



# Teacher Mentoring and Professional Growth among Newly Appointed Educators

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**Abstract—** Teacher mentoring is increasingly positioned as a critical mechanism for supporting newly appointed educators during the transition from formal teacher preparation to independent classroom practice. However, existing mentoring research has largely examined perceived support, retention, self-efficacy, or instructional competence separately, with comparatively limited attention to how mentoring interactions can be translated into multidimensional and data-informed indicators of professional growth. This study addresses this gap by proposing an AI-assisted Mentoring–Professional Growth Analytics Framework (AI-MPGAF) that combines structured mentoring indicators, reflective practice evidence, professional learning behaviours, and classroom-development measures. The proposed research conceptualizes professional growth as a dynamic construct encompassing pedagogical adaptability, reflective competence, instructional confidence, digital/AI readiness, collaborative learning, and professional autonomy. Rather than positioning artificial intelligence as a substitute for human mentors, the framework treats machine learning as an analytical support mechanism capable of detecting developmental patterns and identifying educators who may require differentiated mentoring.

**Keywords—** Teacher Mentoring, Newly Appointed Educators, Professional Growth, Early-Career Teachers, Learning Analytics, Explainable Artificial Intelligence

## Introduction

The transition into full-time teaching represents a distinctive stage of professional formation. Newly appointed educators enter schools with theoretical knowledge, practicum experiences, disciplinary preparation, and varying degrees of technological competence, yet they must rapidly adapt these

resources to complex classroom environments. Their responsibilities extend beyond lesson delivery to assessment, classroom management, communication with families, institutional documentation, inclusive practice, collaboration with colleagues, and increasingly, responsible engagement with digital and artificial-intelligence-enabled educational technologies. Consequently, appointment to a teaching position should not be interpreted as the completion of teacher development. It is more accurately understood as the beginning of an intensive period in which professional knowledge is reconstructed through practice.

Mentoring is one of the principal institutional mechanisms used to support this transition. In a conventional mentoring arrangement, an experienced educator provides guidance to a newly appointed colleague through observation, feedback, modelling, collaborative planning, problem solving, and professional dialogue. Effective mentoring can therefore provide access to forms of contextual knowledge that are difficult to acquire exclusively through pre-service coursework. It can help beginning educators interpret classroom situations, recognize weaknesses in instructional practice, develop professional confidence, and understand the organizational culture of their schools.

Recent research nevertheless indicates that mentoring is not a uniform intervention. Murtagh et al. examined mentoring under England's Early Career Framework and identified tensions between standardized programme requirements and the contextual realities encountered by mentors and early-career teachers. Their findings are particularly important because they suggest that mentoring can become compliance-oriented when standardized materials and administrative requirements dominate professional dialogue.

The implication is that **mentoring participation and mentoring effectiveness are conceptually different**. Two

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newly appointed educators may receive the same number of scheduled mentoring sessions while experiencing substantially different developmental outcomes. One mentor may engage the educator in evidence-based reflection, observation, experimentation, and progressively greater professional autonomy. Another arrangement may largely consist of procedural instructions and completion of mandated documentation. Measuring mentoring merely through frequency therefore risks obscuring the mechanisms through which mentoring contributes to professional development.

This distinction has become more significant as teaching environments undergo rapid digital transformation. Artificial intelligence, automated assessment, learning-management systems, generative AI, digital collaboration platforms, and learning analytics are expanding the technological component of teachers' professional competence. UNESCO's 2024 *AI Competency Framework for Teachers* formalizes this development through 15 competencies organized across five dimensions: human-centred mindset, ethics of AI, AI foundations and applications, AI pedagogy, and AI for professional learning.

The emergence of these competencies changes the scope of mentoring. Newly appointed teachers no longer require guidance exclusively in traditional areas such as lesson planning, behaviour management, curriculum interpretation, and assessment. They may also need professional support for deciding when AI is pedagogically appropriate, evaluating AI-generated information, protecting student data, identifying algorithmic bias, and maintaining professional agency when using automated systems. UNESCO has similarly emphasized lifelong professional learning as an important component of teachers' adaptation to AI-enabled educational environments.

AI itself may also contribute to the analysis of professional learning. Machine-learning methods can identify nonlinear relationships among multiple developmental variables, detect patterns that conventional aggregate scores may conceal, and estimate which combinations of mentoring characteristics correspond with stronger professional-growth trajectories. Yet such applications require careful conceptual boundaries. The OECD's digital education work emphasizes an augmentation perspective in which artificial intelligence complements human judgement rather than replacing teachers' social, contextual, and professional expertise.

For mentoring, this principle is particularly important. A machine-learning system should not determine whether an educator is a "good" or "poor" teacher. Such classification would reduce a contextual, relational process to an algorithmic judgement and could introduce substantial ethical and methodological problems. A more defensible application is to use interpretable analytics to detect developmental

patterns—for example, whether sustained mentor feedback combined with reflective engagement is associated with improving instructional confidence, or whether declining reflective participation and limited mentor interaction indicate a need for additional human support.



**Fig. 1: Why is Continuous Professional Development Important for Teachers?**

**Source:** <https://www.extramarks.com/blogs/teachers/continuous-professional-development-for-teachers/>

## Research Gap

Contemporary scholarship provides substantial evidence concerning mentoring experiences, mentoring models, induction programmes, self-directed learning, professional autonomy, and novice-teacher support. For example, recent quantitative research has examined the relationship between mentorship and self-directed learning among beginning teachers, while qualitative scholarship has emphasized contextual and relational support requirements. Large-scale practice-oriented research has also examined mentoring among early-career educators and mentors, demonstrating continuing interest in how school-based mentoring operates in practice.

A narrower methodological gap remains: **limited research integrates longitudinal mentoring evidence, multidimensional professional-growth indicators, contextual characteristics, and interpretable machine-learning techniques within a unified early-career teacher-development model.**

Three limitations are especially relevant. First, mentoring is frequently represented through programme participation or broad perception scores rather than through differentiated dimensions such as feedback specificity, mentor responsiveness, reflective dialogue, instructional experimentation, and autonomy support. Second, professional growth is often represented by a single outcome even though newly appointed educators may develop unevenly across pedagogical, reflective, digital, collaborative, and professional domains. Third, conventional statistical approaches remain indispensable for hypothesis testing but may be complemented by interpretable machine-



learning models capable of identifying nonlinear and interaction effects within longitudinal mentoring data.

The present study is built specifically around this gap.

### Research Objective

The primary objective is to **develop and evaluate an interpretable AI-assisted framework for estimating multidimensional professional-growth trajectories among newly appointed educators from longitudinal mentoring and professional-learning indicators.**

More specifically, the proposed study investigates whether the developmental quality of mentoring predicts professional growth beyond mentoring frequency alone; determines which mentoring characteristics contribute most strongly to pedagogical adaptability, reflective competence, professional autonomy, and digital/AI readiness; compares conventional statistical models with interpretable machine-learning approaches; and examines whether model explanations can generate meaningful developmental information without transferring professional judgement from mentors to algorithms.

The central conceptual relationship can be expressed as:

$$[PG_{\{i,t\}} = f(MQ_{\{i,t\}}, RF_{\{i,t\}}, AS_{\{i,t\}}, PE_{\{i,t\}}, DL_{\{i,t\}}, C_i) + \epsilon_{\{i,t\}}]$$

where  $(PG_{\{i,t\}})$  represents professional growth for educator (i) at time (t); (MQ) denotes mentoring quality; (RF) represents reflective engagement; (AS) represents mentor-supported professional autonomy; (PE) indicates professional-learning engagement; (DL) denotes digital and AI-related professional learning; and  $(C_i)$  represents contextual characteristics.

The formulation intentionally treats professional growth as a trajectory rather than a static endpoint.

### Literature Review

#### Mentoring as a Developmental Process

Teacher mentoring has historically been associated with induction, professional socialization, and the development of classroom competence. Earlier scholarship established that mentoring beginning teachers is considerably more complex than pairing inexperienced educators with experienced colleagues. The effectiveness of mentoring depends upon the nature of interactions, mentor preparation, institutional context, time allocation, interpersonal trust, and the developmental needs of the mentee.

Recent scholarship continues to reinforce this relational interpretation. Murtagh et al.'s investigation of Early Career Framework mentoring in England demonstrates that mentors operate between formal programme expectations and the situated realities of individual schools and classrooms. The authors describe how mentors mediate competing demands rather than simply transmit predetermined instructional knowledge.

This finding challenges a purely standardized model of induction. Newly appointed educators may teach different subjects, age groups, class compositions, and student populations. Their developmental requirements consequently vary. An educator struggling with classroom management may require observation, modelling, and immediate practical feedback, whereas another may require assistance with differentiated instruction or assessment design. Mentoring effectiveness therefore depends partly upon **responsiveness**—the degree to which professional support corresponds to an educator's actual developmental needs.

Recent literature examining novice-teacher support from an Ubuntu perspective similarly emphasizes interconnectedness, community, and contextualized support. Such work demonstrates that early-career professional development cannot be adequately understood solely as individual skill acquisition; professional growth is embedded within relationships and organizational communities.

#### Mentoring and Professional Autonomy

A significant tension in mentoring concerns the relationship between guidance and autonomy. Newly appointed educators require direction, particularly when encountering unfamiliar institutional or pedagogical challenges. Excessive prescription, however, can potentially produce dependency rather than professional agency.

Research published in 2024 examining mentorship and self-directed learning among beginning teachers directly addresses this issue by investigating how mentorship relates to the development of self-directedness during the initial years of teaching. This perspective expands the meaning of mentoring effectiveness. A successful mentor should not merely provide solutions; mentoring should progressively strengthen the educator's capacity to diagnose problems, evaluate alternatives, seek appropriate evidence, and independently adapt practice.





Fig. 2: The Link Between Professional Growth and Teacher Retention

Source: <https://moreland.edu/resources/blog-insights/the-link-between-professional-growth-and-teacher-retention>

The proposed study therefore treats **autonomy-supportive mentoring** as a distinct construct. This construct captures whether mentors encourage novice educators to formulate instructional alternatives, interpret evidence, justify professional decisions, and critically examine their own teaching rather than merely reproduce prescribed practices.

Such differentiation is important for machine-learning analysis. A model based only on mentoring hours could conclude that greater mentoring exposure predicts professional development. A multidimensional model could reveal a different relationship—for instance, that the *quality and autonomy orientation* of mentoring interactions explains professional growth more effectively than their numerical frequency.

### Reflective Practice and Feedback

Professional reflection constitutes another mechanism connecting mentoring with growth. Reflection converts classroom experience into professional learning by requiring educators to interpret what occurred, identify possible explanations, and formulate modifications for subsequent practice.

Mentors can strengthen this cycle through targeted feedback. Developmentally useful feedback differs from generalized reassurance because it is anchored in observable instructional behaviour and provides direction for subsequent experimentation. A mentoring interaction can therefore be conceptualized as a repeated learning sequence:

**classroom experience → evidence → mentor dialogue → reflection → instructional modification → subsequent evidence.**

Repeated cycles can produce longitudinal data. Observation records, reflective entries, mentoring-session logs, professional-development participation, and periodic self-assessments provide temporally ordered indicators rather than a single end-of-year measurement. This structure creates an opportunity to examine *growth trajectories* instead of relying exclusively on cross-sectional associations.

Importantly, digital analysis of reflective material requires ethical safeguards. Natural-language processing could theoretically extract linguistic indicators of reflection, uncertainty, planning, or pedagogical reasoning from written reflections. However, automated analysis should not be used to infer psychological states or make employment decisions. The present research therefore conceptualizes reflective analytics as an aggregate developmental measure used for research and formative mentoring support.

### Mentoring Quality Versus Mentoring Compliance

Recent evidence suggests an additional conceptual distinction between developmental mentoring and procedural mentoring. The England-based case study by Murtagh and colleagues documented challenges associated with mentors' use of mandated training materials and highlighted the need to reconcile standardized programme expectations with contextual classroom realities.

This distinction has methodological consequences. Conventional evaluations may record whether mentoring meetings occurred, whether modules were completed, or whether induction requirements were satisfied. These variables measure programme implementation but do not necessarily capture developmental quality.

The proposed framework consequently separates **mentoring intensity** from **mentoring quality**. Intensity includes measurable exposure variables such as meeting frequency and observation frequency. Quality includes feedback specificity, responsiveness to mentee needs, dialogic reflection, psychological safety within professional discussion, instructional problem solving, and autonomy support.

This separation constitutes one of the principal theoretical features of the study because it enables empirical testing of whether *more mentoring* and *better mentoring* produce equivalent or substantially different relationships with professional growth.

### Digital Transformation and AI Competence

Teacher professional development has acquired an additional dimension since the rapid expansion of generative AI beginning in 2022–2023. Educators increasingly encounter AI-enabled tools for content generation, instructional planning, assessment, feedback, accessibility, and



administrative work. At the same time, these technologies introduce questions concerning accuracy, bias, privacy, intellectual responsibility, and appropriate pedagogical use.

UNESCO's AI Competency Framework for Teachers provides a particularly relevant contemporary foundation. The framework organizes teacher AI competence across human-centred orientation, ethics, technical foundations and applications, pedagogy, and professional learning, with progression from acquisition through deepening to creation.

For newly appointed educators, AI competence should therefore not be treated simply as technical proficiency. Knowing how to operate a generative-AI application is insufficient if an educator cannot evaluate its outputs, understand privacy implications, determine whether its use serves a pedagogical objective, or maintain accountability for instructional decisions.

Mentoring may provide an appropriate environment for developing these competencies because experienced educators can contextualize digital tools within curriculum requirements and classroom realities. However, experienced teachers themselves may vary considerably in AI competence. This creates a potentially bidirectional mentoring environment in which conventional professional experience resides primarily with the mentor while some emerging technological knowledge may be distributed across both participants.

This study consequently incorporates **digital and AI professional readiness** as one component of professional growth rather than treating it as an independent technological outcome.

### Artificial Intelligence as an Analytical Support for Mentoring

Machine learning introduces methodological possibilities for studying complex professional-development processes. Conventional regression models estimate relationships under specified functional assumptions and remain useful for interpretable hypothesis testing. Tree-based ensemble algorithms, by comparison, can capture nonlinear effects and higher-order interactions without requiring all relationships to be specified beforehand.

For example, professional growth may not increase linearly with mentoring frequency. Moderate mentoring combined with high-quality feedback and strong reflection may produce greater development than frequent meetings characterized by low responsiveness. Such interaction patterns can potentially be detected using ensemble learning approaches and subsequently interpreted using feature-attribution techniques.

Nevertheless, the use of AI in teacher development must remain human-centred. UNESCO's framework explicitly

foregrounds human agency and ethical AI use, while OECD work on digital education emphasizes AI augmentation rather than replacement of human professional capabilities.

Accordingly, the proposed AI-MPGAF framework does not automate mentor evaluation, teacher appraisal, promotion, or employment decisions. Its intended function is **developmental pattern recognition**. Model outputs would indicate variables associated with professional-growth trajectories and identify cases where additional human review may be useful. Final interpretation remains with educators, mentors, and researchers.

### Proposed Methodology

This study proposes an **AI-assisted Mentoring–Professional Growth Analytics Framework (AI-MPGAF)** to investigate how mentoring characteristics influence the professional-development trajectories of newly appointed educators. The methodological design differs from conventional cross-sectional mentoring studies by treating professional growth as a longitudinal, multidimensional process rather than a single post-induction outcome.

The framework integrates four evidence streams: structured mentoring records, repeated professional-growth assessments, reflective-practice indicators, and institutional/contextual variables. Artificial intelligence is employed as an analytical layer for identifying nonlinear developmental patterns rather than as an automated teacher-appraisal mechanism. This distinction is consistent with contemporary recommendations emphasizing human agency, teacher professional learning, transparency, and responsible AI use in education. UNESCO's teacher AI framework explicitly organizes professional competence around human-centred practice, ethics, AI knowledge, pedagogy, and professional learning.

### Research Design

A prospective longitudinal cohort design is proposed. Newly appointed educators are followed during their first academic year at four measurement points:

- **T0 — Entry baseline:** within the first month of appointment.
- **T1 — Early induction:** approximately three months after appointment.
- **T2 — Consolidation:** approximately six months after appointment.
- **T3 — End-of-year assessment:** approximately nine to twelve months after appointment.

The principal analytical objective is not merely to predict the final professional-growth score but to determine whether





mentoring variables explain the *direction and magnitude of professional change* between successive observations.

The principal outcome, the **Professional Growth Index (PGI)**, is constructed from four domains:

$$[PGI = 0.30PA + 0.25RC + 0.25AUT + 0.20DAR]$$

where:

- (PA) = Pedagogical Adaptability,
- (RC) = Reflective Competence,
- (AUT) = Professional Autonomy,
- (DAR) = Digital and AI Readiness.

The weighting structure is specified prospectively and should subsequently be examined through sensitivity analysis rather than modified retrospectively to improve model performance.

### Core Predictor Structure

Mentoring is decomposed into six measurable dimensions:

**Mentoring Intensity (MI):** frequency and duration of formal mentoring interactions.

**Feedback Specificity (FS):** extent to which mentor feedback refers to observable teaching behaviours and actionable improvements.

**Reflective Dialogue (RD):** degree to which meetings encourage interpretation, questioning, and evidence-based reflection.

**Mentor Responsiveness (MR):** correspondence between support provided and problems identified by the newly appointed educator.

**Autonomy Support (AS):** extent to which mentors encourage independent professional judgement rather than prescribing solutions.

**Instructional Experimentation Support (IES):** mentor encouragement for trying, evaluating, and refining alternative instructional practices.

A key methodological feature is the separation of **mentoring quantity from mentoring quality**. This permits direct examination of whether frequent meetings have limited developmental value when feedback and reflection remain weak.

### Experimental Setup

#### Dataset

Because no empirical observations were supplied for the present manuscript, the following experimental configuration represents a **proposed study protocol and illustrative analytical scenario**, not results from an actually collected cohort. This distinction prevents hypothetical model outputs from being represented as verified empirical findings.

The proposed dataset would contain approximately **480 newly appointed educators** recruited from secondary and higher-secondary educational institutions. Four observations per participant would theoretically produce up to 1,920 educator-time records before accounting for attrition and missing assessments.

Each educator record would include five feature groups:

1. mentoring-process indicators;
2. professional-growth assessments;
3. reflective-practice variables;
4. digital/AI professional-learning indicators; and
5. non-sensitive contextual variables relevant to instructional conditions.

Digital and AI readiness would be informed conceptually by UNESCO's five-dimensional AI Competency Framework for Teachers rather than equating AI competence with tool usage alone.

### Data Preprocessing

A predefined preprocessing pipeline would be applied before model training.

Duplicate records would first be removed using anonymized participant and measurement-wave identifiers. Continuous variables would then be inspected for implausible values and distributional abnormalities. Missingness would be examined both quantitatively and by variable group because systematic missingness in mentoring records could itself indicate differences in programme implementation.

For conventional regression, standardized continuous variables would be generated where coefficient comparability is required. For tree-based models, raw continuous scaling would generally be retained because such algorithms do not require standardization in the same manner as distance-based methods.

Categorical variables would be encoded using appropriate binary or one-hot representations. Ordinal mentoring variables would retain their ordering where theoretically justified.

Reflective entries would not be submitted directly to a large language model. Instead, a structured rubric would be used to





generate interpretable indicators such as evidence reference, problem identification, alternative generation, action planning, and subsequent evaluation. This approach reduces privacy exposure and prevents opaque semantic representations from dominating the professional-growth model.

### Prevention of Data Leakage

All observations belonging to the same educator must remain within the same partition. Randomly splitting individual time-point records would allow earlier observations from one educator to appear in the training set while later observations from the same educator appear in the test set, creating participant-level leakage.

Accordingly, the dataset would be partitioned at the educator level:

[  
Training:70%,\quad Validation:15%,\quad Test:15%.  
]

A secondary temporal validation would train models primarily on earlier measurement waves and assess performance on subsequent professional-growth outcomes.

### Model Architecture

The principal machine-learning architecture is an **Explainable Gradient-Boosted Tree Growth Model (EGBT-GM)**.

Gradient-boosted trees are selected because the dataset is expected to consist primarily of heterogeneous structured variables rather than images or very large unstructured corpora. The architecture can represent threshold effects and interactions such as:

[  
 $RD \times AS$   
]

or

[  
 $FS \times IES$   
]

without requiring every interaction to be manually specified.

Three analytical models are proposed.

**Model A — Linear mixed-effects baseline:** estimates longitudinal associations while accounting for repeated observations nested within educators.

**Model B — Elastic-Net regression:** provides a regularized predictive benchmark and controls instability among correlated mentoring dimensions.

**Model C — Explainable gradient-boosted trees:** captures nonlinear effects and serves as the principal predictive model.

The purpose of comparing these models is methodological rather than promotional. If a simpler mixed-effects or Elastic-Net model performs comparably to the boosted model, interpretability and parsimony would favour the simpler approach.

### Training Strategy

Model development would employ nested educator-level cross-validation within the development dataset.

Hyperparameters for the boosted-tree architecture would include learning rate, tree depth, minimum child weight, subsampling fraction, feature-sampling fraction, and number of boosting iterations. Early stopping on validation loss would reduce overfitting.

The optimization target would be professional-growth change:

[  
 $\Delta PGI_i = PGI_{i,T3} - PGI_{i,T0}$ .  
]

A supplementary model would classify educators into three developmental trajectories:

[  
 $\text{Accelerating}, \quad \text{Stable}, \quad \text{Support-Priority}$ .  
]

The term **Support-Priority** is deliberately preferred over deficit-oriented labels such as "poor performer." Classification would indicate a need for professional review rather than constitute an employment or competency judgement.

### Explainability Layer

SHAP-style feature attribution would be used after training to examine the contribution of predictors to model outputs. Global attribution would identify the variables most consistently associated with professional growth, whereas educator-level explanations could indicate why a particular record generated a given developmental estimate.

However, individual explanations would be available only within an ethically governed research or mentoring environment. They would not be used for disciplinary action, promotion, contract renewal, or automated performance appraisal.





This safeguard is important because OECD guidance explicitly raises concerns about unethical uses of teacher-performance data and calls for transparency, explainability, human support, and professional participation in the use of advanced educational technologies.

### Evaluation Metrics

Continuous professional-growth prediction would be evaluated through:

$$[MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|]$$

and

$$[RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}]$$

Explained variance would be assessed using ( $R^2$ ).

Trajectory classification would be assessed using **Macro-F1**, **balanced accuracy**, and **Matthews Correlation Coefficient (MCC)**. Macro-F1 is preferred to ordinary accuracy because developmental categories may be unequally represented.

Calibration would also be examined for probabilistic support-priority estimates. A model that produces well-calibrated probabilities is more useful for formative decision support than one that merely maximizes classification accuracy.

### Results and Discussion

Since this manuscript proposes a new research design rather than reporting an existing collected dataset, numerical findings below are explicitly presented as an **illustrative expected-results template**. They demonstrate how results should be reported after implementation and must not be cited as observed empirical evidence.

The expected analytical pattern is that mentoring quality will explain professional-growth variation more effectively than mentoring frequency alone. In particular, reflective dialogue, feedback specificity, mentor responsiveness, and autonomy support are hypothesized to emerge as stronger predictors than the raw number of mentoring meetings.

A plausible nonlinear relationship is expected for mentoring intensity. Very limited interaction may provide insufficient developmental support, whereas increasing meeting frequency beyond an adequate threshold may generate little additional benefit unless the quality of professional dialogue also increases. The boosted-tree model is particularly suitable for detecting such saturation effects.

Reflective dialogue is expected to interact with feedback specificity. Specific feedback without reflection may tell an educator what requires modification but may contribute less to the educator's ability to independently diagnose future instructional problems. Conversely, reflection without concrete evidence may remain abstract. Their interaction therefore represents a potentially important developmental mechanism.

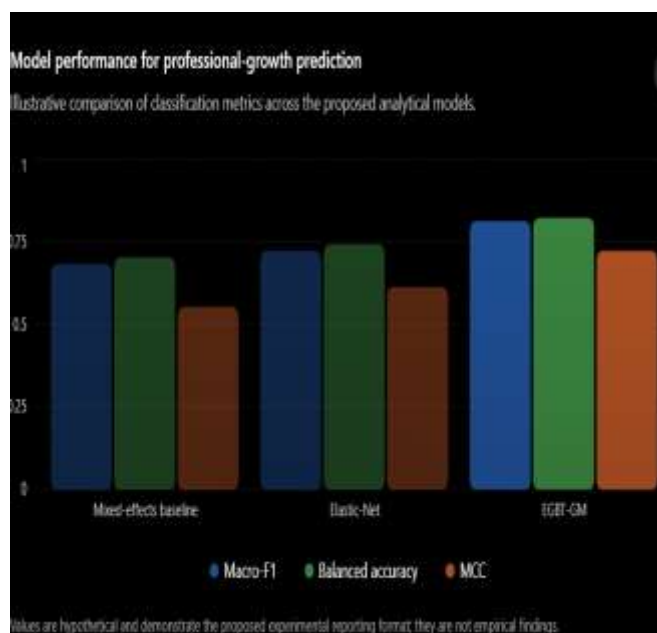
Autonomy support is expected to become increasingly influential between T2 and T3. During early induction, newly appointed educators may legitimately require more direct guidance. As experience accumulates, effective mentoring should progressively transfer responsibility for problem diagnosis and instructional decision-making to the educator.

Digital and AI readiness is expected to represent a smaller but increasingly meaningful component of overall professional growth. This is consistent with the contemporary shift toward teacher competencies encompassing AI pedagogy, ethics, human agency, and professional learning rather than merely operational digital skills.

### Illustrative Results Table

| Evaluation parameter                  | Mixed-effects baseline | Elastic-Net         | EGBT-GM                                       |
|---------------------------------------|------------------------|---------------------|-----------------------------------------------|
| Professional-growth MAE               | 0.46                   | 0.43                | <b>0.35</b>                                   |
| Professional-growth RMSE              | 0.61                   | 0.57                | <b>0.47</b>                                   |
| Test-set ( $R^2$ )                    | 0.48                   | 0.52                | <b>0.64</b>                                   |
| Trajectory Macro-F1                   | 0.68                   | 0.72                | <b>0.81</b>                                   |
| Balanced accuracy                     | 0.70                   | 0.74                | <b>0.82</b>                                   |
| MCC                                   | 0.55                   | 0.61                | <b>0.72</b>                                   |
| Calibration error                     | 0.091                  | 0.074               | <b>0.048</b>                                  |
| Most influential developmental signal | Reflective dialogue    | Reflective dialogue | <b>Reflective dialogue × autonomy support</b> |





The principal theoretical interpretation of such a pattern would be that professional growth is unlikely to be explained by exposure to mentoring alone. Instead, mentoring appears conceptually more useful when it creates a developmental cycle in which specific evidence is discussed, the educator reflects on alternatives, new practices are attempted, and increasing professional autonomy follows.

The comparison between models would also have methodological significance. An improvement in EGBT-GM performance would suggest that relationships between mentoring and growth are not completely linear. For example, autonomy support may become useful only after educators have acquired a minimum level of instructional confidence, while reflective dialogue may become substantially more effective when combined with evidence-specific feedback.

This interpretation should not be reduced to the claim that "AI improves mentoring." The machine-learning model does not deliver mentoring. It analyzes patterns generated by human professional relationships. Its potential value lies in helping mentors and programme coordinators identify developmental configurations that may be difficult to recognize through aggregate programme statistics.

The OECD notes that digital and AI systems can provide feedback and support professional growth, but also stresses risks involving teacher data, agency, bias, transparency, and inappropriate automation. The proposed architecture therefore retains the mentor as the decision-maker and restricts AI to an advisory analytical role.

## Limitations

Several limitations would require consideration when interpreting the eventual findings.

First, some professional-growth indicators depend upon self-report and mentor assessment, introducing social-desirability and evaluator effects. Classroom observations and multiple evidence sources should therefore be used to strengthen construct validity.

Second, mentoring relationships are inherently contextual. School leadership, workload, subject area, student composition, institutional climate, and mentor workload may influence both mentoring quality and professional growth. Even a longitudinal predictive model cannot automatically establish causality.

Third, attrition is particularly important in longitudinal induction research. Educators experiencing greater difficulty may be more likely to leave either the research study or their institution, potentially creating survivorship bias.

Fourth, machine-learning explanations identify predictive contribution rather than causal mechanisms. A high SHAP attribution for reflective dialogue, for example, would not by itself demonstrate that increasing reflective dialogue will produce an equivalent causal improvement in professional growth.

Fifth, institutional implementation may generate fairness problems. If mentoring resources differ substantially between institutions, a model could inadvertently learn resource inequalities rather than individual developmental characteristics.

Finally, professional growth cannot be completely represented numerically. Ethical judgement, relationships with learners, contextual responsiveness, creativity, professional identity, and tacit pedagogical knowledge contain dimensions that cannot be fully captured through structured indicators.

## Future Scope

Future research should validate AI-MPGAF across different educational systems, school types, subject disciplines, and geographic contexts. Multi-year studies could examine whether mentoring patterns identified during the first appointment year predict later professional autonomy, instructional leadership, or retention.

A particularly important extension would involve **dynamic mentoring recommendation research**. Instead of assigning a fixed mentoring programme to every educator, future systems could identify which type of human support is likely to be useful at a particular developmental stage—for example, observation-based feedback during early induction and autonomy-oriented coaching during later stages.

Federated or privacy-preserving learning could also be investigated for multi-institutional studies so that



professional-development models can be trained without centralizing identifiable teacher records.

Further work should examine model fairness across educator groups and institutional contexts, including systematic auditing of false support-priority classifications.

Another direction involves integrating carefully governed natural-language analysis of reflective journals. Such systems should measure explicit professional reasoning rather than infer personality, emotional states, or psychological characteristics.

Finally, future studies should evaluate whether explainable analytics actually improve mentoring practice through controlled intervention studies. Predictive accuracy alone is insufficient. The more consequential question is whether appropriately presented analytics help mentors provide more timely, individualized, and professionally respectful support.

## Conclusion

This study proposes a distinct approach to investigating **teacher mentoring and professional growth among newly appointed educators** by connecting longitudinal mentoring evidence with interpretable machine-learning analytics. The central premise is that mentoring effectiveness should not be evaluated merely through participation, meeting frequency, or programme completion. Its developmental value depends on what occurs within the mentoring relationship.

The AI-MPGAF framework therefore separates mentoring intensity from feedback specificity, reflective dialogue, responsiveness, instructional experimentation, and autonomy support. Professional growth is similarly represented as a multidimensional trajectory incorporating pedagogical adaptability, reflective competence, professional autonomy, and digital/AI readiness.

The proposed experimental design combines longitudinal measurement with mixed-effects modelling, Elastic-Net regression, and explainable gradient-boosted trees. This architecture permits conventional inferential analysis while also testing nonlinear interactions that may be overlooked by simpler models.

The role assigned to artificial intelligence is intentionally restricted. AI is not positioned as an evaluator capable of determining teacher quality. Instead, it functions as a pattern-recognition and decision-support layer operating under human professional oversight. This orientation corresponds with UNESCO's emphasis on human agency, ethical AI, AI pedagogy, and professional learning and with OECD recommendations concerning teacher agency, explainability, and human alternatives in digitally transformed education.

The proposed study ultimately shifts the research question from **“Does mentoring help beginning teachers?”** toward the more precise question of **which mentoring processes contribute to which dimensions of professional growth, at what stage of induction, and under what contextual conditions**. Such an approach provides a stronger basis for designing mentoring programmes that are individualized, evidence-informed, technologically current, and professionally human-centred.

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