Research in Engineering Education Symposium (REES)
Regional Conference in Engineering Education (RCEE) &
Research in Higher Education (RHEd)
September 29 – October 3, 2025
Johor, Malaysia

Implementing iOBE for Visualizing and Interpreting Student Outcomes: A Course-Level Assessment

Zulfaa Mohamed-Kassim[a,b],
Faculty of Aerospace Engineering, i-CATS University College, Kuching, Malaysia[a]
School of Aerospace Engineering, Universiti Sains Malaysia, Nibong Tebal, Malaysia[b]
Corresponding Author's Email: zulfaa@icats.edu.my

ABSTRACT

BACKGROUND

Measuring student outcomes at various levels in the context of Outcome-Based Education (OBE) necessitates computational processes that are often challenging and inefficient due to large datasets and complex mappings. The computational tool presented herein addresses these issues with a mathematically grounded, scalable solution suitable across disciplines.

PURPOSE

This study demonstrates the use of the Integrated OBE (iOBE) software for analysing student performance across multiple cohorts at the course level. Its structured numerical and visual analyses generate valuable insights that support continuous quality improvement (CQI).

METHODOLOGY

Outcome data from three consecutive cohorts were processed in the software using matrix-based mappings between assessment tools and outcomes, leveraging vectorized computations. The software generated box plots and population graphs to visualize statistical patterns and support AI-assisted analysis. Aggregated data analysis was conducted to uncover broader trends and highlight areas for targeted pedagogical improvement.

RESULTS

Students across the cohorts demonstrated higher attainment in project-based outcomes such as Solution Development and Teamwork, likely supported by extended preparation time and collaborative effort. In contrast, Problem Solving consistently showed the lowest median and mean scores, accompanied by pronounced gaps in the lower quartiles. These findings highlight persistent challenges in individually assessed, time-constrained tasks—underscoring the need for more structured interventions to strengthen students' problem-solving abilities.

CONCLUSIONS

Extended analysis across multiple cohorts was conducted using the software, yielding critical information in multidimensional view that enabled the instructor to extract meaningful insights and pinpoint areas for targeted interventions to improve both the course and students' problem-solving competencies. This study thus demonstrates iOBE as a simple but versatile software platform for outcome-based assessment.

KEYWORDS

OBE software; Outcome assessment; Student outcomes.

Introduction

Outcome-Based Education (OBE) is foundational to engineering accreditation worldwide, as guided by the Washington Accord (International Engineering Alliance, 2026). In Malaysia, the Engineering Programme Accreditation Standard 2024 document (EAC, 2024) emphasizes the need for structured and evidence-based assessment of programme outcomes to support continuous quality improvement (CQI). These assessments must be valid, traceable, and capable of demonstrating that students acquire the intended graduate attributes upon completion of their studies.

While the philosophy of OBE is widely embraced, its implementation at scale introduces challenges that extend beyond pedagogical design. Institutions often face technical, operational, financial, and systemic constraints in computing, managing, and interpreting student outcomes in ways that are both reliable and actionable. These challenges are not uniform and frequently depend on the choice of assessment tools, data systems, and institutional practices.

One strategic aim of effective OBE assessment is that outcome data must be transformed into insights that are both analytically sound and practically useful. Beyond data collection, it demands structured computations and proper representations of the data that allow educators to monitor student performance, compare cohorts, and make informed pedagogical decisions. Without these capabilities, the OBE assessment process risks becoming performative rather than informative. Tools with doubtful data processing that lacks interpretability may ultimately compromise the objectives of OBE, especially when used to support student learning, teaching quality, curriculum alignment, or accreditation evidence.

To respond to these challenges, this study examines the application of the Integrated OBE (iOBE) software — an academically developed platform designed to streamline and clarify outcome-based assessment at the course and program levels. Offered as a free, standalone application, iOBE supports consistent outcome computations and visualizations while giving institutions full control over data management. It is introduced here as a practical and scalable solution that aligns with the technical, structural, and institutional needs outlined in current OBE implementation contexts.

This paper presents a multi-year implementation of iOBE in an advanced engineering course offered at Universiti Sains Malaysia. The case study demonstrates how the software enables:

- Rapid computation of outcome metrics at the course and multi-course levels
- Visualization of cohort performance across multiple academic years,
- Comparative analysis of attainment variations to identify patterns and gaps,
- Integration of AI-assisted analysis to support data-informed interpretation.

By sharing this study, we aim to contribute to the ongoing efforts of improving and strengthening outcome assessment practices, particularly in supporting data-informed CQI efforts among engineering—and even non-engineering—education programs.

Background

Outcome-Based Education (OBE) emphasizes the alignment of curriculum design, teaching strategies, and assessment practices with clearly defined learning outcomes. At the programme level, these outcomes are typically articulated as Programme Outcomes (POs), reflecting graduate attributes aligned with accreditation frameworks such as the Washington Accord, while Course Outcomes (COs) are defined at the individual course level. In practice, the term *student outcomes* is often used to describe attainment profiles derived from aggregating CO performance into programme-level indicators. These outcomes form the evidentiary basis for accreditation decisions and Continuous Quality Improvement (CQI) processes.

https://doi.org/10.52202/086293-0066

To support this alignment, various conceptual and computational approaches have been proposed to structure the relationship between course-level and programme-level outcomes. One of the most widely cited frameworks is the CO–PO alignment matrix introduced by Felder and Brent (2003), which established a systematic method for mapping course objectives to programme outcomes. While originally intended as a curricular design and planning tool, this matrix-based approach laid the foundation for subsequent quantitative and computational implementations of outcome assessment.

As OBE implementation scaled across institutions, recurring challenges emerged in managing, computing, and interpreting student outcomes data. A recent study based on stakeholder interviews across Malaysian higher education institutions highlighted persistent issues related to technical misalignment, inconsistent assessment practices, limited faculty ownership, and institutional capacity constraints (Liew et al., 2024). These challenges are consistent with broader concerns reported in the literature, including the complexity of handling large datasets, lack of transparency in computational procedures, and difficulties in presenting outcomes in ways that support meaningful interpretation and decision-making.

In response, many institutions initially relied on spreadsheet-based tools due to their accessibility and flexibility. While spreadsheets can support weighted mappings between assessment tools, COs, and POs, they are inherently prone to manual error, version inconsistency, and limited scalability. Ensuring computational rigor and consistency across instructors and programmes becomes increasingly difficult as the number of courses and cohorts grows.

To address these limitations, some institutions have adopted third-party or cloud-based OBE management systems that automate calculations and provide visual reporting. Although such platforms reduce manual workload, they may introduce new challenges related to cost, limited customization, system performance, and institutional dependence on external vendors. In addition, the external storage of student outcome data raises concerns regarding data ownership, governance, and long-term sustainability, particularly for institutions operating under resource constraints.

Beyond tool selection, the structural design of programme-level assessment models significantly influences the effectiveness of outcome evaluation. Previous studies have identified several commonly adopted models, including cumulative, dominating, culminating, and comprehensive culminating approaches (Liew et al., 2020; Ibrahim et al., 2025). Among these, the Comprehensive Culminating Model has been identified as a balanced and sustainable approach, whereby a carefully selected subset of courses is used to assess programme outcomes while ensuring full PO coverage through structured mappings. This model reduces assessment workload compared to fully cumulative approaches, yet retains sufficient breadth to reflect learning across the programme, making it particularly suitable for accreditation and CQI purposes.

Addressing these combined technical and structural challenges requires an assessment system that is computationally robust, transparent, and adaptable to diverse institutional contexts. The Integrated Outcome-Based Education (iOBE) software was developed to meet these needs through a mathematically consistent framework for computing outcome attainment at both course and programme levels. Its matrix-based architecture supports flexible mappings between assessment tools, COs, and POs, while remaining applicable across different assessment models and disciplinary contexts. Beyond its original implementation, the software has also been employed and referenced in independent studies for analysing student outcomes in different institutional and instructional settings, including its use in evaluating online learning environments (Mallikarjuna et al., 2021) and in extending outcome assessment models through dynamic computational formulations (Chan et al., 2022). These external applications demonstrate the software's adaptability and relevance beyond a single institution or national context, reinforcing its potential as a generalizable platform for evidence-driven CQI in higher education.

Methodology

The study employs a quantitative case study approach, using computational content analysis to evaluate student outcome attainment through institutional assessment data. Key components include:

1. Computational Content Analysis: Assessment data were processed using the iOBE software, which applied matrix-based mathematical models to quantify Course Outcome (CO) and Programme Outcome (PO) attainment.
2. Documented Assessment Review: The study systematically reviewed assessment instruments (e.g., quizzes, exams, essays, projects) over three academic years to map their alignment with COs and Pos according to EAC Standard 2020.
3. Case Study Design: The analysis focuses on a single third-year engineering course across three cohorts, enabling in-depth examination of patterns, trends, and variations in student performance.
4. AI-Assisted Interpretation: Visual and numerical outputs from iOBE were interpreted using ChatGPT-4o to generate structured insights, which were then validated manually for accuracy and pedagogical relevance.

Details on these components are provided further below.

Software Framework

The iOBE software was developed within the MATLAB environment and implements a rigorous computational model to evaluate student outcome attainment. Its numerical process was designed based on the foundational approach on mapping matrices initially proposed by Felder and Brent (2003), where mapping matrices are used to align learning outcomes with course and program-level outcomes. While originally intended as a curricular planning tool, this matrix model was adapted by Mohamed-Kassim (2013) into a quantitative computational framework, rigorously derived into compact, generalizable formulas to compute and aggregate outcomes at the course and program-level, respectively.

In this extended approach, the alignment matrices are operationalized as structured mapping matrices, where each matrix encodes weighted relationships between assessment tools and outcomes. Early implementations into the software by Mohamed-Kassim (2015) utilized linear operations to transform raw assessment marks into outcome attainments. Subsequent upgrades (Mohamed-Kassim & Kamaruddin, 2017) converted these calculations into fully vectorized array operations, allowing the system to solve multiple constraints simultaneously rather than sequentially. This significantly improved processing speed and computational scalability across large datasets, by leveraging optimized subroutines from MATLAB libraries.

To enhance usability and interpretability, iOBE v7.0 (released in March 2025) introduced key visualization and analysis upgrades:

- *Box plots* were adopted to replace bar charts, providing compact statistical summaries that include medians, quartiles, and outliers.
- *Population distribution plots* were redesigned using an intuitive colour scheme to highlight tiers of student performance.
- *AI-assistive capabilities* were incorporated, enabling structured exports compatible with AI platforms like ChatGPT for downstream interpretation and summarization.

Together, these features have strengthened iOBE as a robust and extensible assessment platform, offering not only computational rigor but also built-in error filtration to handle data inconsistencies, and adaptability for use across multiple disciplines and educational levels.

https://doi.org/10.52202/086293-0066

Assessment Data

This study applied iOBE v7.0 to analyse student outcome attainment over three consecutive academic years (2022–2024) in a third-year elective engineering course at the School of Aerospace Engineering, Universiti Sains Malaysia. For confidentiality, the course name is anonymized. Class sizes ranged from 16 to 23 students, representing roughly 39–53% of the cohort populations in those years. While students shared a common academic foundation (having completed the same prerequisites), the elective nature of the course led to variability in cohort composition, which might have influenced performance distributions.

Assessment tools (ATs) included quizzes, tests, team-based projects, presentations, reflective essays, and final exams. In some cases, raw marks were partitioned further to allow more precise mappings to specific outcomes. For example, presentation scores were divided into components evaluating communication, teamwork, and technical contribution. These ATs were mapped to four pre-defined COs, each aligned one-to-one with four corresponding POs from the 2020 Engineering Programme Accreditation Standard (EAC, 2020). The mappings are summarized in Table 1.

Table 1: CO-PO mapping and their assessment instruments

CO	PO	Outcomes	Outcome Assessment
1	2	Problem Solving	Problem-based questions in tests and exams
2	3	Solution Development	MATLAB programming in team projects
3	10	Communication	Essays, written reports, and oral presentations
4	9	Teamwork	Team project contributions, class collaboration, peer reviews, and lecturer evaluations

Due to the one-to-one CO–PO mapping, AT marks were identically used to compute both CO and PO attainments. However, the underlying iOBE framework is flexible enough to accommodate complex configurations such as one-to-many mappings, where a single AT or CO may contribute to multiple POs.

While the learning outcomes remained broadly consistent across the three years, the assessment instruments and weightings varied slightly. These changes reflect instructional evolution rather than methodological inconsistencies. As such, results were interpreted with attention to emerging performance patterns rather than strict cross-year comparability.

Data Processing

To initiate the analysis, raw assessment marks and outcome mappings were entered into a pre-formatted Microsoft Excel input file that came with the software. The file featured flexible rows and columns for separately assigning weighted mappings of ATs to COs and POs, offering a large degree of versatility in this data-entry process. Once completed, the input file was uploaded and processed via the “Calculate Course Data” function on the software’s interface (see Figure 1). All computations were performed offline, preserving institutional control over student data and avoiding reliance on cloud platforms or external servers that may pose security or privacy concerns.

Upon processing (which took a few seconds for each course), iOBE generated multiple graphical outputs to support outcome analysis. The two primary visualizations were: (1) box plots, displaying central tendencies (median and mean), interquartile range (IQR), and outliers for each PO; and (2) population distribution plots, using a color-coded scheme to show the percentage of students within six attainment bands. Together, these plots provided a compact, multidimensional view of performance distribution—highlighting areas of concentration, variability, and performance gaps.

All visuals were saved automatically as high-resolution images, and the corresponding numerical data were exported into Excel files. These structured datasets enabled further interpretation and seamless integration into CQI reports, facilitating both manual review and AI-assisted analysis, as described in the next subsection.

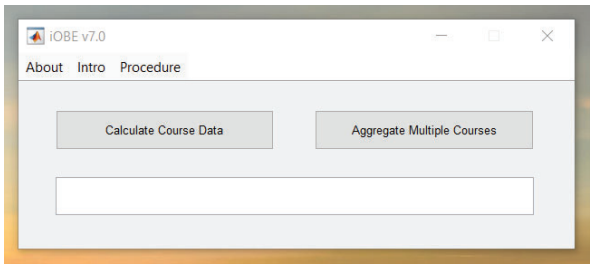


Figure 1: The simple iOBE graphical-user interface (GUI) panel

As part of this study, outcome data from all three cohorts were also aggregated into a unified dataset. This was carried out using iOBE's "Aggregate Multiple Courses" function, which processed the input files collectively and produced composite box plots and population graphs. This enabled higher-level analysis of performance trends and variations that may not have been observable within individual cohorts alone.

AI Assistance

To accelerate interpretation, the visual plots and underlying datasets were analyzed using ChatGPT-4o as an AI-assisted interpretive tool. The AI was able to generate structured insights that included descriptive trends, key performance features, and statistical summaries observable from the visual data. Notably, it also highlighted variations and outliers that warranted further consideration.

Despite the efficiency of this automated process, all AI-generated observations were reviewed and validated by the author to ensure their alignment with course context and pedagogical intent. While not a replacement for expert judgement, this integration of structured outcome data with AI support offered a valuable extension for reflective practice—enabling richer interpretations while reducing the time and effort required for manual analysis.

Results and Discussions

Analysis Overview

The outcome analysis presented in this section is based on data from three different course cohorts spanning 2022 to 2024. Each dataset was processed using the iOBE software, applying consistent one-to-one mappings between COs and POs across all years. While the structural design of the course and intended outcomes remained aligned, minor differences in assessment instruments and their weightings were introduced across cohorts, reflecting authentic instructional evolution over time. These variations, while small, affect the way each PO was operationalized and should be considered when interpreting cross-year comparisons.

Additionally, the demographic makeup of each cohort played a subtle but important role in shaping student performance. The 2022 and 2023 cohorts comprised students from diverse cultural backgrounds, while the 2024 cohort was relatively homogeneous. Such differences may influence collaborative dynamics and communication styles, particularly for outcomes related to teamwork and presentation-based assessment. But more notably, they may contribute to variations in how students individually approach, understand, or strategize through problem-solving tasks—particularly those assessed under time constraints. Acknowledging these context-specific nuances allows for a more responsible and reflective

https://doi.org/10.52202/086293-0066

interpretation of the data, rather than attributing differences solely to instructional or content-related factors.

Individual Cohort Performance

The 2022 cohort (n = 23) exhibited distinct patterns in the attainments of Programme Outcome (PO), as shown in Figure 2. Communication (PO10) recorded the highest median and a relatively narrow interquartile range (IQR), indicating consistently strong performance in presentations, written reports, and oral delivery tasks. Problem Solving (PO2) showed a lower median and a moderate IQR, accompanied by two high-end outliers—suggesting that while most students performed modestly under time-constrained, individually assessed tasks, these two students excelled. Solution Development (PO3) had the widest IQR, reflecting a broad range of performance in team-based programming and design projects. Teamwork (PO9) demonstrated moderate overall attainment with some variability, as seen in the population distribution's concentration around mid-range bands. Overall, the data suggest that students in this cohort performed best in communication-based tasks and faced greater challenges in strategic or time-pressured problem-solving contexts.

Student performance shifted slightly in the 2023 cohort (n = 23), as shown in Figure 3. Two outcomes displayed higher medians compared to the 2022 group: Solution Development (PO3) and Teamwork (PO9). For this cohort, a much lesser weightage was assigned to PO3 compared to the one in 2022, because team-based assessments were distributed across several outcomes using the one-to-many mapping strategies. With a higher weightage on Communication (PO10), student performance dropped in Communication (PO10), potentially due to the increased sensitivity from more assessments on this outcome.

PO9, on the other hand, showed tightly clustered scores with the most outliers. Thus, despite variations on these three individuals of outliers, the clustered scoring on PO9 indicates uniformity in group collaborations. This may be attributed to the nature of these assessments, which involved collaborative projects and rehearsed presentations—contexts that allowed more time and support for completion. However, Problem Solving (PO2) remained relatively underperforming, with its spread larger but its median lower than those in 2022, reaffirming the challenges students faced on individual assessments that demand strong conceptual understanding and critical thinking.

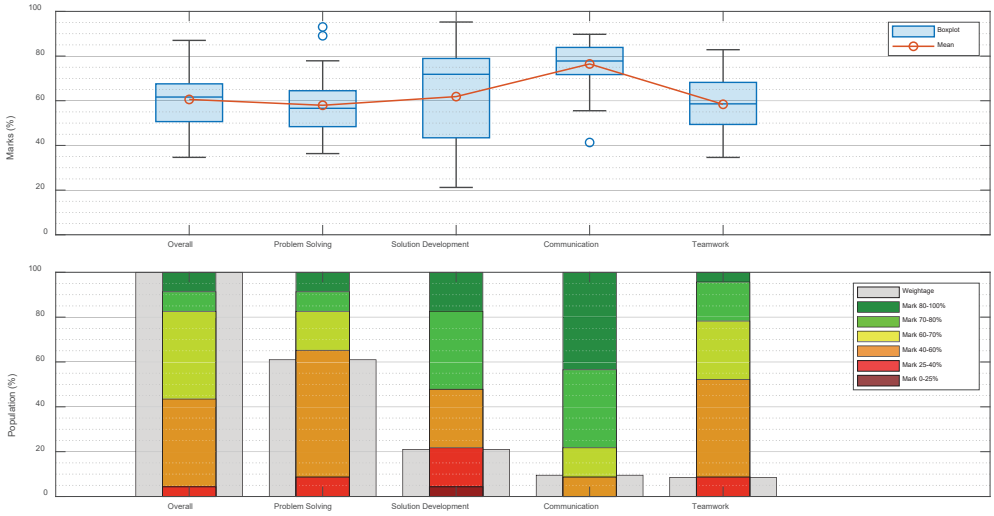


Figure 2: iOBE-generated performance graphs for the 2022 cohort

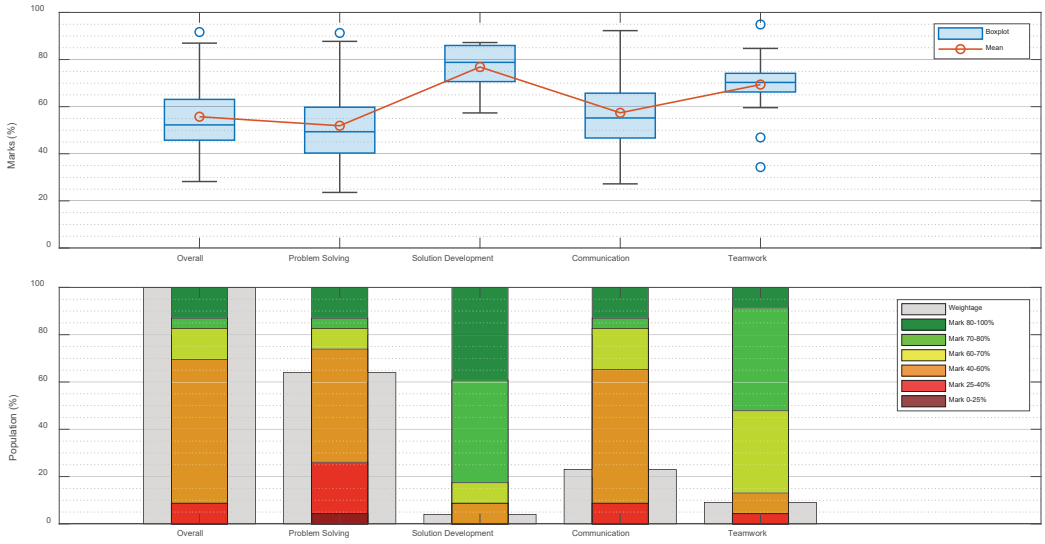


Figure 3: iOBE-generated performance graphs for the 2023 cohort

In Figure 4, the 2024 cohort (n = 16) presented a different pattern. Compared to the previous years, this cohort displayed tight clustering in all the four POs—particularly in the overall outcomes, which showed the narrowest IQR and minimal deviation across individuals. This may reflect the relatively homogeneous demographic composition of the cohort, potentially contributing to aligned thinking styles and cooperative dynamics. However, one team appeared to underperform in both Solution Development (PO3) and Teamwork (PO9), likely due to unresolved team issues. This localized drop affected the group's average performance and was visible as outliers in the respective box plots. As in the previous two years, Problem Solving (PO2) continued to be the most challenging outcome, this time with the lowest median and a highly concentrated distribution, indicating closely similar patterns of conceptual understanding and strategic thinking to solve problems among students in this cohort.

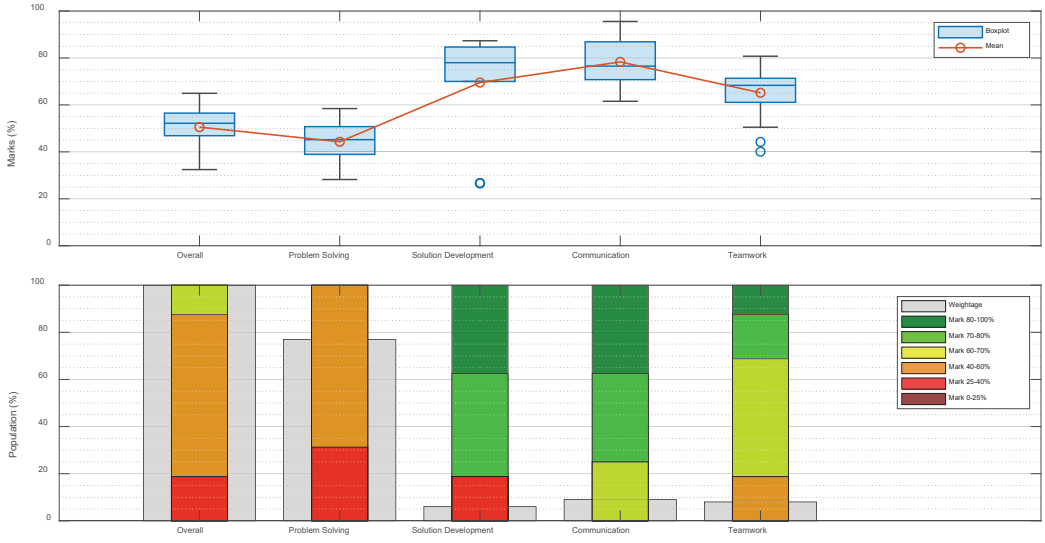


Figure 4: iOBE-generated performance graphs for the 2024 cohort

The consistently low attainment in Problem Solving (PO2) across all three cohorts—most notably in the 2024 group—highlights a persistent area of concern. Despite variations in

https://doi.org/10.52202/086293-0066

teaching context and cohort composition, many students appear to struggle with tackling analytical problems individually under time-constrained conditions. While the outcomes data do not directly reveal students' cognitive approaches, the concentrated clustering observed in the 2024 cohort suggests a narrow range of strategies, possibly shaped by shared habits of surface-level reasoning or limited planning.

To address this, further investigation is planned using a structured problem-solving method through a 3-step approach, which guides students to: *Understand* the problem deeply, *Strategize* an effective solution pathway, and *Execute* it systematically. This approach aims to promote deep understanding and strategic planning in place of ad hoc or intuitive trial-and-error methods. This structured problem-solving method also aligns with professional practices across various industries and organizations, such as the Root Cause Analysis (Reid and Smyth-Renshaw, 2012) and the PDCA and DMAIC cycles (Sokovic et al., 2010)—each of which emphasizes deep understanding, planning, and deliberate execution in solving real-world problems. Findings from this subsequent study will be reported separately.

Aggregated Performance

To provide a broader perspective on programme outcome trends, data from all three cohorts (n = 62) were aggregated using the iOBE software's multi-course integration function. This combined analysis enabled the detection of overarching patterns that may not be fully visible within individual cohorts. In Figure 5, the aggregated box plots and population graphs revealed notable differences in attainments across the four outcomes.

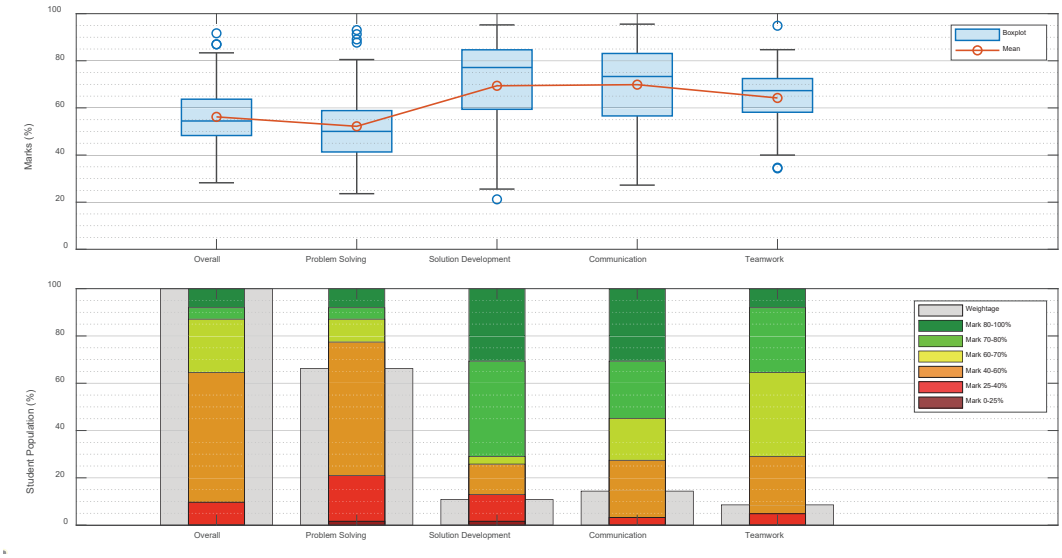


Figure 5: iOBE-generated performance graphs for the three cohorts combined

Solution Development (PO3) recorded the highest median score, but with a pronounced spread on the lower end of the IQR and whiskers—indicating considerable variability in students' abilities to develop solutions, despite strong central performance. In contrast, Problem Solving (PO2) had the lowest median, coupled with a narrow IQR but extended whiskers and several high-end outliers. This pattern suggests that while most students faced difficulties or performed poorly under time-constrained, individual assessments, a few students excelled markedly—pointing to underlying disparities in conceptual understanding and strategic approaches to problem solving.

Communication (PO10) showed good but skewed performance, with a notably broad IQR and an extended whisker on the lower end. These observations on the skewness of the data point to greater variability across students in their ability to communicate well, both orally and in

writing. Teamwork (PO9), on the other hand, demonstrated consistent attainment, with both the narrowest IQR and the smallest whisker spread (albeit the presence of outliers on both ends), suggesting highly clustered performance across the student population.

Collectively, these results reveal a distinct pattern: students tend to perform better in outcomes linked to collaborative, extended-preparation tasks (PO3 and PO10), while struggling more with individually assessed, cognitively demanding problem-solving activities (PO2). Although team-based assessments are essential in engineering education, their structure may inadvertently inflate attainment levels by allowing preparation time, peer collaboration, and uneven individual contributions. These formats risk obscuring true competency gaps that only become evident in individual assessments under pressure.

The contrasting profile of PO2 emphasizes a key concern for programme-level assessment: the need to strengthen individual analytical and problem-solving competencies, which are core expectations in engineering education. Addressing this imbalance calls for more targeted instructional design and assessment strategies that promote critical thinking and cognitive independence. While the present study does not expand on specific interventions, the data strongly suggest the importance of such efforts moving forward and provide a foundation for future work in this direction.

Conclusion

This study demonstrated the application of the iOBE software in analysing and visualizing student outcomes data across three cohorts of an advanced engineering course. Through its structured computation, high-resolution visualizations, and support for AI-assisted interpretation, iOBE enabled both granular and aggregated analyses that revealed key performance patterns in multidimensional view across Programme Outcomes (POs). Notably, the analysis identified consistently lower attainment in Problem Solving (PO2) across all cohorts—highlighting a concerning gap in students' ability to tackle cognitively demanding, time-constrained tasks, despite stronger performance in collaborative or presentation-based assessments.

These findings reaffirm the need for instructional strategies that develop students' individual analytical competencies. In particular, a more structured approach to problem-solving—such as the 3-Step Strategy of Understand, Strategize, and Execute—holds potential for improving conceptual clarity and solution planning under pressure. Although not implemented within this study, future work will explore this method in greater depth to examine its impact on problem-solving proficiency. More broadly, this study showcases iOBE's capability to support evidence-driven decision-making, offering a simple but versatile tool for continuous quality improvement in outcome-based engineering education.

References

Chan, M. K., Wang, C. C., Arbai, A. A. (2022). Development of dynamic OBE model to quantify student performance. Computer Applications in Engineering Education, 30(5), 1293-1306. https://doi.org/10.1002/cae.22520

Engineering Accreditation Council (EAC). 2024. Engineering Programme Accreditation Standard 2024. Accessed at https://eac.org.my/v2/wp-content/uploads/2024/08/Engineering-Programme-Accreditation-Standard-2024.pdf on 5 January 2026

Felder, R. M. and Brent, R. (2003). Designing and Teaching Courses to Satisfy the ABET Engineering Criteria. Journal of Engineering Education, 92(1), 7-25. https://doi.org/10.1002/j.2168-9830.2003.tb00734.x

Ibrahim, A., Mohamad Nor, M. R., Ahmad, H., and Mohamed Latiff, M. F. P. (2025), Reliability of Program Outcome Attainment Evaluation Based on Cumulative Model. Jurnal Kejuruteraan, 37(1), 527-540. https://doi.org/10.17576/jkukm-2025-37(1)-39

International Engineering Alliance. (2026). Washington Accord. Accessed at https://www.internationalengineeringalliance.org/accords/washington-accord on 5 January 2026.

https://doi.org/10.52202/086293-0066

Liew, C. P., Puteh, M., Mohammad, S., Kiew, P. L., and Tan, K. G. (2024). Sustainable Assessment Practices for Engineering Programme Outcomes: Challenges and Recommendations in Malaysian Higher Learning Institutions. International Journal of Engineering Education, 40(2), 216-230.
Liew, C. P., Puteh, M., Mohammad, S., Omar, A. A., and Kiew, P. L. (2020). Review of engineering programme outcome assessment models. European Journal of Engineering Education, 46(5), 834-848. https://doi.org/10.1080/03043797.2020.1852533
Mallikarjuna, B., Sabharwal, M., Kumar, P., and Niranjanamurthy M. (2021). OBE: Perception of Computer Science Learners and Teachers in online learning during COVID-19. EAI Endorsed Transactions on Creative Technologies, 8(29). https://doi.org/10.4108/eai.12-11-2021.172105
Mohamed-Kassim, Z. (2013). A Comprehensive Assessment Framework for OBE-Oriented Programs. International Conference on Assessment for Higher Education Across Domains and Skills (AHEADS), Kuala Lumpur, Malaysia.
Mohamed-Kassim, Z. (2015). A Consistent Numerical Procedure for Integrated Assessment. ASEAN Journal of Engineering Education, 2(1), 14-20.
Mohamed-Kassim Z. and Kamaruddin, N. (2017). Towards an Efficient iCGPA System Using iOBE. 7th World Engineering Education Forum (WEEF), (pp. 103-109). Kuala Lumpur, Malaysia. 10.1109/WEEF.2017.8467131
Reid I. and Smyth-Renshaw, J. (2012). Exploring the Fundamentals of Root Cause Analysis: Are We Asking the Right Questions in Defining the Problem? Quality and Reliability Engineering International, 28(5), 535-545. https://doi.org/10.1002/qre.1435
Sokovic, M., Pavletic, D., and Kern Pipan, K. (2010). Quality improvement methodologies - PDCA cycle, RADAR matrix, DMAIC and DFSS. Journal of Achievements of Materials and Manufacturing Engineering, 43(1), 476-483.

Acknowledgements

The author acknowledges the financial support provided by i-CATS University College to present this work at the Research in Engineering Education Symposium (REES 2025) in Johor, Malaysia.

Copyright Statement

Copyright © 2025 Zulfaa Mohamed-Kassim: The authors assign to the Research in Engineering Education Network (REEN) and educational non-profit institutions a non-exclusive licence to use this document for personal use and in courses of instruction provided that the article is used in full, and this copyright statement is reproduced. The authors also grant a non-exclusive license to REEN to publish this document in full on the World Wide Web (prime sites and mirrors), on portable media and in printed form within the REES and RCEE & RHEd 2025 proceedings. Any other usage is prohibited without the express permission of the authors.