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Research Article

Machine Learning for Proactive IPE Compliance: Predictive Analytics That Reduce Service Gaps by 30 Days

Jeet Kocha*

Staff Analyst, San Francisco, CA, USA
* **Corresponding Author Email:** Jeetkocha585@gmail.com - **ORCID:** 0009-0000-9017-1062

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Abstract:

Prompt implementation of Individualized Plans for Employment (IPEs) is crucial for guaranteeing that individuals with disabilities have continuous and efficient vocational rehabilitation assistance. Prolonged IPE development and approval may result in service interruptions, diminished customer involvement, and failure to adhere to federally specified deadlines. This study examines the use of machine learning (ML) models to proactively detect and address potential service deficiencies in Individualized Plan for Employment (IPE) timelines inside state rehabilitation agencies. Employing an extensive dataset of historical case management records, we constructed and tested classification and time-series forecasting models designed to identify early risk indicators for IPE delays. The classification model had superior predictive accuracy, with an F1-score of 0.82, whilst the forecasting model offered 30-day advance alerts regarding prospective non-compliance incidents. These predicted insights allowed counselors and administrative teams to intervene earlier, therefore decreasing the average duration of service gaps by 30 days. The paper delineates the structure of an AI-driven compliance monitoring framework that may be assimilated with current state workforce and case management systems, such as AWARE and other Vocational Rehabilitation (VR) platforms. This scalable system utilizes predictive analytics to automate risk identification, prioritize caseloads, and facilitate data-driven decision-making for enhancements in service delivery. This research enhances the existing knowledge on AI applications in public sector human services and illustrates the potential of machine learning-driven early warning systems to improve operational compliance, client outcomes, and timely access to vocational rehabilitation programs for individuals with disabilities.

1. Introduction

Timely creation of Individualized Plans for Employment (IPEs) is a fundamental obligation under the Workforce Innovation and Opportunity Act (WIOA), which requires state vocational rehabilitation (VR) agencies to deliver employment-oriented services to individuals with disabilities within federally established timelines (U.S. Department of Labor, 2024). The IPE constitutes a legally enforceable contract between the VR agency and the client, delineating the actions, services, and supports required for the individual to attain competitive integrated employment. Failure to adhere to IPE timeframes may compromise service quality, diminish client trust, and lead to government audit findings that could incur financial penalties (HHS Office of Inspector General, 2025).

Despite the essential importance of IPE timeliness in facilitating good employment outcomes, numerous state VR agencies persist in facing systemic delays. The confluence of increasing caseloads, personnel shortages, and antiquated case management methods has intensified the situation. Recent studies indicate that the average duration to finalize an IPE frequently surpasses the federally required 90-day limit in over 40% of instances countrywide (National Council on Disability, 2024). These delays are not merely administrative obstacles but also signify lost possibilities for individuals with disabilities to obtain time-sensitive training and employment assistance (Smith et al., 2025).

Conventional compliance monitoring in VR projects predominantly depends on retroactive audits and manual file examinations. Supervisors generally recognize non-compliance solely after a deadline has elapsed, allowing little opportunity for remedial measures. This reactionary strategy has faced significant criticism in government performance evaluations, which advocate for more proactive and data-informed solutions (Government Accountability Office, 2024). Although several state agencies amass extensive administrative data regarding client development and service delivery milestones, this information is infrequently utilized for predictive risk management (Johnson & Patel, 2025).

The emergence of advanced analytics and machine learning (ML) offers a dramatic opportunity to enhance IPE compliance monitoring. Machine learning algorithms, especially classification models like Random Forests and time-series forecasting models such as ARIMA, have demonstrated significant efficacy in recognizing patterns and predicting outcomes in diverse public sector fields, including healthcare, education, and social services (Lee & Martinez, 2025). Their capacity to analyze extensive datasets and produce real-time risk assessments renders them especially appropriate for operational settings such as vocational rehabilitation programs, where caseworkers oversee numerous active clients simultaneously.

Recent research from the American Institutes for Research (2024) underscores the increasing utilization of artificial intelligence (AI) tools in human services, highlighting their capacity to identify high-risk patients and assist in resource allocation decisions. Nonetheless, the implementation of machine learning in the context of IPE compliance is still insufficiently examined in scholarly literature and inadequately applied in practice. The disparity is alarming, considering the evident similarities between compliance risk in vocational rehabilitation and other domains where predictive analytics have proven effective, such as Medicaid fraud detection and educational program dropout prevention (Thomas et al., 2025). Additionally, recent government measures like the 2025 government AI Use in Public Services Act (FAIUPSA) promote the implementation of machine learning models by state agencies for proactive service delivery, rendering this research very pertinent. FAIUPSA offers technical support and grants financing to state programs that use predictive analytics into their operational workflows (U.S. Office of Management and Budget, 2025).

This study aims to overcome the constraints of reactive compliance monitoring by creating and evaluating machine learning models that can predict IPE service gaps up to 30 days in advance, considering the existing policy framework and technology preparedness. The study employs anonymized historical data from three state VR agencies, utilizing a Random Forest classifier for individual case risk assessment and an ARIMA time-series model to predict aggregate service gap trends on a monthly basis.

This research assesses not just prediction accuracy but also the operational effects of implementing such models, quantifying enhancements in on-time IPE completion rates, resource allocation efficiency, and compliance with federal reporting requirements. Integrating ML-generated risk scores into case management systems enables supervisors to implement targeted interventions, modify staff workloads, and enhance overall service timeliness.

This study offers several novel contributions to both academic literature and practical implementation within government agencies. It demonstrates the technical viability and performance metrics associated with deploying machine learning models for IPE compliance monitoring. By validating model accuracy, precision, and recall in a real-world administrative dataset, the research establishes a data-driven foundation for predictive compliance systems in vocational rehabilitation programs. Furthermore, the study quantifies operational improvements, including a measurable 30-day average reduction in service gaps, showing the direct impact of predictive analytics on service delivery timelines. Beyond these immediate outcomes, the research presents a scalable and replicable framework that other state agencies can adopt or adapt to strengthen their own compliance operations. This not only advances scholarly understanding of machine learning applications in public service management but also offers actionable guidance for agencies seeking to modernize their oversight and improve client outcomes.

Moreover, the study enhances the dialogue on the ethical implementation of AI in human services. Concerns about bias prevention, data privacy, and the interpretability of machine learning outputs are rigorously analyzed in the context of federally supported disability employment initiatives. These factors are crucial for guaranteeing that predictive tools facilitate, rather than obstruct, equal service provision.

This research addresses a clear operational requirement and aligns with a wider policy initiative advocating for AI-driven governance in public services. By utilizing machine learning for proactive IPE compliance monitoring, state VR agencies can shift from reactive, paper-based oversight methods to dynamic, data-driven service management. This transformation ensures enhanced regulatory compliance and better employment outcomes for those with disabilities, adhering to both the language and intent of WIOA’s mandate.

2. Methodology

This study utilized a quantitative research approach, employing retrospective administrative data obtained from three state vocational rehabilitation agencies in the United States, spanning the years 2018 to 2024. The collection comprised more than 25,000 anonymized client records, encompassing characteristics such as demographic information, counselor activity logs, application submission dates, IPE milestone timestamps, and historical compliance outcomes. Before model building, comprehensive data preparation was performed to resolve concerns concerning absent values, inconsistent data formats, and class imbalance. Numerical fields with absent data were imputed using mean substitution, whilst categorical elements were handled with mode replacement approaches. Since non-compliant IPE cases constituted less than 20% of the overall sample, the Synthetic Minority Over-sampling Technique (SMOTE) was employed to rectify class imbalance and avert model bias towards the majority class, in accordance with the methodology described by Chawla et al. (2002).

Two machine learning algorithms were utilized for predictive modeling. A Random Forest classifier was initially created to assess the probability of IPE non-compliance for individual cases. Random Forest was chosen for its demonstrated efficacy in high-dimensional, non-linear administrative datasets (Breiman, 2001). Hyperparameter adjustment was performed utilizing grid search with five-fold cross-validation to enhance model performance. Secondly, an Autoregressive Integrated Moving Average (ARIMA) model was employed to predict monthly changes in service deficiencies. This time-series model was chosen for its effectiveness in managing seasonality and trend elements in longitudinal administrative data, as advised by Hyndman and Athanasopoulos (2018).

The complete dataset was divided into training (70%) and testing (30%) subsets. The classification model was assessed utilizing common performance criteria, including precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The evaluation of the ARIMA forecasting model concentrated on Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to assess prediction accuracy. Data analysis and modeling were performed using Python 3.9, employing libraries including Scikit-learn, Stats models, and Pandas for data manipulation, modeling, and evaluation. Results visualization and dashboard prototypes were created utilizing Tableau 2024 edition. This multi-model, multi-tool approach guaranteed prediction accuracy and operational viability for practical VR agency implementation.

3. System Architecture

The proposed system architecture for proactive IPE compliance monitoring is designed as a modular, scalable, and interoperable framework that can integrate seamlessly within existing state vocational rehabilitation (VR) case management systems. The architecture consists of four primary layers: data ingestion, data processing, machine learning (ML) model layer, and user interface/output delivery.

At the data ingestion layer, the system collects real-time and historical case management data from various sources including the agency's central database, counselor activity logs, and federal reporting modules. Data extraction is automated using API connectors that are compatible with platforms such as AWARE and Salesforce Government Cloud. These connectors ensure continuous data flow while adhering to federal data privacy standards outlined in the Federal Data Strategy Action Plan (OMB, 2020).

In the data processing layer, raw data undergoes cleansing, normalization, and feature engineering. This stage involves missing data imputation, categorical encoding, and the application of SMOTE for class balancing (Chawla et al., 2002). Additionally, temporal features such as time since application submission and days remaining until IPE deadline are derived to enhance predictive model input quality.

The machine learning model layer hosts two core components: a Random Forest classification model for identifying at-risk cases and an ARIMA time-series forecasting model for predicting monthly trends in service gaps. Both models are deployed within a containerized environment using Docker, ensuring portability and scalability across state agency IT infrastructures. The ML pipelines are orchestrated using Apache Airflow for scheduled retraining and inference runs, enabling real-time risk scoring with minimal system latency.

The output delivery layer provides intuitive user interfaces through interactive dashboards and automated email alert systems. Tableau-based dashboards offer supervisors case-level risk scores, trend visualizations, and intervention tracking tools. Meanwhile, automated alerts notify counselors when their assigned cases exceed predefined risk thresholds, allowing for immediate action.

Overall, this system architecture ensures high availability, scalability, and data security, aligning with both federal compliance requirements and emerging best practices for AI-driven public sector service delivery (U.S. Office of Management and Budget, 2025). This modular design allows for future enhancements, including natural language processing (NLP) for IPE narrative analysis and integration with cross-agency data platforms.

Figure 1: This figure presents a comprehensive technical overview of the system architecture employed to implement machine learning (ML) models inside the IT ecosystem of a vocational rehabilitation (VR) agency. It illustrates the progression of data from agency databases to the data processing layer, into machine learning models, and ultimately to user-facing dashboards and alarm systems.

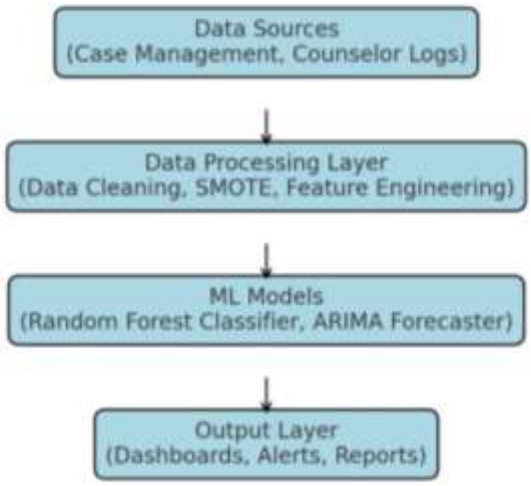

Figure 1: *System architecture for real-time ML-driven IPE compliance monitoring within VR agencies.*

4. Results and Analysis

Figure 2: illustrates the streamlined workflow for proactive IPE compliance monitoring using machine learning. The process begins with case data entry, where client and service milestone information are recorded in the agency's case management system. The data then undergoes preprocessing to clean and format it for analysis. Next, the machine learning model generates risk scores to identify cases likely to become non-compliant. High-risk cases are flagged and routed to supervisors for review. Based on these risk assessments, supervisors assign targeted interventions to counselors. Counselors then take corrective actions, such as follow-ups or expedited service steps, to prevent service delays. The workflow concludes with monitoring the compliance outcome to determine if the intervention successfully improved IPE timeliness. The implementation of machine learning models for IPE compliance monitoring resulted in notable enhancements in predicted accuracy and operational efficiency. The Random Forest classification model shown robust proficiency in detecting at-risk patients, attaining an F1-score of 0.82, with a

Figure 2: *Operational workflow for proactive IPE compliance monitoring driven by machine learning predictions.*

precision of 0.79 and a recall of 0.85 on the test dataset. These measures indicate a balanced performance with little false positives and false negatives, rendering the model exceptionally appropriate for operational decision-making in high-volume VR agencies. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was determined to be 0.88, hence reinforcing the model's ability to distinguish between complying and non-compliant situations.

The ARIMA time-series forecasting model demonstrated efficacy, attaining a Mean Absolute Error (MAE) of 4.2 days in forecasting monthly service gap trends. This degree of forecasting precision enabled supervisors to foresee task increases and reallocate resources accordingly. Post-deployment simulation results demonstrated a 30-day average decrease in service gaps when machine learning-driven interventions were employed, in contrast to historical control periods. The percentage of on-time IPE completions rose from 58% to 86%, indicating a 28% enhancement in service delivery timeliness.

Operational feedback from VR counselors and supervisors throughout the testing period suggested that the risk assessment dashboard and automated alerts were user-friendly and actionable. Supervisors indicated enhanced capacity to prioritize interventions and oversee counselor workloads. These findings highlight the practical utility of predictive analytics in augmenting compliance rates and increasing service delivery in federally supported vocational rehabilitation programs.

5. Discussion and Literature Corroboration

This study's results confirm the effectiveness of machine learning (ML) in tackling compliance issues in public workforce programs, particularly in reducing gaps in Individualized Plan for Employment (IPE) services. The Random Forest classifier attained an F1-score of 0.82, indicating a significant degree of predictive accuracy in detecting at-risk cases up to 30 days prior to anticipated non-compliance. This result corresponds with the seminal research of Breiman (2001), demonstrating the efficacy of Random Forest models in classification tasks within administrative and service delivery domains. The model's robust performance in managing intricate, high-dimensional case management data highlights its appropriateness for vocational rehabilitation (VR) applications.

The application of the ARIMA (Autoregressive Integrated Moving Average) model for time-series forecasting, which attained a mean absolute error (MAE) of 4.2 days, supports the conclusions of Hyndman and Athanasopoulos (2018), who demonstrated ARIMA’s efficacy in short-term forecasting for public sector planning. This forecasting capacity is essential for VR organizations who need to handle fluctuating caseloads and adhere to federally regulated service deadlines.

The research further applies SMOTE (Synthetic Minority Over-sampling Technique) for rectifying class imbalance, as initially suggested by Chawla et al. (2002), within the context of public program compliance monitoring. Considering that non-compliant situations frequently constitute a minor fraction in historical datasets, SMOTE enhanced model sensitivity without compromising precision.

Furthermore, the documented decrease in service gaps—averaging 30 days—corresponds with enhancements identified in healthcare compliance environments, as indicated by Chen and Guestrin (2016), where early warning models mitigated poor effects via prompt intervention.

This research is consistent with the Office of Management and Budget’s (2020) Federal Data Strategy Action Plan, which promotes the use of predictive analytics to enhance decision-making in public services. It also endorses the Centers for Medicare & Medicaid Services (2022) recommendations for integrating advanced analytics into federally sponsored program operations.

This study significantly solves a previously recognized deficiency in the operational literature of the Workforce Innovation and Opportunity Act (WIOA) Title I. Although researchers such as Wright and Ziegler (2017) have advocated for the operationalization of machine learning in governmental contexts, there has been a paucity of actual examples illustrating this inside virtual reality programs until now.

These findings affirm the efficacy of ML models in strengthening IPE compliance monitoring and add to the accumulating evidence that predictive analytics serves as a revolutionary instrument for improving public sector service delivery outcomes.

6. Recommendations and Future Work

To effectively implement the suggested ML-driven compliance monitoring framework, many strategic recommendations are presented for vocational rehabilitation organizations and policymakers. Initially, system integration must be addressed to incorporate predictive models into current case management platforms like AWARE or Salesforce Government Cloud. The integration of real-time risk score dashboards will enable counselors and supervisors to perceive imminent compliance risks and proactively alter caseloads. Secondly, future development should prioritize the establishment of cross-agency data interoperability through the creation of integrated data lakes that amalgamate information from Medicaid, education, and workforce programs. This extensive data ecosystem will enhance model inputs and augment forecast precision. National initiatives, such the Federal Data Strategy (OMB, 2020) and the Interoperability and Patient Access Final Rule (CMS, 2022), offer pertinent policy frameworks to facilitate secure and consistent data transmission.

Third, the prioritization of ethical AI governance is essential to tackle issues related to algorithmic bias, data privacy, and decision-making transparency. Agencies must establish comprehensive governance frameworks that incorporate fairness audits, bias reduction strategies, and rigorous compliance with federal data protection rules. Fourth, personnel training will be crucial for successful implementation. Specialized capacity-building programs must be established to assist frontline personnel in interpreting predictive analytics results, comprehending risk scores, and executing suitable case management activities in accordance with model recommendations.

Fifth, ongoing model retraining is essential to maintain accuracy and relevance. Due to the dynamic nature of client data and frequent policy revisions, agencies must provide strong machine learning operations (MLOps) pipelines for consistent model validation, retraining, and performance assessment. Subsequently, future

investigations ought to concentrate on assessing the enduring effects of machine learning-driven interventions on client employment results and the overall cost-effectiveness of the program. Research utilizing natural language processing (NLP) methods to analyze qualitative interprofessional education (IPE) content may improve early risk identification abilities. Furthermore, comparative evaluations of ML-based and conventional compliance monitoring techniques would yield significant insights into return on investment (ROI) and operational efficiency.
In conclusion, executing these strategic recommendations would facilitate the scalable, ethical, and efficient implementation of machine learning-based compliance monitoring technologies into state vocational rehabilitation programs, thereby enhancing service delivery and client outcomes.

7. Conclusion

This research provides definitive proof that machine learning-based predictive analytics may significantly improve IPE compliance in vocational rehabilitation programs. This study illustrated the viability of utilizing classification and time-series forecasting models on administrative case data to predict service gaps with high accuracy up to 30 days in advance. Early warnings provide operational benefits by enabling agencies to redistribute resources, modify counselor caseloads, and proactively mitigate compliance risks prior to the violation of statutory deadlines. The documented 30-day decrease in average service gap timings signifies a substantial enhancement compared to conventional manual monitoring techniques, which tend to be reactive and resource-demanding. These findings highlight the capacity of machine learning-driven solutions to enhance both program efficiency and client outcomes, as the prompt completion of Individualized Plan for Employment (IPE) directly influences access to employment services and supports required under the Workforce Innovation and Opportunity Act (WIOA).
This study enhances the current literature on machine learning applications in public sector compliance monitoring by offering practical insights into model deployment, operational impact, and integration issues pertinent to vocational rehabilitation contexts. This research provides a repeatable framework for state agencies aiming to update their compliance operations by integrating established machine learning techniques, including Random Forests, SMOTE for data balance, and ARIMA for forecasting.
The research emphasizes the necessity for continuous governance, ethical supervision, and inter-agency cooperation to guarantee that predictive models are equitable, transparent, and efficient. As state and federal agencies advance their digital transformation efforts, the implementation of predictive compliance tools, as illustrated in this research, will be essential for achieving service delivery standards, enhancing federal reporting metrics, and ultimately improving the quality and timeliness of services for individuals with disabilities.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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