# EDM-Based Graduate Curriculum Planning Framework

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***Abstract*—Graduate curriculum planning is critical to ensuring that teacher education programs remain responsive to professional standards, workplace demands, and emerging educational priorities. This study applies Educational Data Mining (EDM) techniques as an exploratory decision-support approach for graduate curriculum planning for in-service teachers in the Philippines. Using survey data from 624 teachers, the study examined professional development motivations, competency expectations, curriculum gaps, graduate learning outcomes, and barriers to participation in advanced studies. Guided by the Knowledge Discovery in Databases framework, the analysis involved data preprocessing, feature engineering, curriculum gap analysis, correlation analysis, and exploratory Random Forest variable ranking. Results revealed notable curriculum gaps in Diversity of Learners, Assessment and Reporting, and Curriculum and Planning within the Philippine Professional Standards for Teachers domains. At the graduate level, advanced professional competencies, research application, leadership, and expertise-based autonomy emerged as priority areas for curriculum enhancement. Financial constraints, workplace demands, and competing personal responsibilities were the most significant barriers to graduate study. The Random Forest results are interpreted as exploratory rankings within a constructed curriculum-needs score rather than as independent predictive validation. Based on the findings, a Data-Driven Graduate Curriculum Planning Framework is proposed to support curriculum prioritization, continuous improvement, and evidence-informed decision-making.**

***Keywords*—Educational data mining; graduate curriculum planning; teacher professional development; curriculum analytics; random forest; curriculum needs assessment; graduate education**

## I. INTRODUCTION

Graduate education plays a critical role in strengthening teacher competence, supporting professional growth, and enhancing educational practice. Beyond credential attainment, graduate programs provide opportunities for educators to deepen disciplinary knowledge, strengthen pedagogical expertise, engage in scholarly inquiry, and assume leadership roles within their institutions and professional communities [1]–[4]. Previous studies have shown that graduate education contributes to professional effectiveness, reflective practice, career advancement, and the development of specialized competencies required in increasingly complex educational environments [1]–[4].

In the Philippines, efforts to improve teacher quality have been reinforced through professional standards frameworks such as the Philippine Professional Standards for Teachers (PPST), which articulate the competencies expected across different career stages. These standards have encouraged greater attention to competency-based development, curriculum alignment, and professional growth within teacher education programs [5], [6]. Consequently, graduate curricula are expected not only to provide advanced academic preparation but also to support teachers in meeting evolving professional expectations and educational challenges.

Designing graduate curricula for in-service teachers, however, remains a complex undertaking. Curriculum developers must consider professional standards, institutional priorities, workplace realities, disciplinary developments, learner expectations, and societal needs. Traditionally, curriculum planning has relied on expert consultation, stakeholder engagement, curriculum reviews, and needs assessment activities. While these approaches remain valuable, several scholars have emphasized the importance of systematic needs assessment in ensuring that educational programs remain responsive to learner and professional requirements [7]–[10]. Curriculum development informed by empirical evidence is more likely to produce programs that are relevant, responsive, and aligned with stakeholder needs.

Recent studies have further highlighted the need for graduate curricula that address emerging professional demands. Graduate education is increasingly expected to foster leadership, resilience, interdisciplinary collaboration, research competence, lifelong learning, and continuous quality improvement [11]–[14]. Teachers likewise pursue graduate studies for a variety of professional reasons, including career advancement, competency development, professional recognition, and improved instructional practice [2], [3], [14]. These findings suggest that curriculum planning should be grounded in evidence regarding teachers' actual professional development needs rather than assumptions regarding what educators ought to learn.

The growing availability of educational data has created new opportunities for evidence-informed educational planning. Advances in educational analytics, machine learning, and predictive modeling have enabled educational institutions to move beyond descriptive reporting toward more systematic and data-driven decision-making processes [15], [16]. Rather than relying solely on traditional curriculum review approaches, institutions can increasingly utilize educational data to identify patterns, predict emerging needs, and support strategic planning initiatives.

One area that has gained considerable attention is Educational Data Mining (EDM), an interdisciplinary field that applies computational, statistical, and machine learning techniques to educational datasets in order to discover meaningful patterns and generate actionable insights [17], [18]. EDM has been successfully applied in diverse educational contexts, including student performance prediction, learning analytics, educational evaluation, institutional effectiveness studies, and decision-support systems [19]–[22]. The integration of machine learning techniques has further enhanced the ability of researchers to examine complex relationships among educational variables and identify influential factors that may not be readily observable through conventional analytical approaches [23], [24].

The growing adoption of educational analytics also reflects broader transformations occurring within higher education. Digital technologies, learning management systems, institutional databases, and educational information systems have generated large volumes of data that can inform educational planning and policy development [25]–[29]. These developments have encouraged institutions to explore data-driven approaches that support continuous improvement and evidence-based decision-making across various educational functions.

Despite the expanding body of Educational Data Mining research, its application to curriculum planning remains relatively limited. Existing studies have largely focused on learning behavior, academic achievement, technology adoption, student engagement, and institutional performance, while curriculum development continues to rely primarily on traditional needs assessment and expert-driven approaches [17], [21], [22]. Consequently, opportunities remain to leverage educational data for identifying curriculum priorities, competency gaps, professional development needs, and barriers affecting participation in graduate education.

The need for data-driven curriculum planning is particularly relevant for in-service teachers. Teachers pursuing graduate education often balance professional responsibilities, workplace expectations, family commitments, and financial constraints while seeking opportunities for career advancement and professional growth. Their curriculum expectations are shaped by professional standards, workplace realities, institutional requirements, and emerging educational challenges. Understanding these interconnected factors requires analytical approaches capable of examining multiple variables simultaneously and identifying those that most strongly influence curriculum needs.

Educational Data Mining offers a promising approach for addressing this challenge. By integrating predictive analytics with curriculum planning processes, institutions can identify priority competencies, examine curriculum gaps, determine factors influencing professional development needs, and develop more responsive graduate programs [15], [17], [18]. Such approaches support evidence-based decision-making while strengthening quality assurance and continuous improvement efforts within higher education institutions.

This study applies Educational Data Mining techniques to examine graduate curriculum needs among in-service teachers in the Philippines. Using data from 624 teachers representing diverse educational contexts, the study employs feature engineering, curriculum gap analysis, correlation analysis, and exploratory Random Forest analysis to identify patterns among curriculum-related indicators. Specifically, the study examines a Graduate Curriculum Needs Index (GCNI) as a descriptive planning score and proposes a Data-Driven Graduate Curriculum Planning Framework that may serve as a decision-support mechanism for curriculum development and enhancement.

By linking Educational Data Mining with graduate curriculum planning, the study contributes to educational analytics and teacher education research. It demonstrates how data-driven analysis can complement conventional needs assessment by organizing multiple sources of survey evidence into curriculum priorities for responsive, standards-aligned, and future-oriented graduate programs.

## II. Methodology

### A. Research Design

This study employed an Educational Data Mining (EDM) research design to identify graduate curriculum priorities and generate evidence-informed recommendations for curriculum planning. Guided by the Knowledge Discovery in Databases (KDD) framework [18], the study involved data selection, preprocessing, feature engineering, exploratory modelling, evaluation, and knowledge generation. A cross-sectional survey design was used to describe teachers' reported needs and to explore relationships among curriculum-related indicators. The machine-learning component was treated as an exploratory variable-ranking procedure rather than as independent validation of a predictive outcome.

### B. Data Source and Participants

The dataset was derived from a national study on the development of graduate curricular programs for in-service teachers' professional development. The survey collected information on teachers' professional development needs, graduate curriculum expectations, competency requirements, career aspirations, motivations for pursuing graduate education, and barriers affecting participation in advanced studies. A total of 624 valid responses were included in the analysis. Respondents represented diverse educational contexts across the Philippines, including different regions, school classifications, educational attainment levels, teaching experience categories, and career stages. The relatively large sample provided a suitable basis for predictive modeling and Educational Data Mining applications.

### C. Research Variables

The study utilized profile variables, professional development indicators, competency ratings, curriculum perceptions, and graduate learning outcome expectations. Profile variables included age, sex, region, school type, years of teaching experience, educational attainment, and career stage.

Professional development indicators covered learning and development, career advancement, salary progression, personal fulfillment, and research opportunities. Competency-related variables included ratings of the importance and perceived curriculum coverage of the seven Philippine Professional Standards for Teachers (PPST) domains. Additional variables examined master's and doctoral learning outcomes, curriculum relevance, and barriers to graduate education. The Graduate Curriculum Needs Index (GCNI) was retained as a descriptive composite planning score; because its components overlap with several variables examined in the exploratory analysis, it was not treated as an independently validated dependent variable.

### *D. Data Preprocessing and Feature Engineering*

Prior to model development, the dataset underwent data cleaning, transformation, and preparation procedures. Duplicate records and irrelevant variables were removed, while categorical variables were converted into machine-readable formats. Numerical variables were standardized to ensure comparability across measures. Feature engineering was subsequently performed to construct indicators that better represented curriculum needs and professional development expectations. These included:

- Professional Development Motivation Indicators;
- PPST Curriculum Gap Indicators;
- Master's Outcome Gap Indicators;
- Doctoral Outcome Gap Indicators; and
- Aggregate Professional Development Measures.

Curriculum gap indicators were calculated as the difference between perceived importance and perceived curriculum coverage. Positive values indicated areas where respondents perceived existing graduate curricula to be insufficient in addressing important competencies or outcomes.

### *E. Construction of the Graduate Curriculum Needs Index*

The Graduate Curriculum Needs Index (GCNI) was developed in the original analytical workflow as a descriptive curriculum-planning score integrating indicators related to competency expectations, curriculum gaps, graduate learning outcomes, professional development priorities, and barriers to participation. The component indicators were standardized, and the resulting score was rescaled to a 0–100 metric, with higher scores representing greater perceived demand for curriculum enhancement and professional development support. The original weighting documentation was not available for independent replication; therefore, the GCNI was not treated as a psychometrically validated scale or as an independent outcome. In this revised analysis, it is used only as an exploratory summary score, and the component-level gap, reliability, barrier, and correlation results remain the primary empirical basis for curriculum recommendations.

### *F. Educational Data Mining Framework*

The study adopted the Knowledge Discovery in Databases (KDD) framework as the guiding Educational Data Mining process [18], [20]. The framework involved five major stages:

- Data selection and preparation;
- Data preprocessing and transformation;
- Feature engineering and indicator construction;
- Predictive modeling and evaluation; and
- Interpretation and knowledge generation.

This framework provided a systematic approach for transforming educational data into descriptive and exploratory insights for curriculum planning.

### *G. Random Forest Predictive Modeling*

Random Forest regression was retained as an exploratory analytical procedure for examining how the available curriculum-related indicators were associated with the constructed GCNI score. Because several predictors were conceptually related to components of the index, the analysis was not interpreted as independent prediction or validation. The dataset was partitioned into training (70%) and testing (30%) subsets, and five-fold cross-validation was used in the original analytical workflow. Feature-importance rankings were examined only as supplementary evidence for organizing curriculum priorities, with due caution regarding correlated predictors and the constructed nature of the outcome.

### *H. Model Evaluation*

The original Random Forest workflow was summarized using the coefficient of determination ($R^2$), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), together with five-fold cross-validation. These metrics describe how closely the model reproduced the constructed GCNI within the available dataset; they do not establish causal relationships, external validity, or the practical effectiveness of the proposed framework. Accordingly, the model results are reported as exploratory internal-fit statistics and are interpreted alongside the descriptive gap, barrier, reliability, and correlation analyses.

### *I. Feature Importance Analysis*

Feature importance analysis was used to rank the relative contribution of variables within the exploratory Random Forest model. Because the predictors are conceptually overlapping and some are related to the construction of the GCNI, the rankings were interpreted cautiously. They are used only to complement the direct curriculum-gap and descriptive analyses and not to establish independent drivers or causal effects.

### *J. Ethical Considerations*

The study was reviewed and approved by the Philippine Normal University Research Ethics Board. Participation was voluntary, and respondents were informed about the purpose of the study and provided informed consent before data collection. Responses were anonymized before analysis and reported only in aggregate form. Access to the dataset was limited to the research team, and the data were handled in accordance with institutional policies and applicable Philippine data-privacy requirements.

## III. Results and Discussions

### *A. Dataset Profile*

The dataset comprised 624 in-service teachers representing diverse educational contexts across the Philippines. Table I presents the demographic characteristics of the respondents and their views regarding the direction of graduate curriculum development.

TABLE I. SUMMARY OF THE RESPONDENT PROFILE AND CURRICULUM DIRECTION INDICATORS

| Indicator | Frequency | Percentage |
|---|---|---|
| Female | 449 | 71.955 |
| Male | 161 | 25.801 |
| Public school | 492 | 78.846 |
| Private school | 132 | 21.154 |
| Career progression = Yes | 595 | 95.353 |
| PPST alignment = Yes | 606 | 97.115 |

The majority of respondents were female and employed in public schools, reflecting the demographic composition of the Philippine teaching workforce. More importantly, respondents expressed overwhelming support for graduate curricula that contribute to career progression and align with the Philippine Professional Standards for Teachers (PPST). The findings suggest that teachers view graduate education not merely as a means of obtaining advanced academic credentials but as an important mechanism for professional growth and career advancement. The strong endorsement of standards-based curriculum alignment further indicates that teachers expect graduate programs to support the competencies required across different stages of professional practice. These findings provide an important context for the Educational Data Mining analyses that follow, as they demonstrate that curriculum priorities are anchored in professional development and competency enhancement rather than personal preference alone.

## B. Professional Development Motivations

Table II summarizes the motivations that influence teachers' decisions to pursue graduate education. Learning and professional development emerged as the strongest motivations, followed by career progression and salary advancement. Research opportunities received comparatively lower ratings.

TABLE II. SUMMARY OF THE PROFESSIONAL DEVELOPMENT SCORES

| Motivation | Mean | SD | Rank |
|---|---|---|---|
| Learning and development | 3.798 | 1.385 | 1 |
| Career progression | 3.373 | 1.110 | 2 |
| Salary increase | 3.159 | 1.227 | 3 |
| Personal fulfilment | 2.518 | 1.447 | 4 |
| Research opportunities | 2.152 | 1.230 | 5 |

The results indicate that teachers primarily pursue graduate studies to enhance their professional practice and improve career prospects. While research remains a defining characteristic of graduate education, the findings suggest that teachers place greater value on learning experiences that directly support instructional effectiveness, leadership development, and professional advancement. This has important implications for curriculum planning, as research components may be more meaningful when explicitly connected to authentic educational problems and workplace contexts.

## C. Reliability of Curriculum Planning Indicators

As shown in Table III, all constructs demonstrated satisfactory to excellent reliability, with Cronbach's alpha coefficients exceeding commonly accepted thresholds.

TABLE III. INTERNAL CONSISTENCY OF MULTI-ITEM CONSTRUCTS

| Construct | Indicators | Valid n | Cronbach alpha | Mean | SD |
|---|---|---|---|---|---|
| PPST Importance | 7 | 624 | 0.937 | 4.561 | 0.681 |
| PPST Coverage | 7 | 428 | 0.934 | 4.348 | 0.705 |
| Master's Outcome Importance | 4 | 624 | 0.864 | 4.504 | 0.628 |
| Master's Outcome Coverage | 4 | 624 | 0.921 | 4.135 | 0.823 |
| Doctorate Outcome Importance | 4 | 624 | 0.924 | 4.435 | 0.711 |
| Doctorate Outcome Coverage | 4 | 624 | 0.953 | 4.082 | 0.870 |
| Barriers to Graduate Education | 15 | 624 | 0.950 | 3.832 | 0.880 |

Cronbach's alpha values ranged from 0.864 to 0.953 across PPST importance, PPST coverage, master's outcomes, doctorate outcomes, and barrier indicators. These values indicate strong internal consistency and support the use of composite indicators in the educational data mining workflow. The consistently high reliability values indicate that the survey items measured coherent dimensions of curriculum needs, professional development expectations, and graduate learning outcomes. These results provide confidence in the validity of the composite indicators used in subsequent analyses and support the suitability of the dataset for Educational Data Mining applications.

## D. Curriculum Gap Analysis

To identify areas requiring curriculum enhancement, curriculum gaps were computed by comparing perceived importance and perceived curriculum coverage across the PPST domains. The results are presented in Table IV. All PPST domains were rated highly important, indicating broad support for standards-informed graduate curricula.

TABLE IV. PPST IMPORTANCE, COVERAGE, AND CURRICULUM GAP

| PPST Domain | Importance Mean | Coverage Mean | Gap |
|---|---|---|---|
| Diversity of Learners | 4.556 | 4.251 | 0.306 |
| Assessment and Reporting | 4.609 | 4.358 | 0.251 |
| Curriculum and Planning | 4.644 | 4.416 | 0.228 |
| Learning Environment | 4.542 | 4.328 | 0.214 |
| Content Knowledge and Pedagogy | 4.688 | 4.496 | 0.191 |
| Community Linkages | 4.269 | 4.115 | 0.154 |
| Personal Growth and Prof. Dev. | 4.622 | 4.480 | 0.142 |

Positive gap values across all domains indicate opportunities for curriculum enhancement and stronger alignment with competency-based teacher development frameworks [5], [6]. The largest gaps were found in Diversity of Learners, Assessment and Reporting, and Curriculum and Planning, suggesting that these competencies are highly important yet inadequately addressed in existing graduate curricula. These findings identify priority areas for intervention and demonstrate how Educational Data Mining can support evidence-based curriculum planning by pinpointing specific competency domains requiring improvement and guiding strategic resource allocation.

## E. Graduate School Learning Outcome Gaps

Tables V and VI present the analyses of learning outcome gaps at the master's and doctoral levels.

TABLE V. MASTER'S OUTCOME IMPORTANCE, COVERAGE AND GAP

| Master's Outcome | Importance Mean | Coverage Mean | Gap |
|---|---|---|---|
| Advanced knowledge and skills | 4.615 | 4.216 | 0.399 |
| Self-directed research | 4.276 | 3.962 | 0.314 |
| Lifelong learning | 4.606 | 4.226 | 0.380 |
| Application in research/professional work | 4.521 | 4.135 | 0.386 |

At the master's level, the largest gaps were associated with advanced knowledge and skills, the application of research to professional practice, and lifelong learning competencies.

At the doctoral level, the greatest gaps were observed in expertise-based autonomy, leadership in research, and advanced professional practice.

TABLE VI. DOCTORATE OUTCOME IMPORTANCE, COVERAGE AND GAP

| Doctorate Outcome | Importance Mean | Coverage Mean | Gap |
|---|---|---|---|
| Advanced systematic knowledge | 4.495 | 4.143 | 0.353 |
| Complex research/professional practice | 4.378 | 4.054 | 0.324 |
| Leadership in research/creative work | 4.417 | 4.056 | 0.361 |
| Expertise-based autonomy/accountability | 4.450 | 4.074 | 0.377 |

The findings indicate that teachers expect graduate programs to offer stronger opportunities for professional growth and scholarly development. The differing priorities between master's and doctoral programs underscore the need for differentiated curriculum pathways. Master's programs should emphasize applied professional competencies, while doctoral programs should focus on research leadership, innovation, and independent scholarship.

## F. Barriers to Graduate Education

Table VII shows that financial cost was the major barrier to graduate education, followed by scheduling conflicts and personal responsibilities. Other challenges included academic workload, publication requirements, and thesis demands. These findings suggest that flexible program structures, delivery modes, and assessment requirements are essential for improving participation and success among working professionals.

## G. Graduate Curriculum Needs Index

To provide a summary measure of perceived curriculum demand, the Graduate Curriculum Needs Index (GCNI) integrated several curriculum-related indicators. Table VIII presents the descriptive results. Because the original weighting documentation was unavailable and the index overlaps conceptually with several analytical variables, the GCNI is interpreted only as an exploratory planning score rather than as a psychometrically validated measure.

The mean GCNI score suggests perceived opportunities for improving graduate curricula in ways that support professional standards, competency development, and career advancement. However, curriculum decisions in this study are based primarily on the component-level gap, barrier, and learning-outcome analyses rather than on the GCNI alone.

TABLE VII. BARRIERS TO GRADUATE EDUCATION

| Barrier | Mean | SD | Interpretation | Rank |
|---|---|---|---|---|
| Financial cost of graduate education | 4.189 | 1.045 | Agree | 1 |
| Conflict with workplace requirements and schedule | 4.106 | 1.042 | Agree | 2 |
| Conflict with other personal responsibilities | 4.000 | 1.081 | Agree | 3 |
| Heavy or too many course requirements | 3.946 | 1.078 | Agree | 4 |
| Limited support for graduate students from the university/college | 3.942 | 1.127 | Agree | 5 |
| Publication or creative work requirement | 3.931 | 1.133 | Agree | 6 |
| Thesis/Dissertation requirement | 3.848 | 1.178 | Agree | 7 |
| Mental health/psychological wellbeing concerns | 3.816 | 1.167 | Agree | 8 |
| Long distance between university/college and workplace | 3.788 | 1.178 | Agree | 9 |
| Long distance between university/college and home | 3.768 | 1.185 | Agree | 10 |
| Physical health and fitness concerns | 3.764 | 1.177 | Agree | 11 |
| Requirement for face-to-face sessions | 3.636 | 1.233 | Agree | 12 |
| Lack of learning or professional growth from the graduate program | 3.625 | 1.272 | Agree | 13 |
| Too many sessions in a course | 3.580 | 1.161 | Agree | 14 |
| Too many hours in a session | 3.545 | 1.159 | Agree | 15 |

TABLE VIII. SUMMARY OF THE CONSTRUCT INDICATORS AND GCNI

| Indicator | Count | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| PPST_Importance | 624 | 4.561 | 0.681 | 1.00 | 5.00 |
| PPST_Coverage | 428 | 4.348 | 0.705 | 1.00 | 5.00 |
| PPST_Gap | 428 | 0.224 | 0.630 | -3.00 | 2.857 |
| Masters_Outcome_Importance | 624 | 4.504 | 0.628 | 1.00 | 5.00 |
| Masters_Outcome_Gap | 624 | 0.370 | 0.766 | -2.75 | 4.00 |
| Doctorate_Outcome_Import-ance | 624 | 4.435 | 0.711 | 1.00 | 5.00 |
| Doctorate_Outcome_Gap | 624 | 0.353 | 0.864 | -3.25 | 4.00 |
| Barriers_Index | 624 | 3.832 | 0.880 | 1.00 | 5.00 |
| GCNI_100 | 624 | 62.488 | 12.435 | 0.00 | 100.00 |

## H. Exploratory Random Forest Analysis

Random Forest regression was retained as an exploratory analysis of the constructed GCNI. The internal-fit statistics are presented in Table IX. No separate actual-versus-predicted figure is reported in the revised manuscript.

TABLE IX. RANDOM FOREST PREDICTIVE PERFORMANCE

| Metric | Value |
|---|---|
| Training R-squared | 0.930 |
| Testing R-squared | 0.835 |
| Five-fold CV R-squared Mean | 0.815 |
| Five-fold CV R-squared SD | 0.051 |
| RMSE | 4.386 |
| MAE | 2.892 |

The model reproduced the constructed GCNI with high internal fit. However, this result is expected to some extent because several predictors are conceptually related to the indicators underlying the index. The statistics therefore do not demonstrate independent predictive validity. Their value is limited to showing internal patterns among the available curriculum-planning indicators, and they should be read together with the direct gap, barrier, reliability, and correlation results. The analysis is predictive neither of actual enrolment nor of the practical effectiveness of the proposed framework, and no causal interpretation is intended.

## I. Feature Importance Analysis

To examine the relative contribution of variables within the exploratory model, feature-importance analysis was conducted. The results are presented in Table X.

Graduate learning outcomes and competency-related indicators received the highest importance scores within the exploratory model, while demographic characteristics and personal motivations received smaller scores. Because these variables overlap conceptually and are related to the constructed GCNI, the rankings are not interpreted as independent drivers.

They nevertheless support the descriptive finding that curriculum planning should focus on competencies and expected learning outcomes rather than demographic factors alone.

TABLE X. RANDOM FOREST FEATURE IMPORTANCE RANKINGS

| Predictor | Importance |
|---|---|
| Master's Outcome Importance | 0.166 |
| PPST Importance | 0.163 |
| Doctorate Outcome Importance | 0.120 |
| Doctorate Outcome Gap | 0.111 |
| Master's Outcome Gap | 0.089 |
| PPST Curriculum Gap | 0.058 |
| Career Progression Need | 0.045 |
| Barrier Index | 0.041 |
| PPST Alignment Need | 0.028 |
| Age | 0.027 |
| Personal fulfilment | 0.010 |
| Research opportunities | 0.009 |
| Salary increase | 0.009 |
| Learning and Development | 0.008 |
| Career Progression | 0.008 |

## J. Correlation Analysis

To further examine relationships among the major variables, correlation analysis was conducted. The results are summarized in Table XI.

TABLE XI. CORRELATION OF MAJOR PREDICTORS WITH GCNI

| Predictor | Pearson r with GCNI | p-value |
|---|---|---|
| Master's Outcome Importance | 0.697 | 0.000 |
| Doctorate Outcome Importance | 0.651 | 0.000 |
| PPST Importance | 0.650 | 0.000 |
| Doctorate Outcome Gap | 0.580 | 0.000 |
| Master's Outcome Gap | 0.502 | 0.000 |
| PPST Curriculum Gap | 0.441 | 0.000 |
| Barrier Index | 0.194 | 0.000 |

The observed correlations were generally consistent with the descriptive and exploratory Random Forest results. However, the correlations should be interpreted as associations among related curriculum-planning indicators, not as independent validation of the GCNI or as evidence of causality.

## K. Curriculum Priority Mapping

The integration of curriculum gap analysis, barrier analysis, correlation analysis, and exploratory variable ranking informed the development of a curriculum priority map. The resulting priorities are presented in Table XII.

The curriculum priority map illustrates how Educational Data Mining can complement traditional needs assessment and curriculum review processes [10]. Rather than treating the statistical outputs as validation of a predictive system, the analysis organizes the strongest descriptive findings into practical areas for curriculum revision, resource allocation, and strategic planning within graduate education programs.

TABLE XII. DATA-DRIVEN CURRICULUM PRIORITY MAP

| Priority Level | Curriculum Area | Planning Implication |
|---|---|---|
| High Priority | PPST-aligned competencies | Embed PPST domains into course outcomes, assessments, and practicum tasks. |
| High Priority | Master's outcome competencies | Strengthen advanced pedagogy, applied research, and professional practice. |
| High Priority | Doctorate outcome competencies | Strengthen doctoral research leadership, innovation, and autonomous expertise. |
| Moderate Priority | Assessment and reporting | Develop assessment literacy, data use, and reporting competencies. |
| Moderate Priority | Diversity of learners | Strengthen inclusive education, differentiated instruction, and learner-responsive pedagogy. |
| Emerging Priority | Educational analytics and digital transformation | Integrate data-driven teaching, AI awareness, and educational technology applications. |
| Support Priority | Flexible delivery and financial/access support | Adopt hybrid, modular, weekend, and scholarship-supported delivery mechanisms. |

## L. Data-Driven Graduate Curriculum Planning Framework

Drawing upon the descriptive and exploratory analyses, a Data-Driven Graduate Curriculum Planning Framework was proposed. The framework is presented in Fig. 1. It integrates teacher needs assessment, curriculum gap analysis, exploratory analytics, curriculum prioritization, and continuous evaluation into a decision-support process. The dataset supports the identification of needs and priorities; the effectiveness of the framework itself has not yet been empirically evaluated.

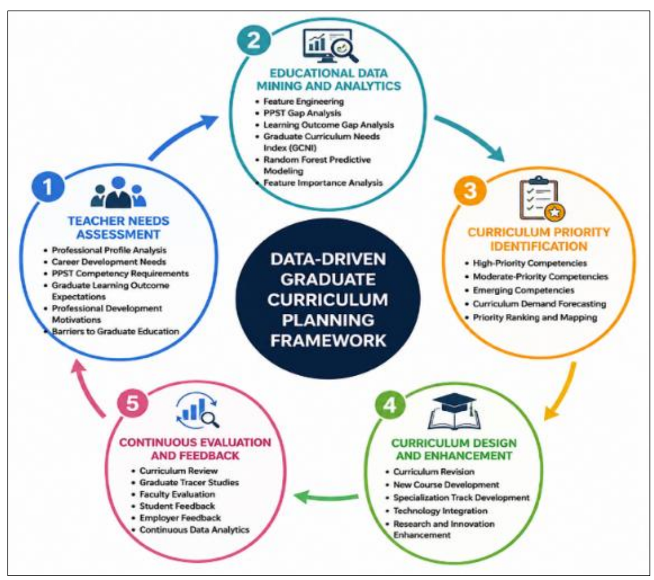


Fig. 1. Data-driven graduate curriculum planning framework.

By combining traditional curriculum planning approaches with Educational Data Mining techniques, the proposed framework provides a systematic mechanism for translating educational data into curriculum recommendations. It builds upon established principles of curriculum needs assessment, evidence-based planning, and educational analytics [7]. The framework should be understood as a data-informed planning proposal rather than a validated intervention. It may be adapted to other national, institutional, or professional contexts by replacing the PPST with the relevant competency standards and by incorporating local curriculum, employer, and stakeholder evidence.

## IV. Conclusion and Recommendations

### A. Conclusion

This study demonstrated the potential of Educational Data Mining (EDM) as an exploratory decision-support approach for graduate curriculum planning. Using data from 624 in-service teachers, the study integrated curriculum needs assessment, competency analysis, feature engineering, and exploratory analytics to identify curriculum priorities and professional development needs. The findings revealed substantial demand for curriculum enhancement, particularly in areas associated with professional competencies, graduate learning outcomes, and standards-based teacher development.

The curriculum gap analyses showed that respondents consistently rated professional competencies and graduate learning outcomes as highly important while identifying areas where existing curriculum coverage could be strengthened. Notable gaps were observed in selected PPST domains and graduate learning outcomes, suggesting opportunities for curriculum enhancement and improved alignment between curriculum provisions and professional expectations. In addition, barriers such as financial constraints, scheduling conflicts, and competing responsibilities highlighted the importance of considering both curricular and structural factors when designing programs for working professionals.

The GCNI provided an exploratory summary of perceived curriculum demand, but it was not treated as a psychometrically validated or independent predictive outcome. The Random Forest analysis was therefore interpreted only as supplementary variable ranking within a constructed score. The stronger empirical contribution lies in the direct curriculum-gap, learning-outcome, barrier, reliability, and correlation analyses, which consistently emphasized competency-based and outcomes-oriented curriculum planning.

Building on these findings, the study proposed a Data-Driven Graduate Curriculum Planning Framework that integrates needs assessment, exploratory analytics, curriculum prioritization, and continuous evaluation. The framework illustrates how educational data can inform curriculum development, but the present study does not demonstrate that the framework improves curriculum-planning outcomes in practice.

The study contributes to Educational Data Mining research by extending its exploratory application toward curriculum planning and educational decision-making. The findings suggest that curriculum analytics can complement traditional curriculum-development approaches in designing responsive, standards-informed, and future-oriented graduate programs.

Several limitations should be acknowledged. First, the cross-sectional design does not support causal conclusions. Second, the GCNI was derived from curriculum-related indicators that overlap with variables examined in the exploratory Random Forest analysis, and its original weighting documentation was not available for independent replication. The model results therefore represent internal exploratory associations rather than independent predictive validation. Third, the findings are based entirely on teachers' self-reported perceptions and were not triangulated with curriculum documents, employer requirements, institutional performance data, or graduate employment outcomes. Fourth, the PPST-specific context limits direct transferability, although the analytical process may be adapted using other national, institutional, or professional competency frameworks. Finally, the proposed planning framework was not empirically evaluated for practical effectiveness. Future studies should use independently measured outcomes, external datasets, longitudinal designs, and additional interpretive methods such as permutation importance or SHAP-based analysis.

### B. Recommendations

Higher education institutions may consider using data-driven analysis alongside traditional needs assessment in curriculum review and development. Graduate curriculum developers may strengthen alignment with professional standards and expected learning outcomes while ensuring that program structures remain responsive to the financial, workplace, and personal constraints faced by working professionals.

Future studies may validate the proposed framework in other disciplinary and institutional contexts, triangulate survey findings with curriculum and employment evidence, and examine independently measured outcomes such as enrolment intention, preferred curriculum tracks, program completion, or graduate outcomes. Comparative baseline models and more stable interpretive methods may also be used before making predictive claims.

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