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INTRODUCTION

Public sector organisations rely on accurate forecasting to support planning, resource allocation, and service delivery. Many public sector organisations rely on legacy spreadsheet-based tools, such as Microsoft Excel, due to their familiarity and ease of access [1]. This project investigates how statistical and machine learning time series forecasting models perform on operational public sector data and how effectively can forecasting outputs be communicated through an interactive Business Intelligence dashboard.

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AIMS & OBJECTIVES

Aim: To design, implement, and evaluate multiple time series forecasting techniques to determine their suitability for supporting decision-making in a public sector environment.

Objectives:

- Review literature on forecasting and Business Intelligence dashboards.
- Implement statistical and machine learning forecasting models.
- Evaluate forecasting accuracy using performance metrics.
- Develop a Power BI dashboard to present forecasting results and comparisons.

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RESEARCH OVERVIEW

Existing research highlights the importance of data analytics and forecasting in supporting organisational decision-making [2]. However, many public sector organisations still rely on legacy spreadsheet tools such as Microsoft Excel, which have limitations in scalability, automation, and advanced analytical capabilities [1]. The literature review identifies Business Intelligence systems and interactive dashboards as effective tools for presenting analytical insights and improving accessibility of complex data [3]. Research also shows a progression from traditional statistical forecasting models, such as ARIMA, to machine learning approaches including XGBoost. While machine learning techniques often achieve higher predictive accuracy, statistical models remain valuable due to their transparency and interpretability [4]. Despite these developments, there is limited research evaluating forecasting techniques and BI dashboards specifically within public sector environments. This project addresses this gap by comparing statistical and machine learning forecasting models using operational DVLA data and presenting the results through an interactive BI dashboard.

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DESIGN AND IMPLEMENTATION

A forecasting pipeline was developed using Python to process historical operational data and generate predictions. Multiple forecasting models were implemented and evaluated using accuracy metrics including MAE, RMSE, MAPE [5].

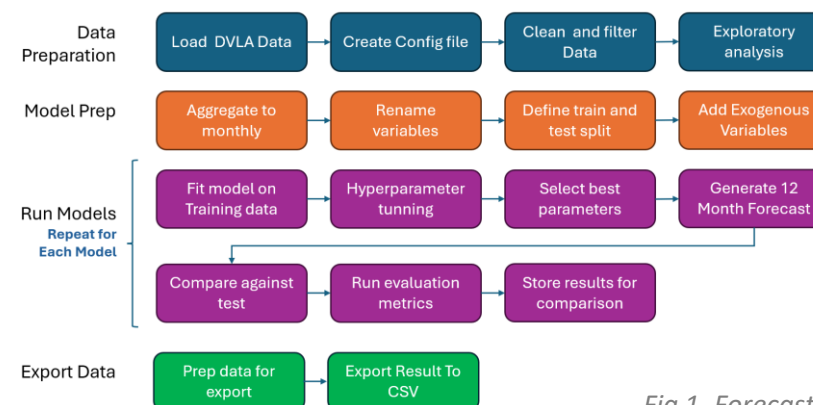


Fig 1. Forecasting Pipeline

Results were integrated into a Power BI dashboard, enabling users to explore forecasts and compare model performance

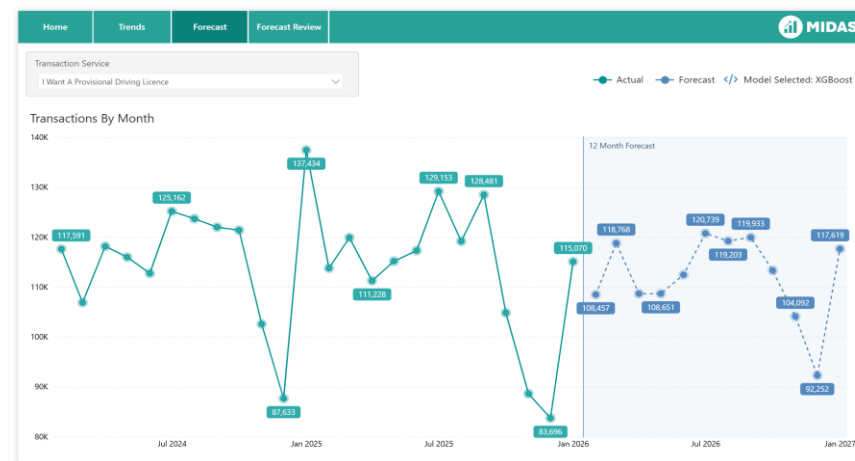


Fig 2. Power BI Dashboard

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RESULTS

The forecasting models showed varying levels of accuracy across the transactions analysed. The machine learning model XGBoost consistently produced the lowest forecasting errors when compared with the statistical models ARIMA and Prophet. However, Diebold–Mariano testing showed that not all results were statistically significant, indicating that while XGBoost generally performed best, traditional statistical models remain competitive depending on the dataset.

Dataset / Service	ARIMA RMSE	Prophet RMSE	XGBoost RMSE	Best Model
Provisional Driving Licence	15,667	15,891	10,346	XGBoost
Renew Driving Licence	39,027	73,170	19,523	XGBoost
Register Vehicle	36,997	23,960	18,510	XGBoost
Tax Vehicle	327,020	273,195	236,189	XGBoost

Fig 3. Forecasting Model Results

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CONCLUSION

This project found that XGBoost produced the lowest forecasting errors across the datasets, although not all improvements were statistically significant. XGBoost is recommended where accuracy and speed are priorities, while ARIMA remains useful where interpretability is important. The Power BI dashboard also showed how forecast outputs can be presented clearly, helping users compare models, explore trends, review performance, and support more informed data-driven decision-making.

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