International Journal of Computer Applications (0975 – 8887)
Volume 187 – No.137, August 2026

DSSOU: A Design Science Framework for NHS Non-Clinical Space Utilisation Optimisation Integrating Time-Series Forecasting, Machine Learning, and Linear Programming

Prince Nweke Onyeka
Data Analytics and Technologies
University of Greater Manchester, United Kingdom

Chinonso Job
School of Built Environment, Engineering, and Computing
Leeds Beckett University, United Kingdom

Festus Chijioke Onwe
Information Technology Department
University of Port Harcourt, Rivers State, Nigeria
Corresponding Author

ABSTRACT
Non-clinical bookable units—meeting rooms, hot-desks, and car-parking spaces—represent a significant but analytically under-examined dimension of NHS facility management. While predictive analytics and optimisation methods are mature in the clinical capacity literature, no published framework integrates these methods specifically for NHS non-clinical space utilisation. This paper proposes DSSOU (Decision-Support System for Occupancy and Utilisation), a four-component design-science artefact grounded in the Hevner et al. design-science research methodology. DSSOU integrates: (i) temporal pattern analysis using ARIMA and Multi-Seasonal ARIMA; (ii) contextual demand prediction using Random Forest and Gradient Boosting; (iii) prescriptive space allocation using Linear Programming; and (iv) an interactive decision-support dashboard. The framework is designed to operate on NHS booking system data spanning 2016–2024 and is specified at sufficient formal detail to support immediate implementation. The data model, the formal optimisation formulation, the prediction model specification, and the artefact evaluation protocol are presented, together with a candid assessment of which components are directly supported by established precedent and which constitute genuinely novel integration. DSSOU is presented as a conceptual design-science proposal: no experimental results are reported, and a detailed, falsifiable evaluation protocol is specified by which the framework's central claims should be tested. This paper constitutes the methodological proposal stage of a planned empirical study.

Categories and Subject Descriptors
H.4.2 [Information Systems Applications]: Types of Systems — decision support; I.2.6 [Artificial Intelligence]: Learning; G.1.6 [Numerical Analysis]: Optimization — linear programming

General Terms
Design, Algorithms, Management, Measurement, Performance

Keywords
Design Science Research, NHS facility management, space utilisation optimisation, ARIMA forecasting, machine learning, linear programming, decision-support dashboard, booking systems

1. INTRODUCTION
A companion critical review of the healthcare capacity planning literature identifies four structural limitations as applied to NHS facility management: an exclusive clinical framing that leaves non-clinical shared spaces unaddressed; the absence of an integrated multi-method framework combining forecasting, prediction, and prescriptive optimisation; insufficient real-time and cross-site validation; and inconsistent performance reporting standards [1]. NHS Property Services data reinforce the urgency of these gaps: 90% of NHS leaders report limited insight into how their estate is being used, and over 50% of facilities lack the data infrastructure to support informed allocation decisions [2]. The consequence is that meeting rooms, hot-desks, and car-parking spaces—which together represent a substantial share of NHS estate cost and staff experience—are managed through intuition and fragmented booking systems rather than data-driven decision support [3].

This paper responds to these gaps by proposing DSSOU (Decision-Support System for Occupancy and Utilisation), a unified analytical framework designed specifically for NHS non-clinical space management. DSSOU is presented as a design-science artefact in the formal sense established by Hevner et al.'s foundational paper, in which knowledge and understanding of a problem domain are achieved through the building and evaluation of designed artefacts, rather than through the verification of descriptive or predictive theories [4]. The framework is not presented as an empirically validated system: it is a rigorously specified design proposal, with an explicit and falsifiable evaluation protocol, at the appropriate stage of design-science research.

A. Contributions
DSSOU makes four contributions:

• A formal specification of the NHS non-clinical space utilisation problem, including a data model for historical booking records and a characterisation of the four booking-failure modes (underutilisation, overutilisation, redundancy, and booking conflict);

• A component-level architectural specification of a four-part analytical framework combining ARIMA/MSARIMA forecasting, Random Forest/Gradient Boosting prediction, linear programming optimisation, and interactive dashboard visualisation;

• A formal linear programming formulation for bookable-unit allocation that incorporates fairness constraints, utilisation thresholds, and conflict resolution logic;

• A design-science evaluation protocol specifying the datasets, baselines, metrics, and expert-review procedures by which DSSOU's central claims should be tested.

2. RELATED WORK AND POSITIONING

DSSOU draws on and extends a body of literature in which the component methods have been individually validated, while the specific integration targeting NHS non-clinical spaces is novel.

Eyles et al. provide the direct NHS precedent for ARIMA-based demand forecasting, demonstrating the accuracy of MSARIMA for NHS bed-occupancy and admission forecasting [5]. Seo et al.'s Bi-LSTM approach establishes the superior performance of dynamic, contextually-enriched prediction models over static baselines for room-level occupancy [6]. Ordu et al.'s hybrid DES+MILP framework establishes the design pattern of combining stochastic simulation with prescriptive optimisation for NHS resource allocation [7], while Parker et al.'s interactive dashboard demonstrates the feasibility and value of integrating real-time prediction and optimisation within a single administrative interface [8]. Grøntved et al.'s scoping review confirms that no published study has applied an integrated multi-method framework to healthcare capacity in a validated operational deployment [9].

The specific gap DSSOU addresses is: non-clinical NHS bookable-unit management, requiring a framework that combines temporal forecasting, contextual prediction, prescriptive optimisation, and interactive visualisation, applied to NHS booking system data across multiple facility types and sites. No existing published study satisfies all four of these design requirements simultaneously.

DSSOU adopts Linear Programming rather than the DES+MILP approach of Ordu et al. for three reasons: (i) the NHS non-clinical space allocation problem has deterministic rather than stochastic resource quantities (number of meeting rooms, desks, and car-parking spaces are fixed and known); (ii) LP is computationally tractable at the scale of NHS booking data without the simulation overhead DES requires; and (iii) LP models are interpretable by facility managers without operations-research specialist support, consistent with Johnson et al.'s evidence that model transparency is critical for operational adoption [10].

3. THE DSSOU ARCHITECTURE

DSSOU comprises four components, as illustrated in Figure 1, operating over a historical NHS booking dataset spanning 2016–2024.

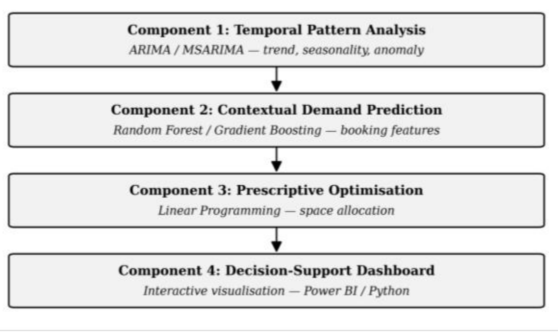

Fig. 1. DSSOU four-component architecture. Historical booking data feeds Components 1 and 2; forecasting and prediction outputs are consumed by Component 3; the optimised allocation plan and analytical outputs are surfaced through Component 4.

A. Data Model and Booking-Failure Taxonomy

DSSOU operates on NHS booking system records. Each record r_i is represented as a tuple:

$$r_i = (u_i,\ b_i,\ s_i,\ e_i,\ c_i,\ t_i,\ \ell_i,\ a_i) \tag{1}$$

where u_i denotes the bookable unit identifier (meeting room, hot-desk, or car-parking space), b_i the booking type (recurring, ad-hoc, or emergency), s_i and e_i the scheduled start and end times, c_i the cancellation flag, t_i the team or organisational unit identifier, ℓ_i the building location code, and a_i the actual check-in timestamp (when available).

Derived utilisation metrics are computed from the record set. For each unit u over period T, the utilisation rate is:

$$\phi_u = \frac{\sum_{i:u_i=u}(e_i - s_i)}{\text{Total available time for } u \text{ in } T} \tag{2}$$

and the no-show rate is:

$$\nu_u = \frac{|\{\,i{:}u_i=u,\ c_i=0,\ a_i=\varnothing\,\}|}{|\{\,i{:}u_i=u\,\}|} \tag{3}$$

DSSOU classifies bookable-unit performance into four failure modes that collectively define the optimisation problem:

- **Underutilisation:** $\phi_u < \phi^{min}$, where ϕ^{min} is a Trust-specified minimum threshold (default 0.40);
- **Overutilisation:** $\phi_u > \phi^{max}$, indicating chronic demand excess over supply (default $\phi^{max} = 0.90$);
- **Redundancy:** $\phi_u < \phi^{red}$ (default 0.10) over a sustained period, signalling decommissioning candidates;
- **Booking conflict:** simultaneous demand exceeding unit supply in a given time slot, leading to denied or displaced bookings.

B. Component 1: Temporal Pattern Analysis

Component 1 applies ARIMA and Multi-Seasonal ARIMA to the aggregate booking demand time-series for each unit type and building, producing three analytical outputs: a decomposition of trend, seasonality, and anomaly components; short-term demand forecasts over a configurable horizon (default 6 weeks, consistent with Eyles et al. [5]); and anomaly alerts for periods where actual bookings deviate significantly from the seasonal pattern.

The MSARIMA specification is:

$$\Phi_P(B^s)\,\phi_p(B)\,\nabla_D^s\nabla^d y_t \;=\; \Theta_Q(B^s)\,\theta_q(B)\,\varepsilon_t \tag{4}$$

where y_t is the booking demand count at time t; $\phi_p(B)$ and $\theta^i(B)$ are non-seasonal AR and MA polynomials of orders p and q; $\Phi_p(B^s)$ and $\Theta^i(B^s)$ are seasonal AR and MA polynomials of orders P and Q at seasonal period s; ∇^d and ∇^{Ds} are non-seasonal and seasonal differencing operators; and ε_t is white noise. For NHS booking data, the primary seasonality is weekly (s = 7) with a secondary annual component (s = 52 on weekly-aggregated data), consistent with the multi-seasonal specification validated by Eyles et al. for NHS demand data [5].

C. Component 2: Contextual *Demand Prediction*

Component 2 trains a supervised prediction model to estimate expected booking counts for each unit, building, and time slot using contextual features that Component 1's time-series specification cannot accommodate. Following the design principles of Seo et al. [6] and Singh et al. [11], two model classes are specified:

- **Random Forest (RF):** an ensemble of T decision trees each trained on a bootstrapped subsample of the training set, with predictions aggregated by majority vote (classification) or mean (regression). RF is robust to outliers, handles mixed-type features natively, and provides feature importances that support interpretability.
- **Gradient Boosting (GB):** a sequential ensemble in which each tree corrects the residuals of its predecessor, typically achieving higher accuracy than RF at the cost of greater sensitivity to

hyperparameter settings. XGBoost or LightGBM implementations are recommended.

The feature vector for each booking record is:

$$\mathbf{x}_i = [\,\text{hour, weekday, month, building, unit type, team, booking type, weather flag, holiday flag}\,] \quad (5)$$

The inclusion of weather and UK public holiday indicators is motivated by both Eyles et al.'s use of annual seasonality [5] and the operational reality that NHS facility usage drops sharply during public holidays and is affected by severe weather disruption. Both contextual factors are available in public data and can be joined to booking records via date key.

D. Component 3: Prescriptive Optimisation

Component 3 formulates space allocation as a linear programme. Let U denote the set of all bookable units, T = {1,...,T} the set of time periods (e.g. daily or hourly slots), G the set of booking groups (teams or organisational units), and $d^g{}_{,t}$ the forecast demand for group g in period t as generated by Components 1 and 2.

Define the binary decision variable $x_{u,}{}^{g}{}_{,t} \in \{0,1\}$ equal to 1 if unit u is allocated to group g in period t, and 0 otherwise. The linear programme is:

$$\min_x \sum_{u\in U} \sum_{t\in T} \sum_{g\in G} c_{u,g} \cdot x_{u,g,t} \;+\; \lambda \cdot \text{slack}_{g,t} \quad (6)$$

subject to:

$$\sum_{g\in G} x_{u,g,t} \le 1 \qquad \forall\, u \in U,\; t \in T \quad (7)$$

$$\sum_{u\in U} x_{u,g,t} \ge d_{g,t} - \text{slack}_{g,t} \qquad \forall\, g, t \quad (8)$$

$$\sum_{t\in T} x_{u,g,t} \ge \phi^{\min} \cdot |T| \qquad \forall\, u \quad (9)$$

$$\sum_{t\in T} x_{u,g,t} \le \phi^{\max} \cdot |T| \qquad \forall\, u \quad (10)$$

$$\frac{\sum_{u,t} x_{u,g,t}}{|G|} \ge \alpha \cdot \max_{g'} \sum_{u,t} x_{u,g',t} \qquad \forall\, g \quad (11)$$

$$x_{u,g,t} \in \{0,1\}, \quad \text{slack}_{g,t} \ge 0 \quad (12)$$

where $c_{u,}{}^{g}$ represents the cost (or inverse preference weight) of assigning unit u to group g; λ is a penalty weight on demand slack (unsatisfied demand); constraint (7) enforces that each unit can be allocated to at most one group per period; constraint (8) ensures demand coverage subject to slack; constraints (9) and (10) enforce minimum and maximum utilisation targets; and constraint (11) is a fairness constraint ensuring that no group receives an allocation more than a factor α^{-1} below the best-served group [12].

The integer constraint on $x_{u,}{}^{g}{}_{,t}$ can be relaxed to a linear programme when unit allocation is fractional (e.g. allocating a proportion of a unit's capacity to a group), or retained as a Mixed Integer Linear Programme (MILP) when whole-unit allocation is required. Python's PuLP or SciPy optimisation libraries provide open-source solvers for both formulations at the scale of NHS booking data.

E. Component 4: Decision-Support Dashboard

Component 4 translates the analytical outputs of Components 1–3 into an interactive management interface following the design principles established by Parker et al. [8] and Johnson et al. [10]. The dashboard comprises five views:

• **Utilisation heatmap:** colour-coded occupancy rates by unit, building, time-of-day, and day-of-week, enabling rapid identification of underutilised or overloaded resources;

• **Demand forecast panel:** rolling MSARIMA and ML forecasts with confidence intervals, selectable by unit type and time horizon;

• **Booking-failure alert panel:** real-time flags for units exceeding or falling below utilisation thresholds, or entering the redundancy range;

• **Optimised allocation plan:** the LP-generated allocation schedule for the upcoming planning period, with drilldown by group, building, and unit type;

• **Scenario simulation:** an interactive interface allowing managers to modify forecast inputs (e.g. assumed demand growth, hybrid working policy changes) and observe the corresponding effect on the LP-optimised allocation, consistent with the scenario-exploration capability identified as central to dashboard adoption by Parker et al. [8].

The dashboard will be developed using Python (Plotly Dash or Streamlit) or Power BI, ensuring compatibility with existing NHS information technology infrastructure.

4. PRAGMATIST RESEARCH PARADIGM AND DESIGN SCIENCE STRATEGY

DSSOU is grounded in two complementary methodological frameworks. First, the pragmatist research paradigm, which prioritises the generation of actionable insight through the most effective combination of methods available, is adopted as the overarching philosophical stance. Pragmatism legitimises the use of both quantitative methods (ARIMA, LP, ML) and qualitative evaluation (stakeholder interviews, expert review) within a single study [4]. Second, Design Science Research (DSR) methodology, as formalised by Hevner et al. [4], provides the research strategy. DSR positions the design and evaluation of practical artefacts as a legitimate and rigorous form of knowledge creation, distinct from but complementary to behavioural-science research that seeks to verify descriptive theories. Under DSR, DSSOU's artefact—the four-component analytical framework—is the primary research output, and the evaluation protocol (Section 6) constitutes the knowledge validation mechanism.

5. ETHICAL CONSIDERATIONS

Research conducted on NHS operational data requires adherence to several mandatory governance obligations that are integral to the DSSOU specification, not peripheral to it.

a) Data protection and anonymisation: All booking records used to train and evaluate DSSOU components must be processed under the UK General Data Protection Regulation (UK GDPR) and the Data Protection Act 2018. Staff identifiers, team names, and building location codes should be pseudonymised before analysis. Access should be restricted to the minimum necessary for the research purpose.

b) Regulatory approvals: A Data Sharing Agreement must be executed with the relevant NHS Trust before data access. Where human participants are involved (e.g. dashboard usability interviews with facility managers), ethical clearance from the University Ethics Committee and, where required, the NHS Health Research Ethics Authority (HRA) must be obtained.

c) Transparency and audit: All model assumptions, hyperparameter choices, and LP formulation parameters should be documented in a reproducible analysis log and made available for independent audit. Dashboard outputs should include confidence intervals and clear indications of prediction uncertainty, ensuring that facility managers can assess reliability as well as recommendation.

6. EVALUATION PROTOCOL

Consistent with design-science research practice [4], DSSOU's evaluation proceeds in four sequential stages, specified here at a level of detail intended to make the protocol directly implementable.

A. Stage 1: Temporal Pattern Analysis Evaluation (Component 1)

Dataset: NHS booking records from 2016–2024 for at least one NHS site with at least three bookable-unit types (meeting rooms, hot-desks, car-parking).

Protocol: Train the MSARIMA model on 2016–2022 data and evaluate on a held-out 2023–2024 test set using a rolling six-week forecast horizon, consistent with Eyles et al.'s methodology [5].

Metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) for booking demand counts. Seasonality decomposition quality assessed via residual autocorrelation function. Baseline: Naïve seasonal baseline (same-week-prior-year demand).

B. Stage 2: Prediction Model Evaluation (Component 2)

Dataset: Same booking records as Stage 1, with contextual features (hour, weekday, month, team, building, holiday flag, weather flag) joined from public UK data sources.

Protocol: Five-fold stratified cross-validation, with stratification on month to ensure all seasonal periods appear in each fold. Random Forest and Gradient Boosting evaluated against MSARIMA baseline.

Metrics: RMSE, MAE, MAPE, and R^2. Feature importance rankings reported to assess which contextual factors drive prediction quality.

C. Stage 3: LP Optimisation Evaluation (Component 3)

Protocol: Apply the LP allocation model to the 2023–2024 test period using forecast demand from Stage 2 as input. Compare the LP-optimised allocation against the actual historical allocation on five criteria: overall utilisation rate, proportion of units below the underutilisation threshold, proportion of booking conflicts resolved, equitable allocation score across groups, and percentage reduction in no-show-related wastage. Metrics: all five criteria above, reported as absolute and relative improvement over the historical baseline.

Validation check: LP feasibility must be verified computationally before any improvement claim is made; infeasibility in any test period must be documented and analysed.

D. Stage 4: Dashboard Expert Evaluation (Component 4)

Protocol: Expert evaluation with a panel of NHS facility managers ($n \geq 6$, purposively sampled across at least two NHS sites) following a structured think-aloud usability protocol. Participants complete five standardised tasks: identifying an underutilised unit; reading a demand forecast; reviewing a booking-conflict alert; interpreting an LP-optimised allocation schedule; and running a scenario simulation.

Metrics: System Usability Scale (SUS) score; task completion rate and time-on-task; qualitative themes from think-aloud coding.

Minimum acceptance threshold: SUS $\geq$ 68 (industry average) to support a usability claim.

7. STATEMENT ON VALIDATION STATUS AND LIMITATIONS

DSSOU has not been implemented or empirically evaluated at the time of writing. The LP formulation in Section 3.D, the MSARIMA specification in Section 3.B, and the feature set in Equation (5) are design specifications grounded in reviewed evidence, not reported results. All claims regarding expected performance are conditional on the evaluation protocol in Section 6 being executed as specified; no performance claim should be read as a finding from this paper.

The principal limitation of the current design is the unresolved question of LP feasibility under real NHS booking data: the constraint system in Equations (7)–(11) may be infeasible under certain combinations of demand-supply imbalance and fairness parameters, and feasibility must be empirically checked before any optimisation result is reported. Additionally, the MSARIMA specification assumes stationarity after seasonal differencing; non-stationarity arising from structural breaks (e.g. COVID-19-era demand collapse) would require model extension or data-period restriction that the current specification does not pre-specify.

8. DISCUSSION: CONTRIBUTION AND GENERALISABILITY

DSSOU makes a three-level contribution. At the domain level, it is the first formally specified analytical framework to address NHS non-clinical space utilisation through a unified forecasting–prediction–optimisation–visualisation pipeline, filling the gap identified in the companion review [1]. At the methodological level, it extends the design-science approach to healthcare operational management, a domain where empirical and simulation studies dominate and design-science artefact papers are uncommon. At the practical level, it provides NHS facility managers with a directly implementable, open-source toolchain (Python, PuLP, Power BI) that does not require commercial licence expenditure.

Generalisability is deliberately bounded. DSSOU is designed for NHS non-clinical space utilisation and may require modification before transfer to other healthcare systems with materially different governance, data infrastructure, or operational norms. The LP formulation's fairness parameter α is Trust-specific and must be calibrated against organisational equity policy rather than assumed. The feature set in Equation (5) is proposed based on theoretical and empirical grounds but must be validated empirically for each deployment context.

9. CONCLUSION

This paper has proposed DSSOU, a design-science framework for NHS non-clinical space utilisation optimisation, comprising temporal pattern analysis, contextual demand prediction, linear programming optimisation, and interactive decision-support dashboard components. The framework is formally specified, grounded in a body of validated component-level precedents, and presented with an explicit evaluation protocol that defines the conditions under which its central claims can be empirically supported. No results are reported; this paper constitutes the design and specification stage of a planned empirical study.

The companion critical review [1] established the gap DSSOU addresses: non-clinical NHS bookable spaces have received no analogous analytical treatment to the rich clinical-space literature, and no published study combines all four methodological components within a single operational framework. DSSOU is designed to close this gap, and the evaluation protocol in Section 6 is designed to generate the evidence necessary to assess whether it does so.

10. REFERENCES

[1] N. P. Onyeka, "Predictive analytics, machine learning, and optimisation for healthcare facility space management: A critical review of methods, evidence gaps, and a research agenda for NHS non-clinical spaces," Companion paper, submitted concurrently, 2025.

[2] NHS Property Services, "Introduction to estate optimisation and space utilisation," https://www.property.nhs.uk/media/bpxhg1tg/introduction-to-estate-optimisation-and-space-utilisation_202425_v4.pdf, 2024, accessed 31 July 2025.

[3] NHS England, "Delivering productivity through the NHS estate," https://www.england.nhs.uk/long-read/delivering-productivity-through-the-nhs-estate/, 2024, accessed 31 July 2025.

[4] A. R. Hevner, S. T. March, J. Park, and S. Ram, "Design science in information systems research," MIS Quarterly, vol. 28, no. 1, pp. 75–105, 2004.

[5] E. Eyles, M. T. Redaniel, T. Jones, M. Prat, and T. Keen, "Can we accurately forecast non-elective bed occupancy and admissions in the NHS? A time-series MSARIMA analysis of longitudinal data from an NHS trust," BMJ Open, vol. 12, no. 4, p. e056523, 2022.

[6] H. Seo, I. Ahn, H. Gwon, H. Kang, Y. Kim, H. Choi, M. Kim, J. Han, G. Kee, S. Park, S. Ko, H. Jung, B. Kim, J. Oh, T. J. Jun, and Y.-H. Kim, "Forecasting hospital room and ward occupancy using static and dynamic information concurrently: Retrospective single-center cohort study," JMIR Medical Informatics, vol. 12, p. e53400, 2024.

[7] M. Ordu, E. Demir, C. Tofallis, and M. M. Gunal, "A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach," Journal of the Operational Research Society, vol. 72, no. 3, pp. 485–500, 2021.

[8] F. Parker, D. A. Martínez, J. Scheulen, and K. Ghobadi, "An interactive decision-support dashboard for optimal hospital capacity management," arXiv preprint arXiv:2403.15634, 2024, available at https://arxiv.org/abs/2403.15634.

[9] S. Grøntved, M. J. Kirkeby, S. P. Johnsen, J. Mainz, J. B. Valentin, and C. M. Jensen, "Towards reliable forecasting of healthcare capacity needs: A scoping review and evidence mapping," International Journal of Medical Informatics, vol. 189, p. 105527, 2024.

[10] M. R. Johnson, H. Naik, W. S. Chan, J. Greiner, M. Michaleski, D. Liu, B. Silvestre, and I. P. McCarthy, "Forecasting ward-level bed requirements to aid pandemic resource planning: Lessons learned and future directions," Health Care Management Science, 2023.

[11] A. Singh, P. E. Farmer, J. L. Tully, R. S. Waterman, and R. A. Gabriel, "Forecasting surgical bed utilization: Architectural design of a machine learning pipeline incorporating predicted length of stay and surgical volume," Journal of Medical Systems, vol. 49, no. 1, p. 67, 2025.

[12] A. Ala, F. E. Alsaadi, M. Ahmadi, and S. Mirjalili, "Optimization of an appointment scheduling problem for healthcare systems based on the quality of fairness service using whale optimization algorithm and NSGA-II," Scientific Reports, vol. 11, p. 9885, 2021.