

AN INTEGRATED DEA–MACHINE LEARNING–SYSTEM DYNAMICS FRAMEWORK FOR FACULTY-LEVEL GRADUATE EMPLOYABILITY EFFICIENCY MEASUREMENT

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Abstract: Graduate employability is an important outcome of higher education, but its evaluation often focuses primarily on employment rates or other individual performance indicators. Such measures may not provide a complete representation of faculty performance because faculties operate with different levels of institutional resources while producing multidimensional graduate outcomes. This concept paper proposes an integrated three-phase framework combining Data Envelopment Analysis (DEA), machine learning (ML), and system dynamics (SD) for faculty-level graduate employability evaluation, with Universiti Teknologi MARA (UiTM) as the intended context. In Phase 1, an output-oriented Multiple-Layer DEA approach is proposed to evaluate how faculties transform academic resources into hierarchically structured graduate employability outcomes. In Phase 2, ML-based clustering will identify faculties with similar efficiency characteristics and improvement patterns. In Phase 3, SD will examine the potential long-term effects of alternative improvement strategies while accounting for feedback relationships and time delays. Faculty-level secondary information from the Graduate Tracer Study and relevant university records will support the proposed analysis, while comparable historical information may be used to support the calibration and validation of the dynamic model. Existing studies have primarily linked two analytical stages, including DEA with regression, clustering or ML, and SD with policy evaluation. The proposed framework extends these approaches by establishing a sequential connection between efficiency diagnosis, faculty profiling, and dynamic policy simulation. The framework is expected to provide a more comprehensive basis for faculty benchmarking and university policy planning.

Keywords: *Data Envelopment Analysis; faculty efficiency; graduate employability; higher education; machine learning; Multiple-Layer DEA; system dynamics*

Introduction

Graduate employability is an important outcome of higher education because it reflects how effectively universities prepare graduates for employment, career development, and changing labour-market requirements. Employability extends beyond obtaining employment and includes the capacity to apply relevant knowledge and skills, secure appropriate employment, manage career development, and respond to changing labour-market conditions (Abelha et al., 2020; Eimer & Bohndick, 2023). Consequently, graduate success cannot be represented adequately by employment status alone. A broader assessment needs to recognise the multidimensional nature of graduate transition, employment quality, career pathways, and employability development.

In Malaysia, graduate outcomes are monitored primarily through the Graduate Tracer Study, which provides information on graduate employment and related employment characteristics across institutions, fields, and qualification levels (Ministry of Higher Education Malaysia, 2024). However, favourable employment statistics do not necessarily indicate that graduates obtain employment that appropriately reflects their qualifications or educational preparation. Abu Rahim and Suhaimi (2022), for example, identified persistent issues involving low starting salaries, overqualification, job dissatisfaction, and difficulties during the transition from education to employment among Malaysian graduates. These findings reinforce the need to consider several dimensions of graduate outcomes rather than relying on a single employment indicator.

Graduate outcomes are also important at the faculty level because faculties influence curriculum delivery, academic resources, programme implementation, student support, and engagement with industry. Nevertheless, faculties may employ different levels of resources to generate their graduate outcomes. DEA has been widely applied to compare universities and academic units involving multiple resources and multiple outputs (Salas-Velasco, 2020; Chen & Chang, 2021). From an efficiency perspective, a faculty recording strong graduate outcomes is not necessarily efficient if comparable outcomes can be achieved by another faculty using fewer resources.

The multidimensional nature of graduate employability also creates a methodological challenge because graduate indicators may represent conceptually different dimensions rather than a single homogeneous outcome. Treating all indicators as independent outputs within a conventional flat structure may overlook relationships among them. Multiple-Layer DEA provides an alternative approach in which hierarchically organised indicators can be incorporated into the efficiency assessment while retaining the information represented by the underlying measures (Shen et al., 2013).

This concept paper therefore proposes an integrated DEA–ML–SD framework for faculty-level graduate employability evaluation, with UiTM as the intended institutional context. DEA provides the initial efficiency diagnosis, ML identifies faculties with similar efficiency characteristics, and SD examines how alternative interventions may influence graduate outcomes over time. The three analytical components are connected sequentially so that findings generated at one stage inform the subsequent stage of analysis.

Motivation of the Study

Malaysia recorded a graduate unemployment rate of 3.2% in 2024, while 32.2% of employed graduates experienced skill-related underemployment (Department of Statistics Malaysia, 2025). These figures demonstrate that relatively low graduate unemployment does not necessarily imply that graduates are employed in positions that fully utilise their qualifications and skills. Similarly, faculty performance cannot be evaluated adequately using employment percentages or other individual outcome indicators alone. Such measures describe realised outcomes but do not account for differences in the institutional resources used to produce them. Studies of higher education efficiency have demonstrated substantial differences in how universities and academic units utilise staff, funding, and other institutional resources (Wolszczak-Derlacz, 2017; Chen & Chang, 2021). An efficiency-based assessment therefore provides a different perspective from conventional performance ranking because it evaluates outcomes relative to the resources available to each academic unit.

DEA can provide such an efficiency assessment, but a single overall efficiency measure may not fully reveal differences in the underlying performance structure of individual faculties. Faculties with similar efficiency levels may experience different types of graduate outcome gaps. ML-based profiling can complement the efficiency analysis by identifying faculties exhibiting similar efficiency characteristics. However, DEA and clustering remain primarily diagnostic approaches based on observed information and do not explicitly represent how interventions, feedback mechanisms, and time delays may alter graduate outcomes over time. SD provides a further analytical stage by representing dynamic relationships among resources, institutional interventions, and graduate outcomes. Previous studies have combined DEA with clustering or ML, while others have connected SD with DEA or policy analysis (Chen & Chang, 2021; Norouzian-Maleki et al., 2022; Shahsavari-Pour et al., 2023). These approaches generally involve two principal analytical stages. The present study proposes a sequential three-phase framework in which efficiency assessment is followed by faculty profiling and subsequently by long-term policy simulation.

Literature Review

Graduate Employability Evaluation

Graduate employability encompasses more than whether graduates obtain employment. It includes relevant knowledge and skills, employment suitability, career development, and the capacity to adapt to changing labour-market conditions (Abelha et al., 2020; Eimer & Bohndick, 2023). Consequently, a single employment indicator provides only a partial representation of graduate outcomes.

At the faculty level, graduate outcomes are produced within an institutional environment involving academic resources, curriculum delivery, student development, and industry engagement. Faculties may therefore achieve similar graduate outcomes while using different levels of resources. Evaluating both resource utilisation and multidimensional graduate outcomes provides a more appropriate basis for efficiency comparison than examining outcome percentages independently.

Data Envelopment Analysis in Higher Education

DEA is a non-parametric technique for measuring the relative efficiency of comparable DMUs involving multiple inputs and outputs. It has been widely applied to teaching, research, and overall university efficiency (Wolszczak-Derlacz, 2017; Moreno-Gómez et al., 2020). DEA is

particularly relevant to faculty-level graduate employability because faculties use multiple institutional resources while producing several graduate outcomes.

DEA also distinguishes between performance and efficiency. A faculty may report strong graduate outcomes but may not be relatively efficient if those outcomes require substantially more resources than those of comparable faculties. Chen and Chang (2021), for example, combined DEA with cluster analysis to evaluate university departments and subsequently classify their efficiency patterns.

Conventional DEA applications frequently represent inputs and outputs within a single analytical layer. However, multidimensional performance systems may contain indicators that form conceptually related higher-order structures. Shen et al. (2013) developed a Multiple-Layer DEA approach to incorporate hierarchical indicator structures within DEA-based performance evaluation. This feature is relevant to graduate employability because different graduate indicators may contribute to broader dimensions of faculty performance.

Machine Learning in Efficiency Analysis

ML has increasingly been combined with DEA to improve the interpretation, classification, and prediction of efficiency results. Previous studies have used clustering, prediction, and feature-selection techniques together with DEA (Mohamad Razi et al., 2022; Zuluaga et al., 2023; Dipierro & De Witte, 2025). Such techniques can reveal patterns that may not be apparent from individual efficiency scores.

The purpose of ML in the proposed framework is not to replace DEA or independently estimate efficiency. Instead, clustering will be applied after the DEA stage to identify faculties sharing similar efficiency characteristics and improvement patterns. This enables differences among faculties to be interpreted more systematically and reduces the assumption that all faculties require identical improvement strategies.

System Dynamics for Policy Evaluation

DEA and ML primarily provide diagnoses based on observed patterns, whereas graduate employability policies may produce effects that unfold over time. Curriculum improvement, industry engagement, student development initiatives, and resource decisions may involve considerable delays before their effects become observable in graduate outcomes. These interventions may also interact through feedback mechanisms.

SD provides a modelling approach for representing these dynamic relationships and evaluating alternative policy assumptions over time. Shahsavari-Pour et al. (2023) applied SD to graduate employment and examined policy scenarios, while Norouzian-Maleki et al. (2022) integrated SD and DEA for forecasting and policy assessment. These studies demonstrate the potential of SD for policy experimentation when the consequences of interventions involve feedback relationships and temporal delays.

Previous Two-Phase Studies

Previous research has combined DEA with regression, clustering, ML, or SD. However, the selected studies generally connect two principal analytical stages, as summarised in Table 1.

Table 1. Selected two-phase studies relevant to the proposed framework

Authors	Context	Phase 1	Phase 2
Wolszczak-Derlacz (2017)	Efficiency of higher education institutions	DEA efficiency measurement	Bootstrapped regression to explain efficiency differences
Salas-Velasco (2020)	Efficiency of Spanish public universities	DEA efficiency measurement	Bootstrapped truncated regression to identify environmental factors
Moreno-Gómez et al. (2020)	Teaching and research efficiency of universities	DEA efficiency measurement	Truncated regression to examine factors affecting efficiency
Chen and Chang (2021)	Efficiency of university departments	DEA efficiency measurement	Cluster analysis based on efficiency patterns
Mohamad Razi et al. (2022)	Academic achievement efficiency	DEA efficiency measurement	Auto-ML model for efficiency prediction
Khoubrane et al. (2024)	Corporate efficiency prediction	DEA efficiency measurement	ML prediction of DEA efficiency scores
Dipierro and De Witte (2025)	Efficiency of European universities	DEA efficiency measurement	ML feature selection to identify efficiency factors
Zuluaga et al. (2023)	Efficiency of higher education institutions	Fuzzy-DEA efficiency measurement	ML-based predictive evaluation
Norouzian-Maleki et al. (2022)	Travel-demand forecasting and policy selection	SD simulation and forecasting	DEA evaluation of simulated policies
Shahsavari-Pour et al. (2023)	Employment of university graduates	SD simulation of graduate employment	Experimental design, sensitivity analysis and policy evaluation

The studies in Table 1 illustrate several complementary methodological combinations. DEA–regression studies investigate factors associated with efficiency, whereas DEA–ML approaches support classification, prediction, or feature selection. SD-based studies provide a different analytical function by representing changes over time and evaluating policy alternatives.

Within the selected literature, however, faculty-level efficiency diagnosis, ML-based profiling, and SD-based policy simulation have generally not been organised into a single sequential framework for graduate employability. The proposed framework addresses this gap by linking the three analytical functions in a structured sequence. Its contribution therefore lies primarily in the analytical connection among the stages rather than simply in the simultaneous use of three methods.

Proposed Methodology

The proposed study adopts a quantitative three-phase methodology integrating DEA, ML, and SD. UiTM faculties will constitute the DMUs, while secondary information will be obtained from the Graduate Tracer Study and relevant institutional records. The analytical framework is designed so that DEA provides an efficiency diagnosis, ML organises the resulting efficiency information into meaningful faculty profiles, and SD examines the potential long-term implications of selected improvement strategies.

The overall analytical sequence is presented in Figure 1.

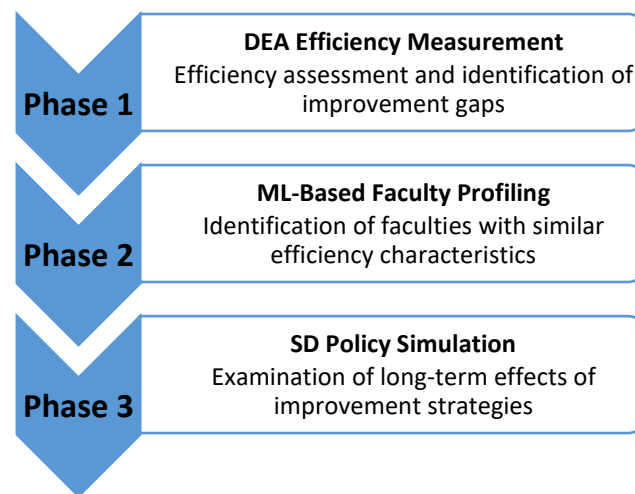


Figure 1: Proposed three-phase DEA-ML-SD framework.

Study Context and Data Structure

The proposed study focuses on 26 UiTM faculties as the units of analysis. Faculty-level secondary information will be obtained primarily from the Graduate Tracer Study together with relevant institutional records. The principal efficiency assessment is intended to use a common observation period so that the faculties can be compared on a consistent basis.

The proposed DEA structure will include institutional resource measures as inputs and multidimensional graduate employability measures as outputs. Resource measures are expected to represent faculty human and financial capacity, while graduate outcomes will be organised into theoretically defined higher-order dimensions derived from the institutional graduate indicators. This structure is intended to retain the multidimensional character of graduate employability without introducing all underlying indicators as unrelated outputs within a single flat DEA model.

The availability and consistency of historical information will be examined separately. Where comparable information is available across earlier periods, it may be used to support the development, calibration, and validation of the dynamic model. Historical observations will therefore complement rather than automatically form part of the initial cross-sectional efficiency comparison.

Phase 1: DEA Efficiency Measurement

The first phase will employ an output-oriented Multiple-Layer DEA approach. The output orientation is consistent with the objective of examining the extent to which graduate employability outcomes may be improved given the institutional resources available to each faculty.

Multiple-Layer DEA is proposed because the graduate employability indicators represent a hierarchical outcome structure rather than a single homogeneous set of measures. The approach allows related indicators to contribute to broader outcome dimensions while retaining the information represented by the underlying measures (Shen et al., 2013). Consequently, the assessment can represent multidimensional faculty performance without requiring the complete indicator system to be treated as a flat collection of outputs.

For a faculty under evaluation, the general output-oriented DEA principle may be represented as

$$\phi_o$$

subject to

$$\sum_{j=1}^n \lambda_j x_{ij} \leq x_{io}, \sum_{j=1}^n \lambda_j y_{rj} \geq \phi_o y_{ro}, \lambda_j \geq 0,$$

where x_{ij} represents the institutional resources used by faculty j , y_{rj} represents the corresponding graduate outcome measures, λ_j denotes the peer-combination weights, and ϕ_o represents the proportional expansion in outcomes attainable by the faculty under evaluation. Within the proposed Multiple-Layer DEA structure, the graduate outcome information will be organised hierarchically rather than treated as an unrestricted flat output set.

The first phase is expected to generate relative efficiency information and identify areas in which faculties exhibit different levels of improvement potential. These diagnostic results will subsequently provide the basis for faculty profiling.

Phase 2: ML-Based Faculty Profiling

The second phase will use ML-based clustering to identify faculties with similar efficiency characteristics. K-means clustering is proposed as the principal technique because the objective is to identify naturally occurring groups within the DEA results rather than to predict a predefined response variable.

The clustering analysis will use selected efficiency-related information generated from the first phase. Prior to clustering, the variables will be standardised where necessary so that differences in measurement scale do not disproportionately influence the resulting groups.

The K-means procedure can generally be expressed as

$$\min K \sum_{j \in C_k} \|z_j - \mu_k\|^2,$$

where z_j represents the selected efficiency characteristics of faculty j , C_k represents cluster k , and μ_k denotes the corresponding cluster centroid.

The number and interpretation of the resulting clusters will be determined empirically rather than based solely on existing administrative classifications. The analysis is intended to identify groups of faculties with broadly similar efficiency conditions and improvement needs. The resulting profiles will subsequently inform the formulation and interpretation of the policy scenarios examined in the SD phase.

Phase 3: SD Policy Simulation

The third phase will employ SD to examine how potential improvement strategies may influence graduate employability outcomes over time. The SD component will represent the dynamic relationships among institutional resources, faculty interventions, and graduate outcomes, with particular attention to feedback mechanisms and time delays.

The model will be informed by the efficiency conditions and faculty profiles identified in the preceding phases. However, DEA and ML results will be used primarily to guide the identification of relevant improvement conditions rather than being interpreted directly as causal parameters within the dynamic model.

The basic stock-and-flow relationship in SD may be represented as

$$S(t + \Delta t) = S(t) + [Inflow(t) - Outflow(t)]\Delta t,$$

where $S(t)$ represents a system state at time t , while inflows and outflows represent processes that alter that state over time. The final model structure will represent selected relationships among institutional interventions, graduate development, and graduate outcomes without assuming that changes occur immediately following an intervention.

Potential scenarios may include improvements relating to curriculum, industry engagement, student support, and resource utilisation. The precise configuration of these scenarios will be determined during model development based on the conditions identified in the earlier analytical phases and the availability of suitable empirical information.

Before policy simulation, the SD model will undergo calibration and validation using available historical information where the relevant variables and definitions are sufficiently comparable across periods. Validation will include structural and dimensional consistency checks together with comparison between simulated and observed historical behaviour. Policy simulations will subsequently examine the possible direction and timing of changes in graduate outcomes under alternative intervention assumptions.

Sequential Integration of the Framework

The proposed methodology follows a connected analytical sequence. DEA initially evaluates the relative efficiency of faculties and identifies areas of improvement potential. ML subsequently uses the resulting efficiency information to identify faculties exhibiting similar performance characteristics. These faculty profiles then provide a basis for identifying relevant improvement conditions to be investigated through SD simulation.

The three techniques therefore perform different but complementary analytical functions. DEA provides measurement, ML provides profiling, and SD provides dynamic policy evaluation. Their integration is intended to support a progression from identifying efficiency differences to understanding patterns among faculties and subsequently examining how improvement strategies may influence graduate outcomes over time.

This sequential connection distinguishes the proposed framework from approaches in which efficiency measurement, profiling, and policy simulation are conducted independently.

Conclusion

This concept paper proposes an integrated DEA–ML–SD framework for evaluating graduate employability efficiency at the faculty level within UiTM. The framework extends conventional graduate evaluation by considering institutional resources together with multidimensional graduate outcomes and by recognising the hierarchical structure of the underlying employability indicators. An output-oriented Multiple-Layer DEA approach provides the initial efficiency assessment, ML-based clustering subsequently identifies faculties with similar efficiency characteristics, and SD examines the potential long-term implications of selected improvement strategies while incorporating feedback mechanisms and time delays. The proposed sequential integration therefore connects efficiency measurement, faculty profiling, and dynamic policy evaluation within a single analytical framework. By maintaining the distinct function of each analytical phase while allowing information to move systematically from one phase to the next, the framework is expected to provide a more informative basis for faculty benchmarking and university policy planning.

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