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Enhancing student centered and technology supported learning in higher education through the BEAM framework

Nurulfajar Abd Manap[1*] and Anis Suhaila Mohd Zain[1]

*Correspondence:
Nurulfajar Abd Manap
nurulfajar@utem.edu.my
[1]Centre for Telecommunication Research & Innovation, Fakulti Teknologi dan Kejuruteraan Elektronik dan Komputer (FTKEK), Universiti Teknikal Malaysia Melaka (UTeM), Durian Tunggal, Melaka 76100, Malaysia

Abstract

The increasing demand for student-centered and technology-supported learning in higher education requires pedagogical frameworks that integrate structured instruction, learner empowerment, technological integration and systematic evaluation. This study introduces the BEAM Framework (Build, Empower, Amplify, Mentor) and its evaluative extension, the BEAM-X Factor, as a structured model for guiding and assessing technology-supported instruction. The framework was implemented in an undergraduate engineering course across eight consecutive semesters involving 542 students. Academic performance was measured using a weighted Performance Index (PI), complemented by Learning Outcome and Programme Outcome attainment and Student Perception data. Descriptive longitudinal analysis, one-way analysis of variance (ANOVA) and thematic coding were employed. Results showed a progressive increase in mean PI from 2.90 in the baseline semester to 3.47 during full implementation, with the proportion of Grade A students rising from 14% to 40%. ANOVA indicated statistically significant differences across semesters ($F(7, 534) = 4.21$, $p < 0.001$, $\eta^2 = 0.05$). The BEAM-X composite index peaked at 4.54/5 during full implementation phases. Qualitative findings highlighted strengthened mentoring, ownership of learning and technology-enabled engagement. These findings suggest that structured integration of empowerment, amplification and mentoring may be associated with sustained improvements in academic performance and student engagement within a single institutional context. BEAM offers a statistically supported and empirically informed framework with potential applicability in advancing technology-supported higher education.

Keywords Student-centered learning, Technology supported learning, BEAM framework, Pedagogical frameworks, Learning analytics

1 Introduction

Higher education is undergoing rapid transformation, driven by increasing demand for student-centered and technology-supported learning. This shift requires pedagogical frameworks that not only integrate digital tools effectively but also cultivate essential 21st-century competencies such as critical thinking, collaboration, creativity and digital literacy [20, 22]. While many pedagogical models have been proposed, they often fall short by focusing narrowly on technology as a tool or lacking a robust, multi-dimensional approach for evaluating their true impact on student learning and engagement. This gap highlights the importance of developing a comprehensive model that integrates structured pedagogy, ongoing mentorship and data-driven evaluation.

Although digital technologies are increasingly embedded in teaching practice, their use often remains limited to substitutional or augmentative purposes, such as digitizing lecture slides or assessments, rather than enabling transformative learning experiences [3]. The Substitution–Augmentation–Modification–Redefinition (SAMR) framework by Puentedura [17] and the Technological Pedagogical Content Knowledge (TPACK) framework by Mishra and Koehler [15] have been influential in guiding technology integration, but they are primarily teacher-centric. These models emphasize instructional design and technological adoption but provide comparatively limited guidance on sustained student empowerment, mentoring integration or multidimensional outcome evaluation.

Research on self-regulated learning (SRL) and student engagement has further highlighted the importance of agency, motivation and reflection in shaping effective learning [8, 24]. Yet these models typically lack mechanisms to embed mentorship into pedagogy or to unify performance, perception and outcome-based evaluations. This indicates a need for frameworks that move beyond single dimensions and instead combine pedagogy, empowerment, technology and mentoring with an integrated approach to evaluation.

This paper introduces the BEAM Framework (Build, Empower, Amplify, Mentor) and its evaluative extension, the BEAM-X Factor, as a structured pedagogical model for higher education. The framework is designed to guide both instructors and students in creating active, technology-rich learning experiences that foster engagement, ownership and mentorship. A distinctive feature of BEAM is its emphasis on technological amplification, encouraging digital tools to be used in ways that transform learning tasks rather than simply replicate traditional methods. The BEAM-X Factor complements this framework with a unified index that integrates perception (student feedback), performance (academic achievement and learning outcomes) and outcome accomplishment (transferable skills demonstrated through digital artifacts), supporting a multidimensional evaluation of teaching and learning practices.

Therefore, the objective of this study is to introduce and empirically examine the implementation of the BEAM Framework and its evaluative extension, the BEAM-X Factor, within undergraduate engineering education. The study investigates longitudinal patterns in academic performance, learning outcome attainment and student perception across phased implementation of the framework. To guide the empirical investigation, the study addressed the following research questions:

RQ1 Are there statistically significant differences in student academic performance (Performance Index) across semesters during phased BEAM implementation?

RQ2 How do Learning Outcome and Programme Outcome (LOPO) attainment patterns vary across baseline, pilot and full implementation phases?

RQ3 How do students perceive structured pedagogy, empowerment, technology amplification and mentoring during BEAM implementation?

RQ4 Does the BEAM-X composite index demonstrate consistent multidimensional trends across implementation phases?
The study adopts a longitudinal cohort-based comparative design, examining naturally occurring semester cohorts under consistent instructional and assessment conditions.

The remainder of this paper is organized as follows: Sect. 2 reviews related literature on pedagogical frameworks, student engagement and learning analytics. Section 3 introduces the conceptual foundation of BEAM, BEAM-X Factor and implementation in an Engineering course. Section 4 presents the results and discussion, and Sect. 5 concludes with limitations and directions for future research.

2 Theoretical and empirical foundations of the BEAM framework

The BEAM Framework and its evaluative extension, the BEAM-X Factor, are grounded in established educational theory and recent advancements in technology integration and learning analytics. This section synthesizes the foundational literature across four areas that provide the conceptual basis for the model: pedagogical theories, frameworks for technology integration, student engagement, mentoring and multi-dimensional assessment through learning analytics.

2.1 Foundational pedagogical theories

Educational practice has progressively shifted from teacher-centered instruction toward approaches that emphasize students as active participants in constructing their own learning. Constructivist traditions, which view learning as a process of constructing knowledge by experience, interaction and reflection, are the foundation of this growth [6, 16]. Even while these traditional viewpoints are still fundamental, they nonetheless influence modern approaches to technology-enhanced and student-centered learning. Recent studies, for instance, show how digital technologies may foster creativity, teamwork, critical thinking and communication, all of which are essential skills for students in the 21st century [20].

Self-regulated learning (SRL), which stresses students' capacity to organize, track and assess their progress toward objectives, is a key element of this pedagogical progression [24]. Numerous studies have demonstrated that SRL improves perseverance and academic achievement, especially in higher education where autonomy is essential. Recent research shows how SRL may be supported in digital settings: augmented reality (AR) and gamification techniques have improved self-regulation and engagement in science education [2], while gamified mobile learning environments have inspired students to become more self-regulatory [4].

This change has been accelerated by the incorporation of digital technologies; yet, early implementations sometimes saw technology as a simple replacement for conventional instruments, with little educational benefit [3]. According to contemporary viewpoints, technology has the capacity to revolutionize education by enabling the creation of radically novel and captivating learning opportunities that complement the development of higher-order skills [20].

The BEAM Framework builds on these foundations by embedding student empowerment, structured pedagogy and sustained mentorship within a constructivist paradigm. BEAM expands SRL methods beyond individual responsibility to a guided, cooperative and quantifiable process of knowledge building in technologically enhanced contexts by integrating traditional insights with new data.

2.2 Frameworks for technology integration

The effective integration of technology in education has been guided by two of the most influential models: the Technological Pedagogical Content Knowledge (TPACK) framework and the Substitution–Augmentation–Modification–Redefinition (SAMR) model. TPACK emphasizes the dynamic interplay between technological, pedagogical and content knowledge, highlighting the competencies required for teachers to design effective technology-enhanced learning environments [15]. Its strength lies in articulating the complexity of instructional design when technology is involved. However, critics argue that TPACK remains largely teacher-centric, focusing on knowledge domains rather than on how technology can empower learners or sustain engagement [23].

The SAMR model offers a continuum that categorizes technology integration into four levels, from basic substitution of existing tools to the redefinition of tasks that were previously inconceivable without digital technologies [17]. While SAMR provides a valuable heuristic for understanding the depth of integration, its application in practice has been inconsistent. A recent scoping review revealed that much of the research employing SAMR remains descriptive, with limited empirical grounding to demonstrate learning impact [3]. This limits its effectiveness as a guiding framework for holistic pedagogical innovation.

Building on and extending beyond these models, recent research has proposed new frameworks that integrate physical and digital learning environments with pedagogy. For example, the Pedagogy Space Technology (PST) framework emphasizes the alignment of teaching practices, physical/digital space and technological affordances to create hybrid and synchronous learning environments [12]. Similarly, studies in STEM education by Wu and Zhao (2025) have shown that teacher preparedness for technology integration is enhanced through targeted online professional development courses, underscoring the need for frameworks that move beyond static models toward dynamic, skill-building approaches.

Together, these frameworks demonstrate the importance of structured approaches to technology integration but highlight ongoing limitations. TPACK provides a knowledge-based perspective, SAMR offers a continuum of digital adoption and newer models such as PST address hybrid learning contexts. However, none of these frameworks fully integrate mentorship, empowerment and multi-dimensional evaluation as central design principles. The BEAM Framework responds to this gap by positioning technology not simply as an enabler of content delivery but as a catalyst for amplifying student empowerment, engagement and measurable learning impact.

In addition to technology-integration models such as SAMR and TPACK, the Community of Inquiry (CoI) framework has been widely adopted in research on online and blended learning. CoI conceptualizes effective learning environments through the intersection of three core presences: cognitive presence, social presence and teaching presence [10]. Subsequent research has refined and validated measurement instruments for assessing these presences [1], and systematic reviews have highlighted its influence in structuring inquiry-based and collaborative learning contexts [9]. While CoI offers a robust theoretical lens for understanding interaction and meaning-making in technology-mediated environments, it primarily explains the dynamics of learning presence rather than outlining phased implementation structures or integrating multidimensional performance-based evaluation within a unified framework.

2.3 Student engagement and mentoring

In higher education, student engagement has become a crucial factor in determining academic achievement. It is commonly understood to be a multifaceted notion with behavioral, emotional and cognitive components [8]. Stronger academic results, deeper learning and more perseverance are all linked to high levels of engagement. Because of the flexibility and possible isolation of online learning, it can be especially difficult to sustain engagement in digitally presented and blended environments Fordyce [7]. It has been demonstrated that structured instructional techniques, like interactive assignments, reflective exercises and group projects, improve student engagement in these settings [20].

The study of participation in technologically advanced learning environments has been expanded by recent studies. Social networking sites, for example, have been demonstrated to have a major impact on graduate students' emotional and cognitive engagement with online learning settings [14]. In a comparable way, research by Chen et al., [4] shows that digital tools that facilitate structured methods to self-regulated learning enhance motivation and engagement. These results highlight how the integration of technology and pedagogical tactics profoundly shapes engagement, which is not just a result of instructional design.

At the same time, mentorship has long been acknowledged as a potent tool for fostering students' growth. Improved retention, academic achievement and a stronger sense of belonging have all been associated with mentoring, whether it takes the form of peer cooperation, instructor supervision or organized programs [5]. Mentoring also offers vital scaffolding in digital contexts to maintain student motivation and lower attrition. However, rather than being a methodical and integrated part of instruction, mentoring is frequently viewed as an unplanned action.

When considered collectively, the literature emphasizes how mentoring and participation are linked in determining student success. However, current frameworks frequently handle both independently, conceptualizing mentorship as an elective support service and engagement as a construct to be measured. In order to bridge this gap, the BEAM Framework incorporates mentoring as one of its four pillars. This guarantees that engagement is maintained by continuous, individualized coaching in addition to being promoted through technology-rich assignments. Because of this integration, BEAM is positioned as a model that integrates mentorship and participation in a single educational design.

2.4 Learning analytics and multi-dimensional assessment

Grades and standardized outcome measures are examples of traditional assessment techniques used in higher education that only give a partial picture of student learning. Even while these metrics measure academic achievement, they frequently overlook more comprehensive aspects of development including creativity, transferable skills and reflective ability (Gérard Poitras [11]). The subject of learning analytics (LA) has developed to solve this constraint as learning settings grow more computerized. In order to better analyze and improve learning processes, LA uses digital trace data, which gives educators valuable information into how students interact with peers, material and assessment assignments [18].

Despite its potential, a lot of learning analytics applications are still centered on specific performance metrics, including clickstream data or time-on-task metrics. These measurements offer helpful but insufficient insights, frequently ignoring the perceptual and emotive aspects of the student experience [21]. In order to give a comprehensive picture of learning, recent literature consequently advocates for multi-dimensional assessment methodologies that integrate quantitative indicators with qualitative evidence [19].

For instance, digital portfolios are now widely acknowledged as useful instruments for documenting student learning beyond grades. They give educators a more comprehensive evaluation perspective and enable students demonstrate reflective practices, creativity and skill development through artifacts [19]. Therefore, to ensure validity and reliability when assessing student achievement, systematic evaluations of assessment procedures also stress the significance of including formative feedback and diverse sources of evidence [13].

By operationalizing an integrated approach to evaluation, the BEAM-X Factor immediately expands upon these advancements. BEAM-X offers a single index that captures both quantitative and qualitative evidence of learning by combining three essential metrics: performance (grades and learning outcomes), course learning outcome attainment and perception (student feedback). This cohesive approach provides a scalable, empirically supported indicator of teaching and learning innovation, which not only fits with current learning analytics trends but also overcomes the drawbacks of conventional assessment.

2.5 Identified research gap

The studied literature shows significant advancements in learning analytics, student engagement, pedagogy and technology integration. Nevertheless, there are still several issues. First, although constructivist and SRL-based theories stress the significance of autonomy and the active engagement of learners, they frequently delegate implementation and assessment to individual teachers. These methods offer little resources for integrating organized mentoring or monitoring student empowerment in a methodical way (Chen et al. 2024; [2]).

Secondly, educators now have useful heuristics for designing technology-enhanced learning through frameworks such as TPACK, SAMR and, more recently, CoI and PST. TPACK emphasizes the integration of technological, pedagogical and content knowledge [15], while SAMR categorizes levels of digital adoption from substitution to redefinition [17]. Empirical reviews, however, suggest that applications of SAMR remain largely descriptive and lack strong evidence of measurable learning impact [3]. In parallel, the Community of Inquiry (CoI) framework explains the interactional dynamics of cognitive, social and teaching presence in online and blended environments [9, 10]. While these models provide valuable conceptual lenses, they operate at different levels of abstraction and do not collectively offer a structured implementation architecture that integrates mentorship, empowerment and multidimensional performance-based evaluation. Emerging frameworks such as PST demonstrate potential in hybrid environments [12, 23], yet a unified model linking pedagogical design, learner agency and systematic evaluation remains underdeveloped.

Third, research on mentorship and student involvement shows that both are essential for perseverance and academic success, particularly in digital settings [5, 7, 8, 14]. However, mentorship is viewed as an optional support system, whereas engagement is frequently thought of as a measuring construct. Few models have tried to incorporate them into technology-enhanced schooling as interconnected design principles. Lastly, there are now more options for data-driven assessment thanks to learning analytics. However, most implementations ignore the perceptual and qualitative aspects of learning in favor of concentrating on specific performance metrics such clickstream data (Gérard Poitras [11, 18, 21]). Despite increasing calls for multidimensional assessment [13, 19], few frameworks operationalize perception, performance and outcome attainment within a single integrated evaluation structure aligned with pedagogical implementation.

When considered collectively, these limitations highlight the need for a comprehensive framework that integrates structured pedagogy, embedded mentorship, learner empowerment and technology amplification within a unified and measurable design. The BEAM Framework was developed to respond to this need by synthesizing constructivist principles, technology-enhanced engagement and sustained mentoring into an operational structure. Its evaluative extension, the BEAM-X Factor, consolidates performance, learning outcome attainment and student perception into a composite indicator. Together, this dual structure seeks to bridge conceptual models of learning with systematic evaluation, contributing a scalable and empirically informed approach to technology-supported higher education.

3 The BEAM framework and BEAM-X factor

3.1 Conceptual foundation of BEAM

The BEAM Framework (Build, Empower, Amplify, Mentor) was developed in response to the conceptual and structural gaps identified in existing pedagogical and technology-integration models. As discussed in Sect. 2, theories of self-regulated learning and engagement emphasize learner agency but provide limited guidance for systematic mentoring and integrated evaluation. Technology integration frameworks such as TPACK and SAMR offer valuable lenses for instructional design and digital adoption [15, 17], while the Community of Inquiry (CoI) framework explains the interaction of cognitive, social and teaching presence in technology-mediated environments [9, 10]. However, these models operate at different conceptual levels and do not collectively provide an operational structure that integrates mentorship, empowerment, technology amplification and multidimensional evaluation within a unified design. The BEAM Framework was therefore conceptualized to synthesize these strands into four interlinked pillars: structured pedagogy (Build), learner agency (Empower), transformative technology use (Amplify) and sustained mentoring (Mentor).

The conceptual foundations of BEAM draw on constructivist theory, which positions learners as active participants in knowledge construction [6, 16], and on self-regulated learning (SRL), which emphasizes planning, monitoring and reflective evaluation of progress [24]. Research on student engagement and mentoring further highlights the importance of agency, feedback and collaborative interaction in shaping meaningful learning experiences [5, 8]. Contemporary studies also stress the development of 21st-century competencies such as creativity, collaboration, critical thinking and digital literacy within technology-supported environments [4, 20].

By specifically integrating these threads into a comprehensive architecture, BEAM sets itself apart. Build offers students scaffolding and clarity through organized information delivery that is in line with learning objectives. Empower encourages students to take charge of their own learning by emphasizing agency and ownership. Amplify moves beyond replacement toward innovation by utilizing the transformational power of technology to produce new kinds of creativity and engagement. Mentor presents advice and criticism as an integral, ongoing process compared to an optional kind of assistance.

These four elements work together to provide a thorough educational framework that is both theoretically solid and practically flexible. The BEAM-X Factor, an evaluation index that combines perception, performance and result accomplishment into a single score, is added to the framework to make sure its influence can be assessed methodically. To ensure that its impact could be examined systematically, the BEAM Framework is complemented by the BEAM-X Factor, an evaluative index that integrates perception, performance and outcome attainment into a composite measure. This dual structure responds to contemporary demands for both pedagogical innovation and accountability in higher education. The framework was developed through synthesis of constructivist theory, self-regulated learning, technology integration models (e.g., TPACK and SAMR) and presence-based perspectives such as CoI, followed by iterative refinement across multiple course-based implementation cycles. These cycles enabled progressive adjustment of pedagogical design elements prior to formal longitudinal cohort comparison. The empirical evaluation of BEAM's implementation is described in Sect. 3.5, where its phased deployment is examined through structured performance and perception measures across independent student cohorts.

3.2 The four pillars of BEAM

The four interconnected pillars of the BEAM Framework: Build, Empower, Amplify and Mentor, each focus on a crucial aspect of modern higher education. These pillars work together to provide a comprehensive model that supports student learning processes as well as pedagogical design. Figure 1 presents the BEAM Model, situating the four pillars at the center of transformative, student-centered learning. Surrounding the framework are the future-ready skills of creativity, collaboration, critical thinking and technological literacy. This visualization highlights how the BEAM pillars are not isolated practices but are interwoven with the competencies required for 21st-century graduates. In this way, the framework simultaneously provides pedagogical structure and nurtures transferable skills essential for future learning.

3.2.1 Build

Build, the first pillar, places a strong emphasis on systematic knowledge generation and structured delivery. This dimension makes sure that students have clear expectations and support for their learning journey by aligning curricular material and activities with course learning goals. Additionally, by ensuring that students are gradually moved from fundamental information to advanced application, structured teaching lessens cognitive

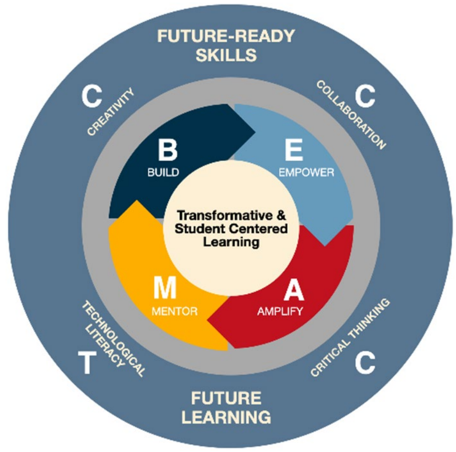

Fig. 1 BEAM Model Framework

overload and fosters mastery. In practice, the Build pillar is operationalized through course design strategies such as outcome-based learning, scaffolded assignments and formative assessments. For example, systematic exercises on algorithm design and implementation were gradually incorporated in engineering courses, aided with animations and visualizations. This guarantees that students get both academic knowledge and practical proficiency.

3.2.2 Empower

The second pillar, Empower, highlights the role of agency, autonomy and student ownership of learning. In BEAM, empowerment is purposefully included into the teaching process rather than being an afterthought, providing students with the chance to take charge of their own educational paths. This covers reflective techniques, assignment decision-making and the use of digital portfolios as venues for students to display their abilities and accomplishments. Activities like group Padlet debates, infographic production and digital portfolio construction promoted student empowerment. Students gained transferable skills including communication, creativity and self-reflection in addition to academic competence by producing unique content and considering their own development. As a result, empowerment increases intrinsic motivation and gets students ready for lifetime learning.

3.2.3 Amplify

The third pillar, Amplify, emphasizes the transformative use of technology to enrich learning experiences. Technology is positioned as an amplifier that pushes the limits of learning and creates chances for creativity, teamwork and customization rather than as a replacement for conventional tools. The use of augmented and virtual reality (AR/VR) to provide immersive experiences, such as robotic simulation, designing electronic circuits using AR or creating theme animations that bring cultural heritage to life, are examples of amplification. Students were also able to illustrate difficult ideas in creative manners using interactive simulations, video-based projects and collaborative digital tools. Thus, Amplify symbolizes the transition from technology as a convenient tool to technology as a catalyst for innovative teaching.

3.2.4 Mentor

The importance of guidance, feedback and ongoing support in student development is reflected in the last pillar, Mentor. BEAM incorporates mentorship directly into pedagogy as an ongoing aspect of teaching and learning, in contrast to conventional frameworks that view it as an optional or external activity. Formative evaluations, organized feedback loops and continuous communication between teachers and students were used to execute mentoring. Peer-to-peer mentoring during group projects, weekly reflections on Padlet and academic mentoring through iterative feedback on digital portfolios are a few examples. Testimonials from students frequently emphasized the importance of mentoring in boosting self-esteem, enhancing learning techniques and creating a feeling of community.

The four BEAM pillars: Build, Empower, Amplify, and Mentor, function together to offer a thorough educational framework that incorporates support, autonomy, structure and creativity. This combination ensures a more comprehensive and quantifiable approach to technology-enhanced higher education while addressing the shortcomings of traditional approaches.

3.3 The BEAM-X factor: an evaluative extension

A systematic approach to measuring is required to support the four pedagogical pillars of the BEAM Framework and ensure that teaching innovation is both innovative and grounded in research. To address this requirement, the BEAM-X Factor was created. It provides a measurable indicator of both student achievement and the efficacy of instruction by combining several aspects of student learning into a single composite index. Performance Index (PI), Learning Outcomes & Programme Outcomes (LOPO) Achievement and Student Perception (SP) are the three parts of the BEAM-X Factor, and they are weighted at 40%, 30% and 30%, respectively. The weighting structure was determined conceptually to balance objective performance measures with outcome alignment and learner perception, rather than derived from psychometric modeling.

The Performance Index (PI) accounts for 40% of the composite score and is derived from students' achievement in quizzes, assignments, tests and final examinations. It offers a straightforward assessment of learning and problem-solving skills, especially in relation to CLO1 (foundational knowledge) and CLO2 (problem-solving). By monitoring grade distributions over several semesters, PI is possible to identify patterns in academic performance that can be linked to the use of BEAM. To assess overall student academic performance, the PI was calculated using a weighted formula and derived using Eqs. (1),

$$\mathrm{PI} = \frac{\sum_{i=1}^{n} (G_i \times N_i)}{\sum_{i=1}^{n} N_i} \tag{1}$$

where G_i is grade point assigned to grade *i*, N_i is number of students who received grade *i* and *n* is total number of grade categories. For example, if a cohort consists of 10 students receiving grade A (4.00), 20 students receiving grade B (3.00), and 10 students receiving grade C (2.00), the PI is calculated as:

$$\mathrm{PI} = \frac{(10 \times 4.00) + (20 \times 3.00) + (10 \times 2.00)}{40} = 3.00$$

The LOPO Achievement, which makes up 30% of the index, evaluates how well course learning objectives (CLOs) are met and how well they match program objectives (POs) in comparison to prior semesters. CLO2 (creating solutions) and CLO3 (using current tools) get particular attention since they are anticipated to demonstrate notable progress under BEAM interventions. Thus, LOPO analysis captures both individual success and institutional responsibility for fulfilling curricular and accreditation requirements. For each semester, the course learning outcome (CLO) and corresponding Programe Outcome (PO) are assessed as percentage achievements. The average LOPO Achievement is derived by averaging the percentage values indicated in Eqs. (2),

$$\mathrm{LOPO}avg = \frac{1}{n}\sum i = 1^{n} A_i \tag{2}$$

where A_i is achievement percentage for each LO or PO and *n* is the total number of outcomes measured.

The Student Perception (SP) component, weighted at 30%, captures learners' voices regarding their educational experience. Course review surveys, Padlet engagement statistics and involvement in buddy learning and peer mentoring programs are some examples of sources. SP sheds light on students' perceived benefits of active, tech-enhanced learning as well as their motivation and level of satisfaction. This element guarantees that the evaluation model strikes a balance between objective performance data and subjective and experience factors by appreciating students' reflections. Table 1 indicated 15 perception items are categorized under the four core components of the BEAM framework. Each student's responses are averaged across these 15 components to yield a single SP average score, which represents the student experience in a quantifiable and comparable way across semesters. To compute the overall SP Score, the average score for all 15 items is given in Eqs. (3),

$$\mathrm{SP}avg = \frac{1}{n}\sum i = 1^{n} S_i \tag{3}$$

where S_i is the average likert score for perception component and *n* is the total number of evaluated components. The final SP score is scaled to a maximum of 5.0, representing the overall student perception of the teaching and learning experience across Build, Empower, Amplify and Mentor domains.

Finally, the overall BEAM-X Factor score is calculated with the three components are first normalized and aggregated according to their weights based on Eq. (4).

$$BEAM - X\ Factor\ =\ 0.4PI\ +\ 0.3LOPO\ +\ 0.3SP \tag{4}$$

All components were first expressed on a comparable scale prior to aggregation. LOPO values, originally measured as percentages, were rescaled to a 5-point scale, while SP was already measured on a 5-point Likert scale. PI values were proportionally aligned from the 4.00 grading scale to ensure consistency across components. For illustration, if a semester records PI = 3.20, LOPO = 90% (equivalent to 4.50 on a 5-point scale), and SP = 4.70, the BEAM-X score is computed as: BEAM-X = 0.4(3.20) + 0.3(4.50) + 0.3(4.70) = 4.16.

Over several semesters, the combined score makes it possible to continuously assess the teaching and learning outcomes. It offers an evidence-based, scalable and reliable index that can be used by academics and courses alike. More significantly, the BEAM-X

Table 1 Table Student Perceptions (SP) instrument mapped to BEAM Components

BEAM Component	Item No.	Evaluation Statement
Build	1	Course materials were helpful and clear
	2	Learning activities helped strengthen understanding
	3	Examples and exercises were relevant
	4	Activities enhanced practical and computational skills
Empower	5	The course allowed me to think creatively
	6	I had the freedom to express ideas
	7	I collaborated with peers meaningfully
	8	I felt confident in taking ownership of my learning
Amplify	9	Use of technology enhanced the learning process
	10	Digital tools made abstract concepts easier to understand
	11	Learning technologies were integrated effectively
Mentor	12	I received timely and useful feedback
	13	The lecturer provided clear guidance and support
	14	I felt continuously supported throughout the course
	15	The overall teaching approach was engaging and student-centered

Factor bridges the gap between institutional decision-making and instructional design by turning innovation from an abstract concept into a measurable objective.

3.4 BEAM in practice: application and differentiation

The BEAM Framework and its evaluative extension, the BEAM-X Factor, were implemented across multiple undergraduate engineering courses over four academic semesters, including Data Structures and Algorithms, Multimedia Technology and Applications and Digital Image Processing. These courses offered a variety of settings for assessing the framework, from theory-heavy modules to project-based, practice-focused learning settings. To ensure that the framework was operationalized in both instructional planning and student learning experiences, the four BEAM pillars were included into the design and delivery of each course.

The planned development of learning assignments, which started with fundamental information and worked their way up to more complicated applications, was how the Build pillar was implemented. For instance, progressive assignments in image processing allowed students to go methodically from theory to application, while algorithm visualization and animation were added to scaffold learning in programming classes. Student-led initiatives including Padlet-based conversations, infographic production and the building of digital portfolios were used to highlight empowerment. Through these activities, students were inspired to take charge of their education, show off their accomplishments and develop transferable skills like teamwork, communication and reflective practice.

The Amplify pillar made sure that technology was used to create life-changing learning experiences rather than just to replace conventional instruments. Students were able to interact creatively and innovatively with the course material using augmented reality technologies. These kinds of activities increased creativity and interest, showing how digital tools may reinvent learning objectives rather than duplicate them. Lastly, the Mentor pillar positioned feedback and assistance as an ongoing activity instead of an afterthought. Iterative feedback on assignments and portfolios was given by the lecturer, while buddy learning and peer mentoring were used to boost self-esteem, maintain motivation and encourage reflective practice. Testimonials from students frequently highlighted the importance of continuing mentorship in guiding their educational paths.

Figure 2 illustrates how BEAM and its evaluative extension, the BEAM-X Factor, are situated in relation to established frameworks such as SAMR, TPACK and Bloom's taxonomy. Rather than replacing these models, BEAM extends their principles by integrating them with a measurable, student-centered approach. The BEAM-X Factor functions as the evaluative core, enabling systematic measurement of transformation, empowerment and learning outcomes. This positioning highlights BEAM as both complementary to and an evolution beyond existing frameworks, offering a unified structure that bridges pedagogical theory with quantifiable practice.

Through these applications, BEAM has demonstrated that a framework grounded in Build, Empower, Amplify, and Mentor, supported by the BEAM-X Factor, can be both

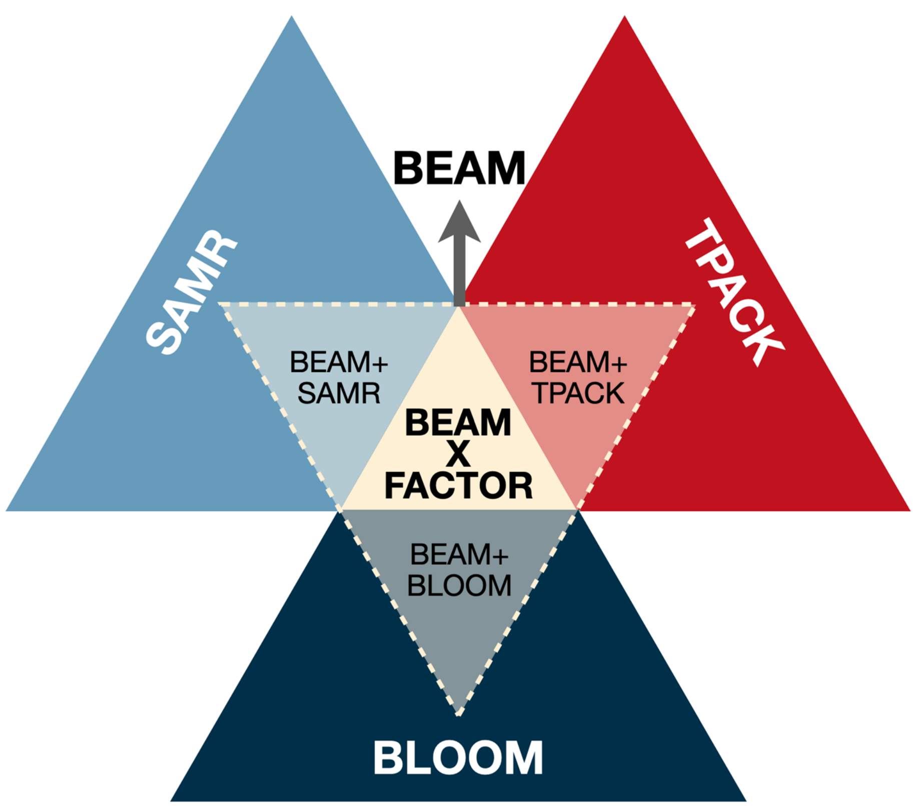

Fig. 2 BEAM-X Convergence Model–Intersecting BEAM with SAMR, TPACK and Bloom's Taxonomy

implemented effectively in diverse courses and positioned as a holistic, evidence-based advancement in technology-enhanced higher education.

3.5 BEAM implementation and research context

Following its conceptual development and iterative refinement, the BEAM Framework was implemented and examined within the undergraduate course Data Structures and Algorithms at Universiti Teknikal Malaysia Melaka (UTeM). The empirical examination spanned eight consecutive semesters from 2020/2021 to 2024/2025 and involved 542 engineering students. The course syllabus, credit structure and learning outcomes remained consistent throughout the study period, enabling longitudinal comparison under stable curricular conditions. The framework was evaluated through structured cohort-based analysis rather than randomized experimental validation. To ensure methodological transparency, the research design, baseline conditions, instructional consistency and analytical procedures are detailed in the following subsections.

3.5.1 Research design

This study adopted a longitudinal cohort-based design to examine academic performance and engagement trends across phased BEAM implementation. Naturally occurring semester cohorts were compared without random assignment, constituting a longitudinal cohort-comparison design without randomized control groups. Each semester represented an independent student group, allowing between-cohort comparison under comparable academic and institutional conditions. This design permits examination of performance variation associated with structured pedagogical changes while maintaining consistent evaluative standards. All enrolled students in the course during each semester were included in the analysis. No sampling or exclusion criteria were applied, as institutional performance and perception data were analyzed at the cohort level. As the study examined phased implementation within a single course context without a parallel control group, findings should be interpreted as longitudinal cohort comparisons rather than controlled experimental effects. No parallel control group was employed; therefore, findings should be interpreted as longitudinal cohort comparisons within a single institutional context. This design allows examination of performance and engagement patterns associated with phased pedagogical integration while maintaining consistent institutional assessment standards, though causal inference is inherently limited by the absence of randomization or parallel control groups.

3.5.2 Baseline and implementation phases

The baseline cohort refers to Semester 2 2020/2021, conducted prior to structured BEAM integration. During this phase, instruction primarily followed lecture-centered delivery with conventional assignment formats and limited integration of empowerment, amplification and structured mentoring components. Subsequent semesters progressed through pilot testing and full implementation phases, during which the four BEAM pillars were systematically embedded into course design. Full implementation included structured scaffolding, digital portfolios, AR/VR-supported learning tasks, collaborative peer systems and continuous formative mentoring feedback.

3.5.3 Instructional and assessment consistency

The course instructor remained the same across all semesters included in the study. Assessment weightage, grading rubrics, CLO–PO alignment criteria and institutional grading policies were maintained consistently throughout the study period. No major revisions to syllabus content, assessment design or evaluation standards were introduced. This stability minimizes confounding variables and supports interpretation of performance differences under progressively integrated BEAM implementation.

3.5.4 Data sources and measures

Three indicators were used to evaluate outcomes. Performance Index (PI) was calculated as the weighted mean grade performance per semester cohort based on the institutional 4.00 grading scale. Specifically, PI represents the average grade point across all students in a cohort, computed by multiplying each grade point with the number of students receiving that grade and dividing by the total number of students.

Learning Outcome and Programme Outcome (LOPO) achievement was computed using institutional outcome-mapping procedures. Student Perception (SP) data were obtained from the institutional end-of-semester course evaluation system administered electronically to all enrolled students. The survey was conducted using a standardized university instrument comprising structured Likert-scale items evaluating instructional clarity, engagement, mentoring effectiveness and technology integration. Participation was voluntary and responses were anonymized. Response rates ranged between 80% and 95% across semesters, and all available responses were included in the analysis. The institutional perception instrument has been routinely used for course evaluation across the university; reliability coefficients are maintained at the institutional level, although internal consistency analysis was not conducted within this study. For integration within the BEAM-X composite index, the SP score was treated as a cohort-level average on a 5-point scale. To ensure comparability across components, LOPO values were rescaled from percentage form to a 5-point scale, while PI values were proportionally aligned from the institutional 4.00 grading scale. This standardization enabled consistent aggregation of performance, outcome attainment and perception into a unified composite index.

These measures were consolidated into the BEAM-X composite index for multidimensional evaluation. Qualitative artifacts including student reflections, digital portfolios and testimonial excerpts were examined thematically to identify recurring patterns related to empowerment, technology amplification, mentoring and collaborative engagement. Qualitative coding was conducted inductively to identify recurring themes aligned with the four BEAM pillars, providing complementary interpretive evidence alongside quantitative cohort comparisons.

3.6 Statistical analysis

To determine whether differences in student academic performance across semesters were statistically significant, a one-way analysis of variance (ANOVA) was conducted using the Performance Index (PI) as the dependent variable and semester as the grouping factor. PI values were calculated from weighted grade distributions aligned with the institutional 4.00 grading scale.

Descriptive statistics, including mean, standard deviation (SD) and 95% confidence intervals (CI), were computed for each semester cohort. The ANOVA examined between-semester differences in mean PI scores. Statistical significance was evaluated at the 0.05 level. Effect size was calculated using eta squared (η^2) to estimate the proportion of variance in PI attributable to semester differences. As each semester represented an independent cohort of students, the independence assumption of ANOVA was satisfied. Qualitative artifacts were analyzed using thematic coding procedures to identify recurring constructs aligned with BEAM pillars. Patterns were examined across semesters to complement quantitative findings.

4 Results and discussion

The implementation of the BEAM Framework was evaluated across eight consecutive semesters ($n = 542$), with particular emphasis on the four semesters representing full implementation ($n = 247$) during the BEAM-X composite analysis. These eight cohorts form the longitudinal basis for statistical comparison, while the full implementation phase provides focused insight into the structured deployment of the BEAM pillars. The analysis focused on the three key components of the index Performance Index (PI), Learning Outcomes and Programme Outcomes (LOPO) Achievement and Student Perception (SP) to provide a holistic view of teaching and learning outcomes. A thorough examination of the ways in which BEAM supports quantifiable academic progress and student empowerment is made possible by the merging of these findings with qualitative information from reflections and digital portfolios.

The Performance Index (PI) showed a steady increase over the course of the semesters, indicating a notable improvement in students' academic performance once BEAM was implemented. The most striking evidence lies in the proportion of students attaining grade A, which increased from approximately 14% in the baseline cohort to over 40% under full BEAM implementation. This indicates that the proportion of students in the lower grade categories has generally decreased, while the number of high-achieving students has increased threefold.

To determine whether the observed differences in PI across semesters were statistically significant, a one-way analysis of variance (ANOVA) was conducted using semester as the grouping variable. The results indicated a statistically significant effect of semester on PI scores, $F(7, 534) = 4.21$, $p < 0.001$, $\eta^2 = 0.05$. This suggests that approximately 5% of the variance in academic performance was explained by the semester of implementation. These findings provide statistical evidence consistent with the progressive improvement observed during the Testing and Full BEAM implementation phases.

Figure 3 presents the comparative grade distribution across semesters, highlighting the progressive shift towards stronger performance as BEAM moved from its testing phase to full implementation. The steady rise in grade A students is consistent with improved academic performance observed during the phased implementation of BEAM. The structured scaffolding of the Build pillar and the integration of digital activities under the Amplify pillar may have supported deeper mastery of course content.

To provide a more detailed statistical overview of academic performance across semesters, descriptive statistics for the Performance Index (PI) were computed. Table 2 presents the number of students (n), mean PI scores, standard deviations (SD), and 95% confidence intervals (CI) for each semester cohort.

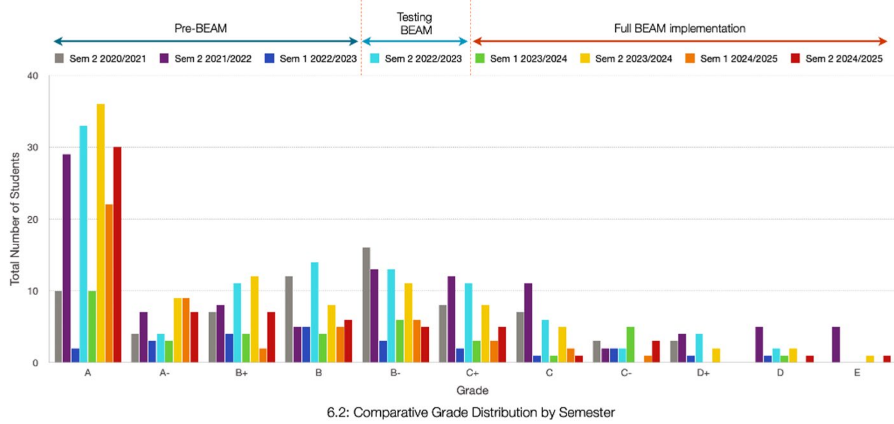

Fig. 3 Comparative Grade Distribution by Semester

Table 2 Descriptive Statistics of PI by Semester

PHASE	Semester	N	Mean PI	SD	95 (%) CI Lower	95 (%) CI Upper
Pre-BEAM	**Sem 2 2020/2021**	70	2.90	0.71	2.734	3.066
	Sem 2 2021/2022	101	2.85	1.12	2.632	3.068
	Sem 1 2022/2023	24	2.90	0.82	2.572	3.228
Testing BEAM	**Sem 2 2022/2023**	100	3.14	0.81	2.981	3.299
Full BEAM Implementation	**Sem 1 2023/2024**	37	3.05	0.86	2.773	3.327
	Sem 2 2023/2024	94	3.29	0.84	3.120	3.460
	Sem 1 2024/2025	50	3.47	0.66	3.287	3.653
	Sem 2 2024/2025	66	3.35	0.84	3.147	3.553

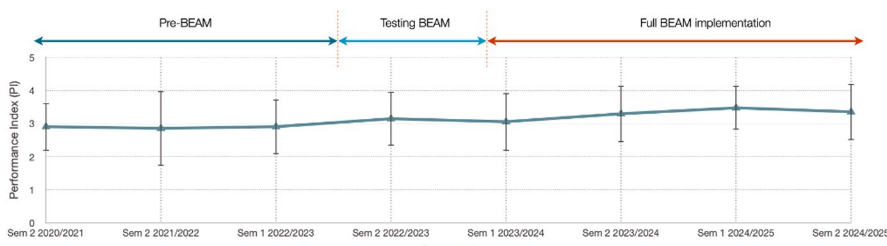

Fig. 4 Performance Index (PI) Trend Through Semesters

As shown in Table 2, the mean PI demonstrates a progressive upward trend from the pre-BEAM phase (M = 2.90) to the full implementation phase (M = 3.47). While variability differs across cohorts, the narrowing confidence intervals in later semesters suggest increasing stability in performance outcomes. Notably, the highest mean PI was recorded in Semester 1 2024/2025 (M = 3.47, 95% CI [3.29, 3.65]). The confidence interval suggests a stable estimate of cohort performance during the full implementation phase. Figure 4 illustrates the trend of mean PI scores across semesters, further highlighting the progressive increase in academic performance following the phased implementation of the BEAM framework. Error bars represent ± 1 standard deviation, indicating the variability within each cohort.

Consistent with the earlier analysis, one-way ANOVA indicated a statistically significant difference in PI across semesters, $F(7, 534) = 4.21$, $p < 0.001$, $\eta^2 = 0.05$. Approximately 5% of the variance in academic performance was associated with semester differences. Although the effect size was small to moderate, the result supports the observed upward performance trend across phased BEAM implementation.

The Learning Outcomes and Programme Outcomes (LOPO) Achievement component provided further insight into how BEAM contributed to student success. The average LOPO achievement was continuously high throughout the semesters, with the majority of results above institutional standards. The two areas that saw the most advancements were CLO2, which focuses on creating solutions, and CLO3, which evaluates the use of contemporary tools. When compared to baseline cohorts, these areas demonstrated higher achievement under BEAM, demonstrating the influence of Empower techniques like portfolio-based learning and Amplify activities that used AR/VR and other digital resources.

At the programme level, outcome mapping confirmed similar patterns. PO1 (using knowledge) and PO5 (using contemporary tools and lifetime learning) continuously attained full or almost full attainment over semesters, whereas PO3 (solving problems) showed more variation, with some cohorts scoring worse than others. This fluctuation highlights the challenges of sustaining complex problem-solving competencies, but the overall upward trend indicates that BEAM interventions supported students in bridging gaps between theory and application.

The comparative LOPO achievement between semesters is shown in Fig. 5. The findings demonstrate how BEAM improved CLO2 and CLO3 specifically, which is consistent with its focus on giving students the tools they need to take charge of their education and enhancing results via the use of technology. These improvements suggest that BEAM aligns learning outcomes with programme-level goals, supporting institutional accountability and performance monitoring.

Throughout the four semesters that BEAM was used, the Student Perception (SP) findings showed consistently high evaluations, with all components receiving average scores above 4.6 on a 5-point Likert scale. Students consistently gave the Build pillar the highest ratings, as seen in Fig. 5, indicating how much importance they put on learning exercises that were clearly scaffolded and delivered in a systematic manner. Strong scores were also given to the Mentor pillar, highlighting the value of ongoing mentoring, peer cooperation and iterative feedback.

The first semester of 2024/2025 saw the greatest overall perception scores, with mean values over 4.8 for all four pillars. The convergence of BEAM practices, including as the methodical usage of digital portfolios, Padlet-based participation and AR/VR-enhanced

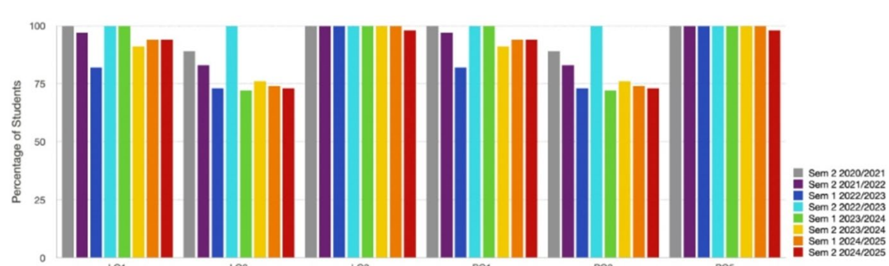

Fig. 5 Comparative Course Assessment Based on LOPO Achievement by Semester

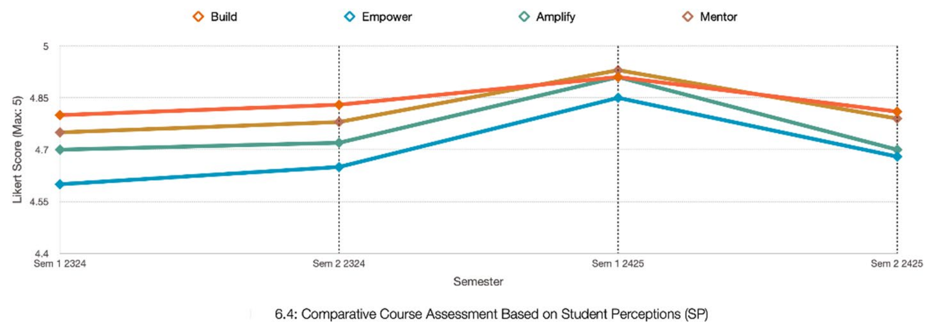

Fig. 6 Comparative Course Assessment Based on Student Perceptions (SP)

Table 3 BEAM-X Factor Based on PI, LOPO Achievements and SP

Table 6.5: BEAM-X Factor Based on PI, LOPO Achievements and SP

PHASE	Semester	PI	Average LOPO Achievements (%)	SP	BEAM-X Factor (%)	BEAM-X Factor (Rate 1 to 5)
Pre-BEAM	**Sem 2 2020/2021**	2.90	96.33	-	-	-
	Sem 2 2021/2022	2.85	93.33	-	-	-
	Sem 1 2022/2023	2.90	85	-	-	-
Testing BEAM	**Sem 2 2022/2023**	3.14	100	-	-	-
Full BEAM Implementation	**Sem 1 2023/2024**	3.05	90.67	4.7	85.9	**4.30**
	Sem 2 2023/2024	3.29	89	4.7	87.8	**4.39**
	Sem 1 2024/2025	3.47	89.33	4.9	90.9	**4.54**
	Sem 2 2024/2025	3.35	88.33	4.74	88.4	**4.42**

projects, coincided with this peak in perception scores. In their remarks, students emphasized how these exercises promoted confidence, increased digital creativity and ownership of learning. Overall SP scores stayed strong, averaging 4.74 across all components, despite minor variations in Semester 2 2024/2025. This consistency shows that the BEAM Framework was accepted and flexible enough to deal with various cohorts.

The comparison findings for Build, Empower, Amplify, and Mentor across four semesters are shown in Fig. 6, which emphasizes how students consistently have a good opinion of BEAM. The results highlight the value of continual mentorship, empowerment, technology amplification and organized delivery as integrated practices in higher education.

The BEAM-X Factor, a unified indicator of teaching and learning effectiveness, reflects the combined outcomes. The BEAM-X Factor increased gradually throughout complete deployment, as seen by Table 3 and tabulated in Figs. 7 and 8, with all composite scores above 4.3/5. The BEAM-X Factor peaked in Semester 1 of 2024–2025 at 4.54, demonstrating a significant integration of perception, performance, and results. The BEAM-X Factor integrates Performance Index (PI), LOPO Achievement and Student Perception (SP) into a composite indicator of teaching and learning outcomes. As shown in Table 3; Figs. 7 and 8, BEAM-X scores increased progressively across implementation phases, with all full implementation semesters exceeding 4.30 on a 5-point scale. The highest composite score was observed in Semester 1 2024/2025 (4.54), coinciding with the highest mean PI and strong perception ratings.

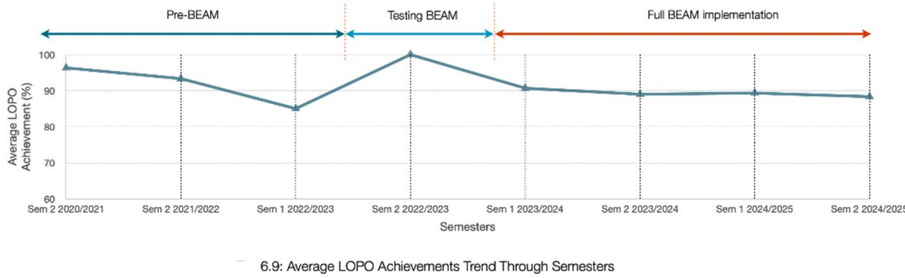

Fig. 7 Average LOPO Achievement Trend Through Semesters

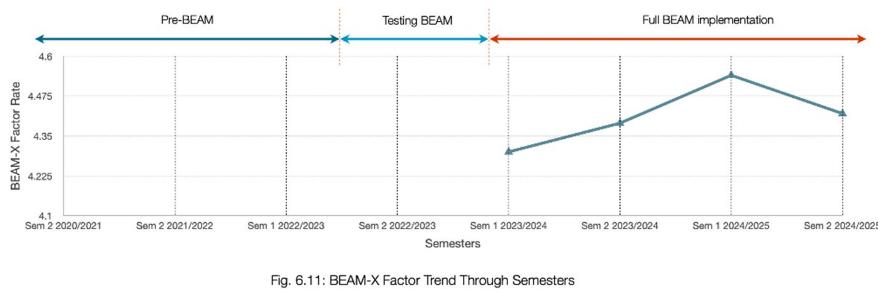

Fig. 8 BEAM-X Factor Trend Through Semesters

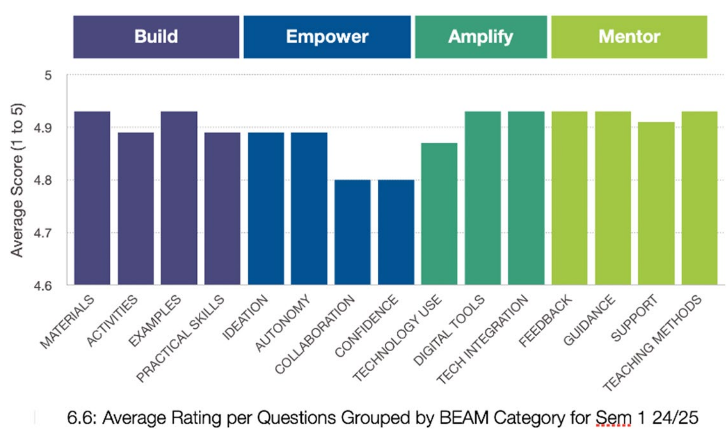

Fig. 9 Sample of average rating per questions grouped by BEAM category

While the one-way ANOVA confirmed statistically significant differences in PI across semesters ($F(7, 534) = 4.21$, $p < 0.001$, $\eta^2 = 0.05$), the effect size indicates a small-to-moderate magnitude of change. Therefore, the upward BEAM-X trend should be interpreted as a consistent and statistically supported improvement pattern across cohorts rather than definitive causal proof of intervention impact. Its scalability and flexibility in higher education environments are further suggested by the consistency of results across several cohorts. Collectively, these findings support RQ4, indicating that the BEAM-X composite index demonstrates consistent multidimensional improvement trends across implementation phases.

To further unpack the contribution of student empowerment and mentoring within BEAM, perception data were also analyzed at a more granular level. Figure 9 presents average student ratings grouped by the four BEAM pillars for Semester 1 2024/2025. The results highlight that Build was valued for clear materials, activities, and practical examples; Empower was reflected in autonomy, collaboration, and the use of digital portfolios as part of assignments; Amplify was emphasized through the integration of digital tools and technology-enhanced tasks; and Mentor was strongly associated with continuous feedback, guidance, and support both inside and outside the classroom. These findings illustrate how BEAM fostered not only academic achievement but also ownership, confidence, and engagement, reinforcing the framework's role in developing transferable skills alongside measurable performance outcomes.

Together, these results provide converging quantitative and qualitative evidence supporting the BEAM Framework, as operationalized through the BEAM-X Factor, as a structured pedagogical model and evaluative instrument. Rather than replacing established models such as SAMR and TPACK, BEAM extends these approaches by integrating empowerment, mentorship and technology amplification within a unified and measurable framework. The consistency of findings across cohorts suggests that BEAM may serve as a promising approach within similar technology-supported higher education contexts, contributing to academic performance, learning outcome alignment and student engagement.

Beyond the quantitative and qualitative findings, the results suggest several implications for higher education practice. First, BEAM illustrates how established models such as SAMR and TPACK may be complemented by a framework that integrates technological integration, mentorship, empowerment and structured delivery within a measurable structure. Rather than replacing these models, BEAM extends their application by incorporating a multi-dimensional evaluation component.

Second, consistent patterns observed across cohorts and course contexts indicate potential scalability of the framework within similar institutional settings. While further research across disciplines and institutions is necessary, the current findings suggest that BEAM may be adaptable beyond engineering education.

Third, by integrating perception, performance and learning outcomes into a composite index, the BEAM-X Factor contributes a structured approach to multidimensional evaluation. Such an approach may support evidence-informed instructional reflection and institutional monitoring practices.

Finally, the integration of AR/VR projects, digital portfolios and collaborative platforms highlights how technology-supported pedagogies may be aligned with the development of transferable skills such as creativity, collaboration, critical thinking and digital literacy. Collectively, these implications position BEAM as a structured and potentially scalable framework for technology-supported higher education practice.

While the findings demonstrate statistically supported and consistent patterns across cohorts, several considerations should be acknowledged. The study was conducted within a single institutional context, and cohort characteristics varied across semesters. Although the ANOVA analysis indicates statistically significant differences in academic performance, the effect size was small to moderate, suggesting that additional contextual factors may also contribute to performance variation. Therefore, the results should be interpreted as evidence of association rather than definitive causal impact. In addition, student perception data were derived from voluntary institutional feedback instruments, which may be subject to self-selection bias and social desirability effects.

5 Conclusion

This study introduced the BEAM Framework (Build, Empower, Amplify, Mentor) and its evaluative extension, the BEAM-X Factor, as an integrated pedagogical and measurement approach for student-centered and technology-supported learning in higher education. Applied across four consecutive semesters within an undergraduate engineering course, the framework was associated with consistent improvements in academic performance, sustained learning outcome attainment and positive student perception ratings.

By consolidating quantitative indicators (Performance Index and LOPO achievement) with qualitative and perceptual measures, the BEAM-X Factor provided a structured method for examining multidimensional learning outcomes. The statistical analysis indicated significant differences in academic performance across semesters, although the observed effect size was small to moderate, suggesting that BEAM implementation should be interpreted as one contributing factor within a broader instructional context.

The findings further suggest that BEAM may support the development of transferable competencies such as collaboration, creativity, reflective practice and digital engagement when implemented through structured scaffolding, technology amplification and ongoing mentorship. Rather than replacing established frameworks such as SAMR and TPACK, BEAM extends these models by integrating a measurable evaluation component and embedding mentorship as a core pedagogical pillar.

Several limitations should be acknowledged. The study was conducted within a single institutional and disciplinary context involving engineering undergraduates, which may limit generalizability to other disciplines or educational systems. Additionally, although longitudinal comparisons were conducted, the absence of randomized control groups limits definitive causal interpretation. Future research should explore cross-institutional validation, application across diverse academic disciplines and integration with advanced learning analytics systems to further examine the robustness and scalability of the BEAM Framework.

In summary, BEAM offers a structured and empirically informed approach that may support the integration of pedagogy, empowerment, technology and mentorship within higher education contexts. While further validation is warranted, the present findings indicate that BEAM may serve as a scalable framework for guiding technology-supported and student-centered instructional innovation.

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Author contributions
N.A.M. conceptualized the study, designed the BEAM Framework, conducted the data analysis and drafted the main manuscript. A.S.M.Z. contributed to data collection, visualization and critical review of the manuscript. Both authors discussed the results, refined the interpretations and approved the final version of the manuscript for submission.

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Data availability
The datasets generated and analyzed during this study include student grade distributions, programme-level learning outcome attainment, perception survey results, reflective journals and digital portfolio artifacts from the undergraduate Data Structures and Algorithms course. Due to institutional policies and student privacy considerations, these datasets are not publicly available. Anonymized summary data supporting the findings (e.g., aggregated grade distributions, outcome attainment and survey results underlying Figs. 3, 4, 5, 6, 7, 8 and 9; Table 2, and 3) are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

This study involved the analysis of anonymised student learning data and voluntary course feedback collected as part of routine teaching and learning activities. All procedures were conducted in accordance with the ethical standards of Universiti Teknikal Malaysia Melaka (UTeM) and adhered to the principles of the Declaration of Helsinki (1964) and its later amendments. Ethical clearance was reviewed and approved by the Mesyuarat Eksekutif Fakulti (MEFA), Fakulti Teknologi Kejuruteraan Elektrik dan Elektronik (FTKEK), UTeM, which confirmed that the study met institutional guidelines for research involving human participants, specifically enrolled students. An approval number was not issued for this category of institutional educational research. The study originated from structured institutional teaching innovation evaluation. Although conducted within routine academic practice, the systematic data analysis and longitudinal design extend beyond internal quality improvement, supporting its classification as educational research. Informed consent was obtained from all participating students prior to data collection. Participation was voluntary, had no impact on grades or course standing and all data were anonymised before analysis.

Consent for publication

Consent to publish anonymised, aggregated data was obtained from all participants. No identifiable information is included in the manuscript.

Competing interests

The authors declare no competing interests.

Financial interests

The authors declare that they have no relevant financial or non-financial interests to disclose.

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