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An AI-Powered Client Intake and Consultant Assignment System for Small Business Development Centers

Executive Report

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December 17, 2025

Pennsylvania Department of Community & Economic Development
Partnerships for Regional Economic Performance (PREP)

DUQUESNE UNIVERSITY Palumbo-Donahue School of Business

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Abstract

Small Business Development Centers (SBDCs) provide consulting and technical assistance to a large and diverse population of small businesses. As demand for services increases, many SBDCs continue to rely on manual and experience-based approaches for client intake review and consultant assignment. These methods can result in delays, inconsistent consultant-client matching, and uneven workload distribution. This paper presents the design and implementation of an AI-powered client intake and consultant assignment system developed and adopted at the Duquesne University Small Business Development Center. Using supervised machine learning and natural language processing (NLP), the system analyzes client intake data and generates decision-support recommendations for consultant assignment while maintaining human oversight. The project demonstrates how explainable, center-level artificial intelligence solutions can improve efficiency, transparency, and scalability in public service organizations.

Introduction

Small Business Development Centers play a critical role in supporting entrepreneurship, innovation, and local economic development across the United States. Each year, SBDCs assist thousands of clients with business planning, financial analysis, market research, and operational strategy. As client volume and service complexity increase, traditional methods for reviewing intake information and assigning consultants have become increasingly strained. Consultant assignments are often based on staff familiarity or immediate availability rather than systematic analysis of client needs, industry alignment, and workload capacity.

These challenges can lead to slower onboarding, inconsistent service quality, and consultant burnout. To address these limitations, the Duquesne University SBDC undertook the development of an AI-powered client intake and consultant assignment system. The purpose of this project was to modernize the intake process using artificial intelligence while preserving human judgment and accountability in final decision-making.

Keywords: *artificial intelligence, machine learning, natural language processing, decision support systems, SBDC.*

Project Overview and Scope

The project was completed between July and December 2025 by a team of five students, Alexis Ropelewski, Alicia Redington, Tyler Padezan, Ty Martin, and Mackenzie Cahill—under the supervision of Rafique Iddrisu as part of the AI U Student Engagement Initiative. The system represents Phase One of a broader effort to modernize SBDC intake and assignment workflows through intelligent automation.

The tool was developed for center-level adoption and is currently piloted at the Duquesne University SBDC. Rather than enforcing automated assignments, the system functions as a decision-support tool, providing recommendations that staff may accept, reject, or modify. This approach ensures alignment with organizational governance requirements and ethical AI principles.

Data Sources and Methodology

Data Sources

The system is trained using historical SBDC operational data already collected through Neoserra and exported in Excel format. Key input variables include product or service descriptions, NAICS industry codes, company status or stage, and historical primary consultant assignments. These data reflect real-world service patterns and provide a strong foundation for supervised learning.

Machine Learning and NLP Techniques

The project employs supervised machine learning using a Random Forest classifier to predict the most appropriate consultant for new client intakes. Natural language processing techniques are applied to unstructured client descriptions using term frequency–inverse document frequency (TF-IDF) vectorization. This approach allows the system to extract meaningful patterns from written text and combine them with structured categorical data such as NAICS codes and company status.

Categorical variables are encoded using one-hot encoding, and missing values are addressed through imputation. Models are retrained whenever new data is uploaded, allowing the system to adapt to evolving service demands over time. The emphasis on explainability and robustness makes this approach suitable for public-sector decision support.

System Architecture and Workflow

The application was developed using Python and Flask for backend processing, with a web-based interface built using HTML and CSS. Authorized users log in at the center level and follow a structured workflow. First, historical intake data is uploaded and used to train the machine learning model. Next, staff enter new client intake information, and the system generates a ranked consultant recommendation.

Crucially, users retain full control over the final decision. Staff may accept, reject, or reassign the recommendation, ensuring human oversight. An analytics dashboard provides visual insights into consultant workloads, industry distribution, and specialization trends, supporting managerial planning and transparency.

Challenges and Solutions

One significant challenge was the unstructured nature of client intake data, particularly free-text descriptions of products and services. This was addressed through NLP preprocessing and TF-IDF vectorization, enabling the model to interpret textual data effectively. Another challenge involved ensuring that AI recommendations did not replace professional judgment. The solution was to design the system as a human-in-the-loop decision-support tool, reinforcing trust and accountability.

Differences in readiness and governance across the broader SBDC network also influenced design decisions. Rather than enforcing network-wide standardization, the system was intentionally scoped for center-level adoption, allowing flexibility while serving as a proof of concept for future expansion.

Outcomes and Impact

The project resulted in a fully functional AI-powered client intake and consultant assignment system adopted at the Duquesne University SBDC. The system reduces manual review time, improves consistency in consultant matching, and provides real-time visibility into workload distribution and industry demand. These improvements support faster client onboarding, better resource allocation, and more informed managerial decision-making.

Lessons Learned and Future Work

Students gained practical experience applying artificial intelligence in a real organizational environment. Key lessons included the importance of data quality, stakeholder engagement, and ethical AI deployment. The project also demonstrated that successful AI adoption depends not only on technical performance but also on usability, governance, and organizational trust.

Future development phases may include workload optimization metrics, automated notifications, and secure cloud deployment to further enhance scalability and impact.

Conclusion

This project illustrates how explainable, responsibly designed AI systems can improve operational efficiency in public service organizations. By integrating machine learning and natural language processing with human oversight, the AI-powered client intake and consultant assignment system offers a scalable and ethical model for modernizing SBDC service delivery.

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