ABSTRAK

Perencanaan sumber daya manusia (SDM) di rumah sakit sangat dipengaruhi oleh ketepatan estimasi beban kerja pelayanan. Pada rumah sakit baru seperti Rumah Sakit Umum Pusat (RSUP) Surabaya, pola kunjungan pasien masih bersifat dinamis dan fluktuatif sehingga pendekatan konvensional berbasis data historis tahunan menjadi kurang responsif. Penelitian ini bertujuan untuk merumuskan strategi optimasi alokasi SDM berbasis prediksi jumlah pasien menggunakan pendekatan machine learning guna meningkatkan efisiensi operasional rumah sakit. Penelitian ini menggunakan desain kuantitatif dengan pendekatan integratif antara *predictive modelling* dan *optimization modelling*. Prediksi jumlah kunjungan pasien rawat jalan harian dilakukan menggunakan model machine learning, yaitu Random Forest, XGBoost, dan Ensemble, serta dibandingkan dengan metode statistik konvensional SARIMAX. Model terbaik dipilih berdasarkan evaluasi kinerja menggunakan metrik Macro MAE, Global MAE, RMSE, dan koefisien determinasi (R^2). Hasil prediksi kemudian diintegrasikan ke dalam metode *Workload Indicators of Staffing Need* (WISN) untuk menghitung kebutuhan SDM harian pada unit admisi, perawat, apoteker, dan dokter spesialis. Efektivitas strategi optimasi diuji melalui studi simulasi retrospektif dan analisis statistik *paired-samples t-test*. Hasil penelitian menunjukkan bahwa model XGBoost merupakan prediktor terbaik pada segmen Non BPJS, sedangkan model Ensemble memberikan kinerja terbaik pada segmen BPJS. Integrasi hasil prediksi ke dalam WISN mengungkap adanya ketidakseimbangan alokasi SDM, terutama berupa kelebihan tenaga dan ketidaktepatan penjadwalan pada beberapa unit layanan. Penerapan strategi optimasi berbasis prediksi terbukti menurunkan kesenjangan alokasi SDM secara signifikan ($p < 0,05$). Temuan ini menegaskan bahwa pendekatan prediktif berbasis data mampu mendukung perencanaan SDM rumah sakit yang lebih efisien, adaptif, dan rasional.

Kata kunci: *machine learning*, prediksi pasien, WISN, optimasi SDM, rawat jalan

ABSTRACT

Human resource (HR) planning in hospitals is highly influenced by the accuracy of service workload estimation. In newly established hospitals such as Surabaya Central General Hospital (RSUP Surabaya), patient visit patterns remain dynamic and fluctuating, making conventional approaches based on annual historical data less responsive. This study aims to formulate a strategy for optimizing HR allocation based on patient volume prediction using a machine learning approach to improve hospital operational efficiency. The study employed a quantitative design with an integrative approach combining predictive modelling and optimization modelling. Daily outpatient visit predictions were conducted using machine learning models, namely Random Forest, XGBoost, and Ensemble, and were compared with the conventional statistical method SARIMAX. The best-performing model was selected based on performance evaluation using Macro MAE, Global MAE, RMSE, and the coefficient of determination (R^2). The prediction results were then integrated into the Workload Indicators of Staffing Need (WISN) method to calculate daily staffing requirements for admission units, nurses, pharmacists, and specialist physicians. The effectiveness of the optimization strategy was tested through a retrospective simulation study and paired-samples t-test statistical analysis. The results showed that the XGBoost model was the best predictor for the Non-BPJS segment, while the Ensemble model demonstrated the best performance for the BPJS segment. Integrating prediction results into WISN revealed imbalances in HR allocation, particularly in the form of overstaffing and inappropriate scheduling in several service units. The implementation of the prediction-based optimization strategy was proven to significantly reduce staffing allocation gaps ($p < 0.05$). These findings confirm that a data-driven predictive approach can support hospital HR planning that is more efficient, adaptive, and rational.

Keywords: machine learning, patient prediction, WISN, human resource optimization, outpatient care.