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UNVEILING TOMORROW'S EDUCATORS: HARNESSING AI-DRIVEN PREDICTIVE MODELS TO ENHANCE TEACHER RETENTION AND PROFESSIONAL DEVELOPMENT IN COLLEGES OF EDUCATION

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Abstract
As the quality of education is compromised with high rates of turnover and a lack of professional development possibilities, teacher retention in education colleges and professional growth remain the major issues. This article considers the potential to revolutionize the approach to these issues with by contribution of AI-driven predictive models to enhance retention strategies and personalised professional development strategies. The research paper explores the role of predictive analytics, predicting professional needs and in-service environments through an extensive synthesis of secondary sources, such as academic and institutional reports and case studies. The examination demonstrates inadequacies in professional development and retention frameworks already present and in particular lack of proactive strategies and customized interventions. This piece of work seeks to guide policymakers, administrators, and educators to tap AI to produce strong, skilled, and committed teaching personnel in the colleges of learning by establishing a set of recommendations that are practical.

Keywords: Artificial Intelligence, Predictive Models, Teacher Retention, Professional Development, Colleges of Education, Educational analytics, workforce Sustainability.

Introduction
Their teaching staff is important to the survival of the education colleges since they have to retain the staff and develop them on a continuous basis. Having a consistent and qualified workforce is a continuous challenge to these institutions, they are the ones charged with the role of training future teachers. The high turnover rates mean that the stability of these institutions becomes compromised and threatens the quality of teacher preparation programs since they are attributed to factors such as burnout, lack of support, and less professional development opportunities (Ingersoll, 2001). As Darling-Hammond et al. (2017) reveal, on one hand, the phenomenon of professional development training often lags behind, as it offers a generalized training that fails to address the needs of a person and aligns them with the emerging requirements in education. These issues are particularly evident in colleges of learning where the faculty members often lack resources and have to juggle mentoring, teaching, and research.

Artificial intelligence can be seen as a possible solution to these issues with its capability to forecast something. Predictive models run by AI are used to examine large-scale datasets and estimate the probability of a teacher leaving their job, identify areas that require professional growth, and propose area-specific interventions. The models can also develop an environment in which teachers thrive through transforming reactionary retention methods to proactive, personalized, solutions with the help of machine learning and data analytics. Nonetheless, the use of AI in this context remains very young and the available institutional readiness, ethical concern and implementation flaw restricts the possibilities. This article will provide an insight into how AI-based predictive models can enhance the retention and professional growth of teachers by synthesizing secondary data to bridge the gap between theoretical possibilities and the field of application adoption. The research offers a guide to sustainable educator ecosystems, as the research addresses the significant gaps in the existing knowledge, including the underutilisation of predictive analytics within the environment of higher education and the lack of tailored retention frameworks.

The problems are compounded in developing countries such as Nigeria where South east institutions of higher learning such as Alvan Ikoku Federal College of Education (Owerri) and Nwafor Orizu College of Education (Nsukka) are faced with a drastic deficiency of resources, loss of faculty due to brain drain and lack of digital infrastructure (NUC, 2023). Thus, the potential of AI should be put into context to deal with these localized realities.

Following the History of AI Implemented in Educator Support Systems.

Since initial research into automated instruction through complex predictive analytics, AI has been applied in education processes (Papert, 1980). To predict outcomes and make decisions, machines guided by predictive models based on the working of a machine learning algorithm use both past and present data. Such models rely on such aspects as job satisfaction, workload, professional development opportunities, and institutional support as the independent variables to predict the training requirements and risks of turnover within the context of teacher retention and professional growth (Borman and Dowling, 2008). According to the ability of AI to identify facets of complexity, the pioneering theories such as the Two-Factor Theory of Motivation suggest that considering those elements of retention which are intrinsic and extrinsic is also important (Herzberg, 1966).

Empirical studies prove that AI is effective in the management of the workforce. To put it differently, in corporate contexts, predictive models have been useful in reducing employee turnover based on the identification of people at risk and proposing interventions (Hoffman et al., 2018). The initial uses of AI in education have focused on student results, including early warning systems that predict dropout (Bowers et al., 2013). Nevertheless, the effect of AI on professional growth and teacher retention among education colleges has little literature. The earlier studies highlight the potential of data-driven strategies, yet they often overlook such ethical concerns as algorithmic bias or data privacy or do not apply to higher education contexts (Selwyn, 2022). Additionally, predictive models have not been sufficiently integrated into institutional processes due to the reliance on infrastructures and technology change resistance (Crompton, 2020).

These shortcomings mean that a dedicated research on the use of AI to support teachers is needed. This paper explores the ways in which predictive models can be used to resolve the very specific challenges that college of education experiences through the integration of secondary data in the form of peer-reviewed journals, policy papers, and case studies. It gives insights on design, implementation and the impacts of such models. To achieve the sustainability of the proposed strategies and measures, the feasibility and moral considerations of implementing AI are also considered during the analysis.

The Revolutionary Potential of AI-driven predictive models in the field of professional development and educator retention in educational colleges Shining a Light on Retention and Growth Routes AI-driven predictive models have the potential to transform how education colleges operate. This section will support with data provided by secondary sources to analyze the key applications, their benefits, and how they can help to solve systemic factors.

Anticipating Turnover Threats to proactive Retention.

Teacher attrition in the colleges of learning institutions disrupts student education and destabilizes the institutions. To identify the faculty members who are in danger of leaving, predictive models analyse such data points as workload, job satisfaction surveys, and exit interview trends (Ingersoll & Strong, 2011). As an example, administrators can provide workload adjustments or mentorship in case a model finds a teacher who is accepting more responsibilities of the administration and being involved in fewer professional activities. Studies in K-12 settings indicate that predictive analytics are able to reduce turnover by up to 15 percent with combined with targeted interventions (Kraft et al., 2018). The same results would be obtained in applying such models to education colleges so that they become capable of retaining talent proactively.

There are numerous strengths of predictive retention. By identifying the risks at an early stage, the administrators can work on issues such as burnout or career advancement even before they escalate. Besides, these models can ensure the retention initiatives focus on areas that have the greatest influence by permitting the allocation of resources. Nevertheless, the implementation would demand robust data systems and the confidence of the staff in AI-based processes, which explains why an open channel of communication and participation of the stakeholders are crucial (Holmes et al., 2019).

Personalizing the Professional Development.

College of education often apply one-size-fits-all philosophy of professional development, and the workshop offered may not suit the aforesaid needs or career stage of the students. Through analysis of self-reported goals, teaching assessment, and faculty performance statistics, teaching prediction models can be customized using AI. Here are a few examples of the type of models this could be: an intervention based on a model that proposes a teacher struggling with digital technology could have technology introduction workshops and a professor in their mid career interested in administrative fields could be offered leadership training. Recent studies by Guskey (2002) indicate that AI could assist in the pertinent, ongoing professional growth through making adaptive suggestions.

The possibilities of individual growth are proved by case studies in higher education. As an example, one university in Australia has boosted their effectiveness scores in teaching by 20 percent through predictive analytics to develop faculty training programs (Siemens, 2013). The AI-based development strategies could enhance the knowledge and job satisfaction rates within the educational colleges where the educational staff members would have to keep informed about the innovations in pedagogy and research. Enhancing the accuracy of the data and addressing the issue of faculty interested in surveillance are the reasons why clear policies regarding data usage and privacy are needed (Selwyn, 2022).

Nurturing and Constructive Institutional Cultures.

The institutional policies can also be directed on the basis of the predictive models to ensure that the teachers are provided with a learning environment besides being taken care of individually. By looking at aggregate-level data, such as faculty morale surveys or retention trends, AIs have the warability to identify the problematic issues going on within the system, such as the lack of mentor programs or unfair resource allocations. Peer mentoring networks can be developed, such as when a model reveals that faculty at a college of education that is junior do not feel supported. Studies show that supportive cultures enhance professional growth and reduce the turnover significantly (Boyd et al., 2011).

Also, these models make the best practices possible in the colleges since benchmarking is possible with peer institutions. But, those colleges that lack sufficient funding can be short of technological infrastructure and leadership dedication to institutional adoption (UNESCO, 2021). There is the need to have strategic investments and partnerships with technology suppliers to overcome these challenges.

Table 1

Applications of AI-Driven Predictive Models in Colleges of Education

Application	Key Features	Benefits	Challenges
Turnover Prediction	Analyzes workload, satisfaction, and engagement data to identify at-risk faculty	Enables proactive retention strategies, reduces turnover costs	Requires robust data systems, faculty trust
Personalized Development	Recommends tailored training based on performance and career goals	Enhances teaching effectiveness, boosts job satisfaction	Data accuracy, privacy concerns
Institutional Culture Analysis	Identifies systemic issues through aggregate data analysis	Fosters supportive environments, informs policy decisions	Leadership buy-in, infrastructural limitations

Navigating the Journey with Evidence

To explore the role played by predictive models being operated by AI, the paper will utilize secondary data, which will be the aggregation of knowledge obtained through academic sources, institutional reports, and case studies in the period between 1980 and 2025. Having focused on teacher retention, professional development, and the use of AI in higher education, the procedure will be a systematic review of peer-reviewed articles in the databases such as ERIC, Scopus, and Google Scholar. Policies that are adopted by the agencies like the U.S. Department of Education and UNESCO may be used to place institutional challenges into context. The application Case studies of other universities that utilize predictive analytics present real-life examples of use and outcomes.

Applying the thematic approach, it is in the patterns, how an issue on development and retention is tackled based on the predictive models, that trends are identified. Some of the themes include personalization, proactivity and systemic change, each having sub-themes that consider the barriers such as moral dilemma, infrastructural inadequacy, etc. The secondary data will ensure a well-rounded evidence-based perspective by overcoming the limitations of primary data collection like limited respondent confidence on small sample size or the setting. The approach however acknowledges some downsides like the chance of publication bias and lack of research peculiar to education colleges.

Contextualization of the Problems: Faculty Retention and Demographics in Colleges of Education in South East Nigeria.

This new part is a summary of the recent empirical evidence on faculty in public colleges of education of South East Nigeria so as to cast the gap of the Western setting of the article. These institutions train over 50,000 student-teachers each year and are approximately ten in the area and benefit such states as Anambra, Enugu, and Imo. The estimates put turnover, however, at 18 to 25 percent (according to national higher education rates; TETFund, 2024). Although due to the lack of funds and infrastructure hindrances, professional development remains to be impaired, the demographic profiles indicate gender differences and qualification gaps that enhance retention issues.

Table 2

Demographic Profile of Lecturers in Public Colleges of Education, South East Nigeria (Aggregated from 2022–2024 Studies, N ≈ 1,200 Across 6 Institutions)

Characteristic	Distribution/Percentage	Key Retention Insight
Gender	Male: 65–70% Female: 30–35%	Females report 1.5× higher attrition intent due to family-work conflicts and lower promotion rates (AJSTME, 2023)

Age	Under 35: 25% 35–50: 55% 50+: 20%	Mid-career (35–50) faculty, predominant in sample, cite workload and stalled advancement as primary exit drivers
Ethnicity/Rank	Igbo-dominant (85%+); Lecturer: 60% Senior Lecturer: 25% Professor: 15%	Ethnic homogeneity aids cohesion but limits diversity; entry-level lecturers (0–10 years exp.) turnover ~22%
Qualification	Bachelor's: 14% Master's: 60% PhD: 26%	PhD holders 2× more likely to migrate abroad; only 26% meet NUC senior rank thresholds (NUC, 2024)
Experience	0–9 years: 35–40% 10–20 years: 50–55% 20+: 10%	Early-career staff (0–9 years) face mentoring gaps, contributing to 20% voluntary exits within 5 years
Tenure/Contract Status	Permanent: 70% Contract: 30%	Contract staff 3× higher turnover; influenced by irregular promotions and salary delays

*Sources: AJSTME (2023) survey of 120 Computer Education lecturers across 6 colleges; NUC/TETFund aggregated reports (2024); extrapolated from regional samples due to data scarcity.

Such an organization is characterized by high turnover due to systemic elements: low pay (40 percent of employees), lack of incentives (no hazard allowance), and infrastructure (poor internet connectivity to conduct online PD) (TETFund, 2024). To lower adoption rates, digital literacy is low (45 percent of the faculty is ICT-proficient; AJSTME, 2023), but predictive AI has the ability to find at-risk cohorts, including females in the early-career, heavy-workload category.

Table 3

Key Factors Influencing Faculty Turnover in South East Nigerian Colleges of Education (Mean Scores from 2023–2025 Surveys, N=450)

Factor Category	Specific Influences (Mean Score ≥3.0/5.0 Indicates High Impact)	Estimated Contribution to Turnover (%)	Mitigation via AI Predictive Models
Economic/Compensation	Delayed salaries/allowances (4.2); Low pay vs. private sector (4.1); Inadequate incentives (3.8)	35–40%	Forecast financial stress via payroll data integration; recommend equity adjustments

Work Environment	Heavy workload/multiple roles (3.9); Lack of facilities/security (3.7); Poor mentoring (3.5)	25–30%	Analyze workload patterns to predict burnout; suggest personalized mentoring matches
Professional Growth	Limited PD opportunities (3.6); Delayed promotions (3.4); No career progression (3.2)	20–25%	Tailor PD recommendations based on performance/evaluations; predict promotion risks
External/Social	Brain drain to urban/private jobs (3.8); Family/health issues (3.3); Strikes/policy instability (3.1)	15–20%	Aggregate morale surveys for systemic alerts; benchmark against national trends

*Sources: Sumarianz Journal (2023) factors adapted to higher ed; TETFund (2024) regional report. Turnover rate: ~20% annually (vs. national 15–18% in higher ed; NUC, 2024).

Envisioning a Resilient Future for Educators

The findings outline the possibility of AI-based predictive models to transform education. Such models assist organisations in minimising the occurrence of attrition as they predict the turnover threats and make timely intervention such as the workload changes or work recognition activities. Personalized professional development plans enable faculty members to progress according to their career goals thereby enhancing their effectiveness in teaching and are also able to increase contribution to job satisfaction. At the institutional level, predictive analytics is applied to the formulation of policies that can cure structural issues such as poor mentoring or resource differences and behavioral cultures.

Nonetheless, there are significant gaps that should be bridged in order to achieve this potential. To facilitate predictive models, colleges have to invest in the infrastructure of the data, in particular, in the ones that have only few resources. Second, faculty training programs should be provided with AI literacy in order to increase confidence and reduce the opposition. Third, ethical framework is essential to safeguard faculty trust, and ensure the privacy of the data and minimize the bias of the algorithm. The adoption can be expedited by agreement with technology firms and higher education organizations as well as policy encouragement can stimulate investment in solutions based on AI.

The study implications extend beyond the educational institutions. Although the predictive models can be adapted across other contexts of higher education by administrators, the policymakers can use these findings to develop national systems of sustaining teachers. As the focus of underrepresented colleges, further research using primary data should be conducted to confirm these results in specific institutional contexts. The longitudinal designs can be used to evaluate the effects of AI-driven interventions on retention and professional development in the long term.

Table 4

Strategies to Overcome Barriers to AI Adoption

Barrier	Strategy	Expected Outcome
Limited Infrastructure	Invest in cloud-based data systems, partner with tech providers	Enhanced data processing, scalable solutions
Faculty Resistance	Offer AI literacy training, involve faculty in model design	Increased trust, effective utilization of tools
Ethical Concerns	Develop transparent data policies, implement bias audits	Protected privacy, equitable outcomes

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