving technological landscape.

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