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Design, Development and Feasibility Evaluation of and Excel and Power BI-Based Workforce Decision-Support Framework for Behavioural Healthcare Staffing

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Abstract: Effective workforce allocation in behavioural healthcare requires the simultaneous consideration of patient acuity, staff competencies, shift coverage, workload variability, operational costs, and regulatory staffing constraints. Conventional spreadsheet-based scheduling and static staffing-ratio approaches frequently lack the analytical flexibility required to accommodate these interdependent factors. This study proposes the design, development, and preliminary feasibility evaluation of an integrated Microsoft Excel and Power BI-based workforce decision-support prototype for behavioural healthcare staffing. The proposed framework incorporates a novel Acuity-Adaptive Multi-Objective Workforce Optimization Algorithm (AAMOWOA), formulated to balance staffing adequacy, skill-mix compatibility, workload equity, overtime expenditure, and operational efficiency through dynamically weighted optimization objectives. The methodological framework adopts a design science research approach involving workforce requirements analysis, mathematical model formulation, iterative prototype development, scenario-based simulation, and structured feasibility assessment. Excel is proposed as the computational environment for workforce data preparation, constraint validation, and optimization, while Power BI will support interactive visualization, staffing-gap detection, scenario comparisons, and managerial interpretation. The proposed AAMOWOA will be benchmarked against Linear Programming (LP), Mixed-Integer Linear Programming (MILP), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) approaches using standardized synthetic behavioural healthcare staffing scenarios. Comparative performance will be examined through staffing coverage rate, patient-acuity alignment, skill-mix compliance, workload imbalance, overtime hours, computational runtime, and solution feasibility. Planned sensitivity analyses will investigate algorithmic responsiveness to changes in patient demand, workforce availability, acuity distributions, and staffing constraints. Comparative line graphs, normalized performance profiles, Pareto-front visualizations, and feasibility matrices will support systematic interpretation of prototype performance. As the framework remains under development, numerical performance improvements and operational effectiveness are treated as hypotheses requiring computational verification rather than established findings. The anticipated contribution is a technically reproducible, transparent, and adaptable decision-support prototype that provides a foundation for subsequent empirical validation and implementation within behavioural healthcare organizations.

Keywords: *Behavioural Healthcare Staffing; Workforce Decision-Support; Microsoft Excel; Power BI; Feasibility Evaluation.*

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I. INTRODUCTION

- *Background of Behavioural Healthcare Workforce Planning and Staffing Decision-Support Systems*

Behavioural healthcare workforce planning represents a multidimensional operational challenge requiring the coordination of clinical competencies, patient safety requirements, fluctuating service demand, and institutional resource limitations. Unlike conventional staffing environments, psychiatric and behavioural healthcare facilities must accommodate unpredictable behavioural escalation, continuous patient observation, therapeutic engagement, and specialized nursing interventions. Frawley and Culhane (2024) emphasized that psychiatric nursing shortages constitute a significant organizational challenge requiring improvements in workforce planning and professional sustainability. Similarly, Gehri et al. (2024) examined nursing care left undone across 114 psychiatric units in Switzerland, identifying associations between insufficient staffing and omitted nursing activities. Their findings highlight the importance of evaluating workforce adequacy beyond numerical staff-to-patient ratios.

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Consequently, effective workforce planning requires analytical mechanisms capable of translating patient-related demand into measurable staffing requirements while incorporating professional competencies, shift availability, workload distribution, and organizational operating conditions.

The proposed research addresses these challenges through the conceptual development of an integrated Excel and Power BI-based workforce decision-support prototype. The framework is intended to combine structured workforce information, patient-acuity classifications, staffing demand calculations, and interactive operational dashboards within an accessible analytical environment. Its computational component will incorporate the proposed Acuity-Adaptive Multi-Objective Workforce Optimization Algorithm (AAMOWOA), designed to evaluate staffing adequacy, workforce utilization, skill compatibility, and scheduling efficiency simultaneously. Consistent with the workforce sustainability concerns identified by Frawley and Culhane (2024), the prototype will incorporate workload equity and overtime exposure as evaluation dimensions. Furthermore, the evidence presented by Gehri et al. (2024) supports incorporating indicators of potential unmet care demand into staffing assessments. At this developmental stage, the proposed framework constitutes a methodological and computational design requiring iterative implementation, scenario-based testing, and subsequent feasibility evaluation rather than an operationally validated staffing system.

- *Patient Acuity, Workforce Availability, Skill-Mix Requirements, and Operational Staffing Constraints*

Patient acuity constitutes a critical determinant of workforce demand because individuals receiving behavioural healthcare exhibit heterogeneous levels of clinical instability, behavioural risk, observation requirements, and therapeutic dependency. Staffing decisions based exclusively on occupied beds may therefore underestimate actual care intensity. Kucera et al. (2023) investigated the implementation of an acuity assessment tool within a psychiatric intensive care unit, demonstrating the practical relevance of moving beyond census-based staffing considerations. Zipp et al. (2024) further examined psychiatric unit-level acuity assessment and identified limitations concerning usability, responsiveness, and the incorporation of changing patient conditions. These findings provide a clinical justification for developing staffing models that accommodate changing acuity classifications and incorporate the availability of appropriately qualified personnel. In the proposed framework, patient demand will be represented using acuity-weighted care-hour requirements, while workforce availability will be determined by scheduled hours, attendance status, contractual limitations, and authorized clinical competencies.

The proposed AAMOWOA will formulate workforce allocation as a constrained multi-objective scheduling problem in which staff assignments must satisfy minimum coverage, competency eligibility, maximum working hours, mandatory rest periods, and patient-specific observation requirements. Acuity weights will be parameterized using clinically reviewed inputs rather than assumed to represent universally validated staffing thresholds. Skill-mix compatibility will distinguish registered psychiatric nurses, licensed practitioners, healthcare assistants, and other eligible support personnel according to their permitted responsibilities. Drawing on the implementation considerations discussed by Kucera et al. (2023), the prototype will include adjustable acuity parameters and staffing configuration controls. Furthermore, the usability limitations identified by Zipp et al. (2024) support the planned development of transparent Excel calculation sheets and Power BI dashboards capable of highlighting staffing deficits and skill mismatches. These functions remain proposed design specifications pending computational verification and clinical review.

- *Limitations of Conventional Staffing Models, Spreadsheet-Based Scheduling, and Existing Workforce Optimization Approaches*

Conventional healthcare staffing methodologies commonly rely on fixed staff-to-patient ratios, historical shift allocations, manual roster preparation, and deterministic workforce assumptions that inadequately represent changing clinical demand. Although spreadsheet-based scheduling offers accessibility and relatively low implementation costs, conventional workbooks frequently lack systematic constraint enforcement, integrated optimization procedures, and mechanisms for evaluating competing staffing objectives. Chen and Zeng (2020) demonstrated the relevance of combining heuristic procedures with metaheuristic search to address hard and soft constraints in nurse rostering problems. Their investigation established that solution quality depends substantially on the construction and refinement of feasible staffing assignments. Similarly, Chen et al. (2023) developed a combined mixed-integer programming and neural network-assisted heuristic approach, demonstrating how computational methods can coordinate mathematical optimization and intelligent search. Nevertheless, adapting these approaches to behavioural healthcare introduces additional requirements concerning rapidly changing patient acuity, specialized professional competencies, continuous observation, and operational risk.

The proposed prototype seeks to investigate these methodological limitations through an acuity-adaptive optimization architecture integrating dynamic clinical demand assessment with workforce scheduling constraints. Unlike manually maintained staffing spreadsheets, the intended Excel computational environment will incorporate structured input validation, assignment eligibility checks, objective-function calculations, and scenario evaluation. The proposed AAMOWOA will investigate whether dynamically adjusted objective priorities can accommodate changing patient-acuity distributions while preserving staffing feasibility and workload equity. Building upon the constraint-management principles examined by Chen and Zeng (2020), the algorithm will distinguish mandatory clinical and contractual requirements from negotiable operational preferences. Furthermore, the hybrid optimization concepts investigated by Chen et al. (2023) provide a methodological basis for benchmarking the proposed algorithm against MILP

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and alternative heuristic procedures. Comparative evaluation will examine feasible solution rates, coverage deficits, computational runtime, and workload inequality. Any relative performance advantages remain unverified until reproducible experimental testing is completed.

➢ *Applications of Microsoft Excel, Power BI, and Multi-Objective Optimization in Healthcare Workforce Management*

Integrating spreadsheet-based computational models with interactive business intelligence platforms presents a practical approach to developing accessible healthcare workforce decision-support systems. Microsoft Excel provides established facilities for structured data entry, relational lookup operations, workforce demand calculations, and mathematical optimization through compatible computational extensions. Power BI complements these capabilities through data transformation, interactive dashboards, multidimensional filtering, and graphical representations of operational performance. Park et al. (2022), in a systematic review of data visualization and decision-making, identified the potential of graphical information presentation to influence comprehension, perceptions, and managerial decisions. Their findings support the development of interpretable analytical interfaces capable of transforming complex workforce information into actionable indicators. Furthermore, Gülmez et al. (2026) investigated multi-objective evolutionary optimization for healthcare personnel scheduling, emphasizing workforce fairness, contractual obligations, and work-life balance alongside organizational requirements. These contributions establish a methodological basis for integrating computational optimization with transparent performance visualization in healthcare staffing applications.

The proposed framework will employ Excel as a structured computational interface for staffing data preparation, acuity-weighted demand estimation, allocation modelling, and candidate schedule evaluation. Power BI will subsequently visualize staffing coverage, skill-mix adequacy, overtime exposure, workforce utilization, and algorithmic trade-offs using standardized analytical measures. The proposed AAMOWOA will incorporate multiple objective functions covering acuity-adjusted staffing demand, operational expenditure, and workload equity. Consistent with Gülmez et al. (2026), alternative nondominated staffing allocations will be considered where operational objectives conflict. The visualization principles discussed by Park et al. (2022) will guide dashboard usability specifications, including consistent metrics, readable comparisons, and transparent reporting. Planned computational assessments will compare AAMOWOA with LP, MILP, GA, and PSO under equivalent problem instances and resource limits. The resulting dashboard architecture and algorithmic components remain under development; consequently, their usability, computational effectiveness, and implementation feasibility require systematic verification.

➢ *Research Problem and Justification for an Acuity-Adaptive Workforce Decision-Support Prototype*

The central research problem concerns the absence of a sufficiently integrated, transparent, and operationally accessible staffing decision-support approach that jointly accommodates behavioural healthcare patient acuity, professional competencies, workforce availability, and competing organizational objectives. Conventional staffing decisions frequently depend on predetermined establishment levels and managerial judgment without consistently incorporating changing clinical workload or systematically comparing alternative allocations. Johnson et al. (2024) examined psychiatric inpatient staffing evidence and cautioned against universally applying individual staffing indicators, emphasizing the importance of evaluating staffing against patient, workforce, and organizational outcomes. Similarly, Woodnutt et al. (2025), in a systematic review of 35 observational studies, identified inconsistent relationships between staffing levels, skill mix, and conflict-related incidents in acute mental healthcare. Their findings demonstrate the need for improved case-mix adjustment, stronger analytical methods, and carefully specified safety indicators. Collectively, these studies establish the justification for investigating an acuity-responsive workforce planning framework while avoiding unsupported assumptions that numerical staffing improvements necessarily produce superior clinical outcomes.

Accordingly, this research proposes the iterative development and feasibility assessment of an Excel and Power BI-based workforce decision-support prototype incorporating the proposed AAMOWOA algorithm. The intended framework will translate acuity classifications into estimated care-hour requirements, apply competency-specific allocation constraints, and generate alternative staffing configurations for managerial evaluation. Consistent with Johnson et al. (2024), the proposed decision-support architecture will accommodate multiple workforce indicators rather than relying exclusively on staffing ratios. The methodological uncertainties identified by Woodnutt et al. (2025) further justify separating computational staffing performance from actual clinical safety outcomes. Proposed benchmark experiments will assess coverage adequacy, skill-mix compliance, workload equity, overtime requirements, and computational efficiency against established optimization algorithms. Technical feasibility will be examined through functional testing, reproducibility, data-processing reliability, and dashboard usability criteria. However, the framework remains a developmental prototype, and claims regarding superiority, organizational effectiveness, or clinical benefits will require subsequent empirical evidence.

➢ *Research Aims, Objectives, Research Questions, and Proposed Performance Hypotheses*

- *Research Aim*

To design, develop, and establish a preliminary feasibility evaluation methodology for an Excel and Power BI-based behavioural healthcare workforce decision-support prototype incorporating the proposed AAMOWOA, with the

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objective of investigating acuity-responsive staffing allocation, skill-mix compliance, workload equity, and computational efficiency through reproducible experimental comparisons.

- *Research Objectives*

✓ To develop a conceptual workforce decision-support architecture integrating Microsoft Excel-based staffing calculations, patient-acuity modelling, workforce availability records, and Power BI visualization components.
✓ To formulate mathematical objective functions and operational constraints representing acuity-adjusted staffing demand, employee competencies, workforce availability, workload distribution, overtime expenditure, and mandatory scheduling requirements.
✓ To design and progressively implement the proposed AAMOWOA algorithm, incorporating dynamic objective weighting and feasibility-preserving workforce allocation procedures.
✓ To establish standardized benchmark experiments comparing AAMOWOA against Linear Programming (LP), Mixed-Integer Linear Programming (MILP), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) methods.
✓ To evaluate preliminary prototype feasibility using synthetic staffing scenarios, computational performance indicators, sensitivity analysis, functional verification, and proposed usability assessment procedures.

- *Research Questions*

✓ How can Microsoft Excel and Power BI be integrated into an accessible, transparent, and technically reproducible workforce decision-support prototype for behavioural healthcare staffing?
✓ How can acuity-weighted demand estimation, professional competency requirements, workforce availability, and scheduling regulations be represented within a unified mathematical optimization model?
✓ To what extent can the proposed AAMOWOA algorithm generate feasible staffing allocations under varying patient-acuity distributions and operational constraints?
✓ How will AAMOWOA compare with LP, MILP, GA, and PSO regarding staffing coverage, acuity alignment, workload equity, overtime requirements, and computational efficiency?
✓ What technical, operational, computational, and usability considerations will determine the preliminary feasibility of the proposed prototype and its suitability for subsequent organizational pilot testing?

- *Proposed Performance Hypotheses*

The following numerical hypotheses are prospective, testable propositions rather than observed research results.

✓ H_1: AAMOWOA will achieve a higher mean acuity-adjusted staffing coverage rate than the specified baseline scheduling approaches under equivalent feasible problem instances.
✓ H_2: AAMOWOA will produce lower workforce workload imbalance, measured through the coefficient of variation of allocated work hours, than GA and PSO across comparable scenarios.
✓ H_3: AAMOWOA will achieve lower mean overtime hours per planning period than at least one baseline algorithm without increasing violations of mandatory staffing constraints.
✓ H_4: AAMOWOA will demonstrate superior multi-objective solution quality, measured using a consistently defined hypervolume indicator, relative to the heuristic benchmarks within identical computational budgets.
✓ H_5: The proposed Excel and Power BI prototype will satisfy predefined functional correctness, data integrity, computational reliability, and usability acceptance criteria during preliminary feasibility testing.

➢ *Scope, Significance, Research Contributions, and Prototype Development Boundaries and Structure of the Paper*

The study focuses on the conceptual design, mathematical formulation, iterative development, and prospective feasibility evaluation of an Excel and Power BI-based workforce decision-support prototype for behavioural healthcare staffing, particularly within inpatient psychiatric units and related structured care environments. Its methodological scope includes patient-acuity classification, workforce demand estimation, employee availability, competency-sensitive scheduling, workload equity, overtime management, and multi-objective workforce allocation. The principal intended contribution is the proposed AAMOWOA algorithm, which will be examined against LP, MILP, GA, and PSO using standardized synthetic datasets, reproducible computational experiments, sensitivity analyses, and comparative graphical evaluations. The research also proposes an integrated analytical architecture connecting structured Excel staffing models with Power BI dashboards to support interpretable workforce decisions. Its significance lies in investigating whether relatively accessible analytical technologies can provide a practical foundation for transparent, acuity-responsive staffing assessments without requiring immediate investment in comprehensive enterprise workforce management systems. The developmental boundaries explicitly exclude claims of completed clinical implementation, proven algorithmic superiority, demonstrated patient-safety improvement, or established organizational effectiveness. Synthetic datasets will support initial technical experimentation, while real clinical records, prospective staffing trials, and implementation outcomes will require separate ethical, governance, and institutional approvals. The paper is organized into five principal sections: Section 1 introduces the research problem, objectives, and justification; Section 2 reviews relevant staffing theories, optimization approaches, and conceptual frameworks; Section 3 describes the system architecture, mathematical formulation, algorithm development, and proposed methodology; Section 4 presents available design outputs and discusses planned computational comparisons and feasibility assessments, distinguishing observations from anticipated results; and Section 5 provides conclusions,

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recommendations, development limitations, and future validation priorities.

II. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

- *Behavioural Healthcare Staffing Models, Patient Acuity Classification, Workforce Demand Forecasting, and Skill-Mix Optimization*

Behavioural healthcare staffing requires analytical coordination between patient acuity, workforce availability, professional competencies, and fluctuating clinical demand. Conventional establishment-based approaches frequently estimate workforce requirements from average occupancy or historical staffing ratios, potentially overlooking differences in observation intensity, behavioural instability, therapeutic dependency, and specialist intervention requirements as represented in figure 1. Griffiths et al. (2020) identified substantial methodological variation in nursing workload measurement and highlighted limitations associated with translating workload indicators into reliable staffing decisions. Saville et al. (2021) further demonstrated through simulation that planning around average demand can create operational consequences when staffing requirements fluctuate. Complementing these findings, Frank (2026a) emphasized standardized healthcare quality measurement, risk adjustment, and performance monitoring, while Frank (2026b) discussed predictive resource allocation within healthcare inventory systems. Although inventory optimization differs from workforce scheduling, its demand-responsive resource planning principles provide a transferable conceptual foundation for anticipating staffing requirements and evaluating resource constraints.

The proposed prototype will incorporate an acuity-weighted workforce demand model that estimates required clinical care hours from patient classifications, observation intensity, and predefined competency requirements. Workforce availability will be represented through shift eligibility, contracted hours, planned absences, and professional qualifications. Consistent with Griffiths et al. (2020), the model will distinguish workload measurement from staffing allocation decisions, thereby allowing clinical managers to review underlying assumptions. The demand variability investigated by Saville et al. (2021) will inform planned low-, moderate-, and high-acuity simulation scenarios. Drawing on the performance-monitoring principles discussed by Frank (2026a), the proposed Excel–Power BI interface will report staffing coverage, competency compliance, and workload distribution. The forecasting perspective of Frank (2026b) will inform scenario-based resource planning without assuming that inventory prediction models directly predict clinical demand. These components remain under development and require parameter calibration, computational verification, and subsequent clinical assessment.



Fig 1 Conceptual Framework for Machine Learning-Based Behavioural Healthcare Workforce Planning, Patient Acuity Assessment, Forecasting, and Skill-Mix Optimization (Turley, J. 2026).

Figure 1 illustrates the integration of machine learning, predictive workforce analytics, and data-driven staffing management within a hospital environment, providing a conceptual representation of the proposed Excel and Power BI-based behavioural healthcare workforce decision-support framework. Healthcare professionals are depicted reviewing staffing analytics displayed on a laptop, including workforce demand trends, staffing distributions, and graphical performance indicators. Within the context of behavioural healthcare, the displayed analytical interface represents a proposed mechanism for integrating patient-acuity classifications, workforce availability, clinical competency requirements, and shift-specific staffing demands. Patient acuity can be categorized according to psychiatric symptom severity, behavioural instability, self-harm risk, observation frequency, therapeutic intervention intensity, and dependency on specialized nursing care. These classifications inform an acuity-weighted demand function that estimates required clinical care hours for each unit and shift. Predictive analytics can subsequently examine historical occupancy, patient admission patterns, acuity fluctuations, and anticipated employee absenteeism to estimate future staffing requirements. The proposed Acuity-Adaptive Multi-Objective Workforce Optimization Algorithm (AAMOWOA) would translate these requirements into competency-constrained workforce allocation decisions while simultaneously addressing staffing coverage, skill-mix compliance, workload equity, overtime expenditure, and

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operational efficiency. The line graphs conceptually represent projected staffing demand and workforce capacity fluctuations, while the bar and pie charts illustrate potential comparisons of staffing allocations and professional skill distributions. Microsoft Excel would support structured data processing, mathematical calculations, and optimization, whereas Power BI would provide interactive visualization and comparative scenario analysis. Importantly, the image represents a conceptual demonstration of the intended decision-support workflow rather than evidence of an operationally validated system. The proposed framework remains under development, with predictive accuracy, allocation feasibility, algorithmic performance, and organizational suitability requiring subsequent computational testing and clinical evaluation.

- *Mathematical Optimization Approaches for Healthcare Staff Scheduling: Linear Programming, Mixed-Integer Linear Programming, Genetic Algorithms, and Particle Swarm Optimization*

Healthcare workforce scheduling is commonly formulated as a constrained optimization problem involving shift coverage, employee availability, qualification requirements, working-hour limitations, and competing operational objectives. Linear Programming (LP) provides a computationally efficient formulation when allocation variables can remain continuous, whereas Mixed-Integer Linear Programming (MILP) accommodates binary scheduling decisions and discrete employee assignments. Burke et al. (2004) systematically examined mathematical programming, artificial intelligence, and heuristic approaches to nurse rostering, emphasizing the importance of satisfying hard constraints while balancing workforce preferences as shown in table 1. Van den Bergh et al. (2013) subsequently classified personnel scheduling methods and discussed the operational conditions influencing algorithm selection. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) provide alternative population-based search mechanisms for complex scheduling landscapes, although their feasibility handling and computational performance depend on problem representation. In related computational domains, Folorunso et al. (2025) examined ensemble-based predictive modelling, while Idowu et al. (2025) discussed artificial intelligence integration into risk management systems, supporting the broader methodological importance of hybrid analytical architectures.

Building on these foundations, the proposed AAMOWOA will investigate a constrained optimization strategy combining acuity-sensitive objective weighting, competency-aware assignment encoding, and feasibility-preserving search operations (Bamidele, et al., 2025. LP will serve as a continuous allocation benchmark, while MILP will provide a discrete optimization reference for tractable instances. GA and PSO will represent established heuristic comparison methods. Following the methodological distinctions outlined by Burke et al. (2004) and Van den Bergh et al. (2013), identical staffing instances, operational constraints, and computational budgets will be specified for comparative evaluation. The model integration concepts discussed by Folorunso et al. (2025) and Idowu et al. (2025) will inform modular computational design rather than serve as evidence of scheduling effectiveness. Planned experiments will measure feasible solution rates, acuity-adjusted coverage, overtime expenditure, and runtime. The proposed algorithm has not yet demonstrated superiority over these benchmarks.

Table 1 Comparative Summary of Mathematical Optimization Approaches for Healthcare Staff Scheduling and Workforce Allocation

Optimization Approach	Mathematical and Computational Principles	Application to Behavioural Healthcare Staffing	Strengths and Limitations
Linear Programming (LP)	Optimizes a linear objective function subject to linear equality and inequality constraints using continuous decision variables.	Estimates workforce requirements, minimizes staffing costs, and allocates available clinical care hours across shifts and units.	Computationally efficient and transparent; however, continuous solutions may require conversion into feasible individual staff assignments.
Mixed-Integer Linear Programming (MILP)	Extends LP through binary and integer decision variables, enabling discrete staffing assignments and mandatory scheduling constraints.	Assigns qualified psychiatric nurses and support personnel while enforcing shift coverage, skill-mix requirements, working-hour limits, and competency restrictions.	Produces mathematically optimal solutions when solved to proven optimality, but computational complexity can increase substantially with problem size.
Genetic Algorithm (GA)	Employs population-based evolutionary search involving selection, crossover, mutation, and fitness evaluation to identify high-quality solutions.	Explores alternative staffing schedules while balancing patient-acuity coverage, workload equity, employee preferences, and overtime expenditure.	Flexible for complex multi-objective scheduling; however, solution quality depends on parameter tuning, constraint handling, and stochastic variability.
Particle Swarm Optimization (PSO)	Uses coordinated particle movements, individual best solutions, and population-wide information exchange to explore optimization spaces.	Investigates alternative workforce allocations and staffing configurations under varying patient demand, staff availability, and operational conditions.	Supports flexible heuristic search but requires discrete scheduling adaptations and may experience premature convergence or infeasible solutions.

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- *Multi-Objective Workforce Optimization, Dynamic Priority Weighting, Fairness Constraints, and Computational Decision-Support Techniques*

Multi-objective workforce optimization addresses the competing requirements of clinical coverage, operational expenditure, equitable workload distribution, professional competency compatibility, and employee welfare. These objectives cannot always be optimized independently because increasing workforce coverage may increase expenditure, while restricting overtime may reduce scheduling flexibility. Griffiths et al. (2021) examined flexible staffing alternatives through simulation and economic modelling, illustrating the importance of evaluating resilience and cost-effectiveness jointly. Komarudin et al. (2013) demonstrated the relationship between personnel structure and achievable roster quality, establishing that workforce composition influences scheduling feasibility. In a different healthcare optimization context, Ifiala et al. (2026) proposed constrained multi-objective learning to address competing fairness and performance considerations in clinical trial representation. Folorunso et al. (2026) similarly integrated multiple analytical dimensions into a business intelligence framework for risk prioritization. Although these latter approaches address different decision problems, their principles of constraint management, transparent priority assessment, and composite decision evaluation provide transferable methodological insights.

The proposed AAMOWOA will incorporate dynamically weighted objective functions reflecting acuity-adjusted staffing deficits, overtime costs, workload imbalance, and soft scheduling preferences. Mandatory competency, coverage, and employment constraints will remain non-negotiable, preventing dynamic weighting from permitting clinically unacceptable assignments. Building on Griffiths et al. (2021), the prototype will assess cost–coverage trade-offs under variable staffing demand. The personnel-structure considerations of Komarudin et al. (2013) will inform skill-mix eligibility modelling, while the fairness principles explored by Ifiala et al. (2026) will guide workload-equity indicators without equating staffing fairness with demographic parity. Furthermore, Folorunso et al. (2026) provide a conceptual basis for communicating composite risk and priority scores through analytical dashboards. Planned Pareto-front analyses, normalized objective comparisons, and sensitivity experiments will examine potential trade-offs. Algorithmic benefits and fairness improvements remain hypotheses requiring reproducible evaluation.

- *Microsoft Excel-Based Workforce Modelling, Power BI Analytics, Dashboard Integration, and Healthcare Decision-Support Architecture*

Microsoft Excel and Power BI offer complementary analytical capabilities for developing transparent workforce decision-support prototypes without immediately deploying complex enterprise software infrastructure. Excel supports structured workforce datasets, formula-driven calculations, validation rules, and integration with optimization procedures, whereas Power BI provides interactive filtering, dimensional modelling, and comparative performance visualization as shown in figure 2. Dowding et al. (2015) reviewed healthcare dashboard applications and identified their potential to improve information accessibility and support clinical decisions, while emphasizing limitations in evaluating their actual effects. Griffiths et al. (2020) examined a standardized nursing staffing measurement tool, demonstrating the importance of systematically translating patient-related workload information into workforce estimates. In another operational sector, Jalloh et al. (2026) proposed Power BI and SQL-based analytics for monitoring project performance and executive decisions, illustrating transferable principles of data integration and dashboard design. Frimpong et al. (2024) examined privacy-preserving healthcare data integration, providing additional considerations for protecting sensitive clinical information within analytical systems.

The proposed decision-support architecture will organize workforce information into interconnected Excel modules for employee records, shift availability, patient-acuity classifications, staffing requirements, and optimization outputs. AAMOWOA will operate through a defined computational interface, with results exported into standardized tables for Power BI visualization. Drawing on Dowding et al. (2015), dashboard specifications will prioritize interpretability, consistent indicators, and meaningful comparisons. The staffing measurement principles examined by Griffiths et al. (2020) will guide coverage calculations, while Jalloh et al. (2026) will inform data-refresh and managerial reporting workflows. Frimpong et al. (2024) additionally support incorporating role-based access, data minimization, and privacy controls. Initial experimentation will use synthetic records. The proposed architecture remains subject to development, data-integrity verification, interoperability testing, and formal usability assessment before implementation with identifiable clinical information.

Figure 2 illustrates the proposed integration of Microsoft Excel-based workforce modelling, Power BI analytics, and healthcare decision-support systems within a collaborative behavioural healthcare environment. It depicts a multidisciplinary team of healthcare professionals, including physicians, nurses, and administrators, examining graphical workforce indicators displayed on a digital dashboard to support evidence-informed staffing decisions. Within the proposed framework, Microsoft Excel serves as the primary computational platform for organizing patient-acuity classifications, employee competency profiles, shift availability, contracted working hours, and workforce demand estimates. These inputs are intended to support the proposed Acuity-Adaptive Multi-Objective Workforce Optimization Algorithm (AAMOWOA), which will evaluate alternative staffing configurations while considering clinical coverage, skill-mix compliance, workload equity, overtime expenditure, and operational constraints. The digital dashboard represents the intended Power BI visualization interface, displaying workforce demand trends through line graphs, staffing distributions through bar charts, and resource allocation patterns through circular charts. Such visualizations would enable healthcare managers to identify

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potential staffing shortages, compare alternative scheduling scenarios, assess workforce utilization, and examine the implications of changing patient-acuity levels. The interaction among healthcare professionals emphasizes the importance of combining computational recommendations with clinical expertise and managerial judgment, particularly when addressing psychiatric observation requirements, specialized nursing competencies, and unpredictable behavioural healthcare demands. The proposed architecture will also incorporate data validation, automated performance calculations, and comparative algorithmic assessments to support transparency and reproducibility. However, the image represents the conceptual functionality of a prototype under development, rather than an implemented or clinically validated system. Its anticipated analytical capabilities, usability, computational performance, and organizational feasibility will require systematic testing before operational deployment.



Fig 2 Conceptual Integration of Excel-Based Workforce Modelling, Power BI Analytics, and Decision-Support Systems in Behavioural Healthcare Staffing.

- *Design Science Research, Prototype Development Methodologies, Computational Benchmarking, and Technical Feasibility Evaluation*

Design Science Research (DSR) provides a systematic methodological foundation for developing and evaluating computational artefacts intended to address identifiable organizational problems. Hevner et al. (2004) established that design-oriented information systems research should integrate practical relevance, methodological rigor, artefact construction, and demonstrable evaluation as represented in figure 3. Peffers et al. (2007) subsequently proposed a structured design science methodology incorporating problem identification, solution objectives, design and development, demonstration, evaluation, and communication. These principles are particularly relevant to a behavioural healthcare workforce prototype requiring iterative refinement before operational adoption. Dada and Abutu (2022) proposed a multidimensional readiness framework for clinical artificial intelligence applications, emphasizing risk visibility, documentation continuity, and organizational preparedness. Although focused on cybersecurity workforce development, Odozor et al. (2025) discussed competency development and practical training, providing transferable considerations for assessing staff readiness to adopt technology-supported decision processes. Collectively, these contributions support evaluating not only computational functionality but also the institutional conditions required for responsible implementation.

The proposed study will adopt an iterative DSR methodology comprising requirements specification, conceptual architecture development, mathematical modelling, algorithm implementation, dashboard construction, and preliminary feasibility assessment. Following Hevner et al. (2004), artefact evaluation will address both technical performance and practical relevance. The sequential methodological structure described by Peffers et al. (2007) will guide development documentation and testing milestones. Readiness dimensions adapted from Dada and Abutu (2022) will inform proposed assessments of data governance, system reliability, and operational suitability. Similarly, Odozor et al. (2025) will inform stakeholder training considerations. Computational benchmarking will compare AAMOWOA against LP, MILP, GA, and PSO through controlled synthetic scenarios, using repeated trials, normalized performance measures, and appropriately

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selected statistical procedures. However, prototype feasibility will remain preliminary until functional tests, usability assessments, and documented stakeholder evaluations have been undertaken.

Figure 3 illustrates a three-branch Design Science Research (DSR) framework integrating prototype development, computational benchmarking, and technical feasibility evaluation for the proposed Excel and Power BI-based behavioural healthcare workforce decision-support system. The first branch, Design Science Research and Prototype Development, outlines the systematic identification of workforce planning challenges, specification of functional requirements, conceptual system architecture, and iterative development of the proposed Acuity-Adaptive Multi-Objective Workforce Optimization Algorithm (AAMOWOA). This stage establishes the methodological foundation for integrating patient-acuity assessment, workforce availability, professional competency requirements, and staffing allocation constraints into an accessible computational environment. The second branch, Computational Benchmarking and Algorithmic Evaluation, describes the planned generation of synthetic workforce datasets and comparative assessment of AAMOWOA against Linear Programming (LP), Mixed-Integer Linear Programming (MILP), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). Performance evaluation will examine staffing coverage, acuity alignment, skill-mix compliance, workload equity, overtime expenditure, computational runtime, and Pareto-front solution quality under varying operational scenarios. The third branch, Technical Feasibility and Operational Readiness Evaluation, addresses system functionality, data integrity, computational reliability, Excel–Power BI interoperability, dashboard usability, clinical staffing constraints, and organizational implementation requirements. The feedback relationship connecting feasibility assessment to prototype development represents an iterative refinement mechanism through which identified limitations will inform subsequent design modifications. Collectively, the framework establishes a structured methodology for progressively developing and evaluating the proposed decision-support prototype without presuming completed implementation, demonstrated algorithmic superiority, or validated clinical outcomes.

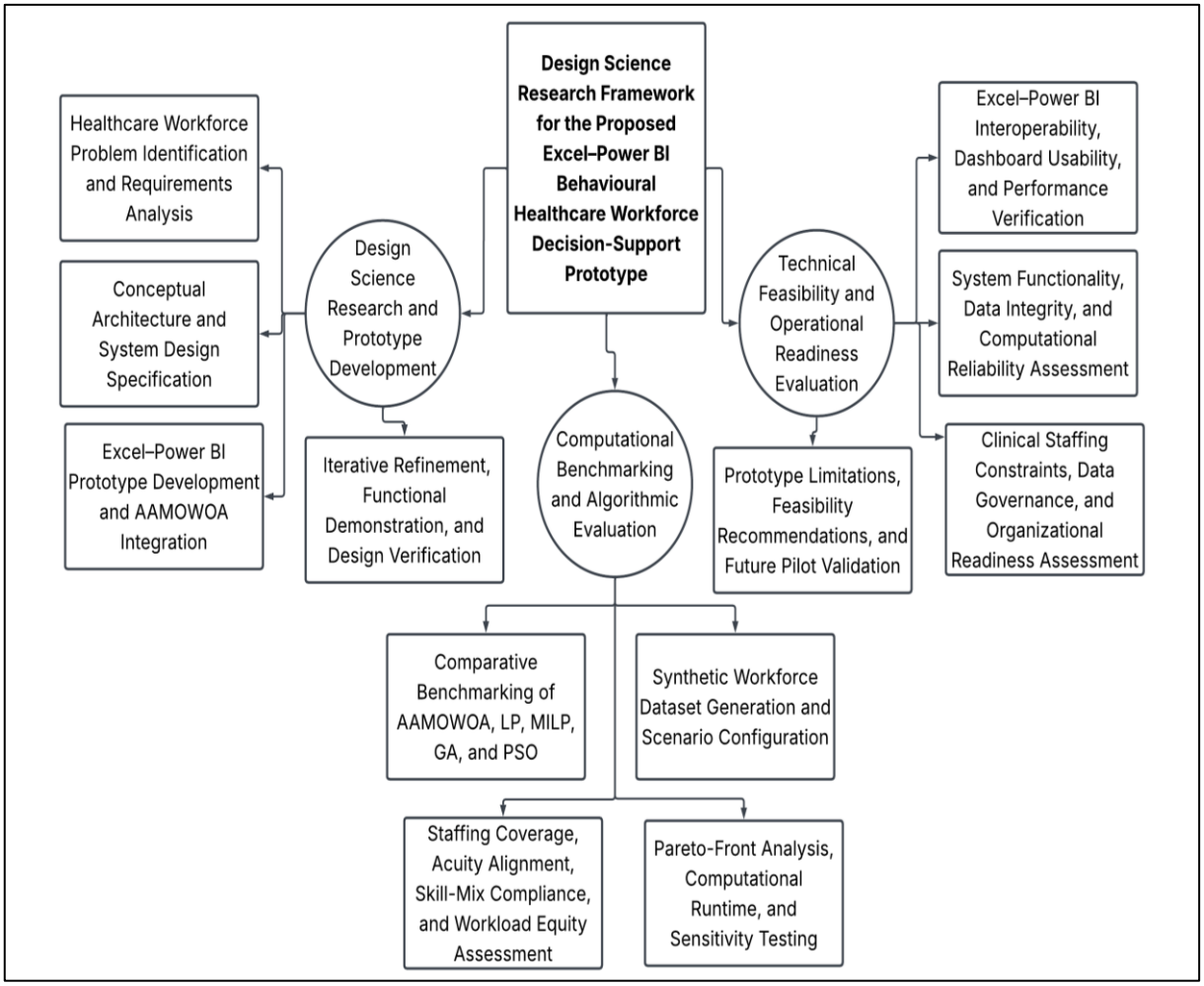

Fig 3 Conceptual Design Science Research Framework for Workforce Decision-Support Prototype Development, Computational Benchmarking, and Technical Feasibility Evaluation.

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- *Research Gaps and Conceptual Development of the Proposed Acuity-Adaptive Multi-Objective Workforce Optimization Framework*

Existing healthcare workforce optimization research establishes mathematical approaches for personnel scheduling but leaves important methodological questions concerning acuity-responsive allocation, algorithmic transparency, and accessible decision-support implementation. De Causmaecker and Vanden Berghe (2011) categorized nurse rostering problems according to scheduling characteristics and constraints, demonstrating the diversity of computational formulations required across healthcare environments. Saville et al. (2019) reviewed operational research techniques for determining nurse staffing requirements and highlighted the importance of connecting quantitative workforce models with service demand and implementation conditions. Related analytical studies, including Idowu et al. (2026) on real-time cybersecurity threat detection and Frank (2026c) on artificial intelligence-supported infection surveillance, illustrate the broader importance of responsive monitoring in changing operational environments. However, neither domain directly establishes the effectiveness of adaptive behavioural healthcare staffing algorithms (Akinleye, & Ijiga, 2025). An important research opportunity therefore concerns investigating whether dynamically adjusted staffing priorities can be combined with competency-sensitive allocation, workforce equity, computational benchmarking, and transparent decision visualization within a unified prototype.

The proposed AAMOWOA framework will address this research opportunity through an acuity-responsive multi-objective optimization model integrating staffing demand, employee eligibility, operational restrictions, workload equity, and overtime considerations. Following the scheduling taxonomy of De Causmaecker and Vanden Berghe (2011), the framework will explicitly distinguish hard feasibility constraints from optimizable preferences. The operational research considerations discussed by Saville et al. (2019) will inform demand estimation and comparative evaluation procedures. The monitoring concepts associated with Idowu et al. (2026) and Frank (2026c) will provide limited cross-domain inspiration for scenario-triggered recalculation and early-warning indicators, rather than direct evidence of staffing performance. The proposed Excel and Power BI architecture will communicate alternative allocations, staffing deficits, and optimization trade-offs through interpretable dashboards. Planned experiments will investigate feasibility, robustness, computational efficiency, and comparative solution quality (Ogundola, 2024; Ogundola, 2026). The framework's novelty, technical effectiveness, and practical suitability remain subject to systematic verification, preserving its status as a prototype in progress.

III. SYSTEM MODEL DESCRIPTION AND METHODOLOGY

The proposed methodology adopts a Design Science Research (DSR) approach to guide the development of the Excel–Power BI workforce decision-support prototype and its Acuity-Adaptive Multi-Objective Workforce Optimization Algorithm (AAMOWOA). The mathematical framework integrates patient-acuity demand estimation, competency-constrained staff allocation, workload equity, overtime minimization, and operational feasibility. All computational experiments, comparative performance measures, and validation procedures described in this section constitute proposed development and evaluation activities rather than completed experimental findings.

- *Design Science Research Architecture, Prototype Development Stages, Synthetic Workforce Dataset Construction, and System Requirements Specification*

The proposed prototype will follow an iterative DSR architecture encompassing problem identification, requirements specification, mathematical modelling, computational development, demonstration, and feasibility evaluation. Hevner et al. (2004) established DSR as an appropriate methodology for constructing and systematically evaluating information-system artefacts. Accordingly, development will proceed through five interconnected stages: clinical workforce requirements assessment, synthetic dataset generation, Excel-based optimization modelling, Power BI dashboard integration, and preliminary prototype verification. The architecture will separate data acquisition, computational processing, optimization, and visualization layers to improve traceability and maintainability. Synthetic records will represent employee qualifications, shift availability, contracted working hours, hourly costs, patient-acuity categories, and observation requirements. A provisional experimental configuration will comprise 120 employees, four behavioural healthcare units, three daily shifts, and a 28-day scheduling horizon. These quantities are proposed simulation parameters rather than observed organizational characteristics.

Synthetic workforce demand will be generated using a bounded stochastic formulation:

$$N_{ut}^{(s)} = \max\left\{0, \text{round}\left[\mu_{ut}(1+\delta_s) + \varepsilon_{ut}^{(s)}\right]\right\} \quad (1)$$

Where $N_{ut}^{(s)}$ represents the simulated patient census in unit u, shift t, and scenario s; μ_{ut} denotes baseline expected occupancy; δ_s represents scenario-specific proportional demand variation; and $\varepsilon_{ut}^{(s)}$ captures a stochastic disturbance generated from a documented, reproducible distribution. The rounding operator produces integer patient counts, while the maximum operator prevents negative occupancy. Generated values will also be checked against predefined unit-capacity limits.

Workforce availability will be modelled as:

$$A_{it}^{(s)} = B_{it}\left(1 - L_{it}^{(s)}\right), \qquad A_{it}^{(s)} \in \{0,1\} \quad (2)$$

Where $A_{it}^{(s)}$ indicates whether employee i is available for shift t under scenario s; B_{it} represents baseline contractual availability; and $L_{it}^{(s)}$ shows a binary indicator of simulated absence.

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System requirements will specify validated inputs, reproducible calculations, secure data handling, auditable optimization outputs, and interpretable dashboard indicators. Initial testing will use synthetic records exclusively, thereby avoiding the need to process identifiable clinical information during preliminary prototype development.

- *Mathematical Formulation of the Behavioural Healthcare Staffing Problem, Patient-Acuity Demand Functions, Workforce Allocation Variables, Multi-Objective Optimization Functions, and Operational Constraints*

The behavioural healthcare staffing problem will be represented as a constrained multi-objective integer optimization model. Let $i \in I$, $u \in U$, $t \in T$, and $k \in K$ denote employees, clinical units, shifts, and acuity categories, respectively. Patient demand will depend on the number of patients, clinically specified care-hour coefficients, and shift duration. The acuity-adjusted workforce demand function is defined as:

$$D_{ut} = \sum_{k \in K} N_{utk}\, h_k \tag{3}$$

Where D_{ut} shows the required clinical care hours for unit u during shift t; N_{utk} represents the number of patients in acuity category k; and h_k denotes the required direct-care hours per patient for that shift. These coefficients will require clinical justification before operational use.

The employee allocation variable is:

$$x_{iut} = \begin{cases} 1, & \text{if employee } i \text{ is assigned to unit } u \text{ in shift } t \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The model will minimize four measurable objectives: uncovered acuity-adjusted demand, overtime expenditure, workload inequality, and soft preference violations. The integrated objective function is:

$$\min F(\mathbf{x}) = \sum_{j=1}^{4} w_j \hat{f}_j(\mathbf{x}), \qquad \sum_{j=1}^{4} w_j = 1, \quad w_j \geq 0 \tag{5}$$

Where $\mathbf{x}$ represents the complete staffing allocation; $\hat{f}_j$ denotes the normalized value of objective j; and w_j shows its nonnegative priority weight. All objectives will be minimized, and normalization parameters will be established from predefined reference bounds rather than adjusted independently for each algorithm.

Mandatory operational constraints include:

$$\sum_{u \in U} x_{iut} \leq A_{it}, \qquad x_{iut} \leq q_{iu} \tag{6}$$

$$\sum_{i \in I} d_t\, x_{iut} + z_{ut} \geq D_{ut}, \qquad z_{ut} \geq 0 \tag{7}$$

Here, q_{iu} shows a binary competency-eligibility indicator; d_t captures shift duration; and z_{ut} represents uncovered care hours, penalized in the optimization objective. Equation (6) prevents simultaneous assignment to multiple units and excludes unqualified employees. Equation (7) quantifies coverage deficits rather than concealing infeasibility. Additional constraints will regulate mandatory observation coverage, skill-specific staffing minima, rest periods, contracted hours, and overtime limits. These distinctions are consistent with established nurse-rostering formulations (Burke et al., 2004).

- *Development of the Proposed Acuity-Adaptive Multi-Objective Workforce Optimization Algorithm (AAMOWOA), Excel Computational Modules, and Power BI Decision-Support Dashboard*

AAMOWOA is proposed as an acuity-responsive optimization procedure incorporating adaptive objective weighting, feasibility-preserving assignment operations, and multi-objective solution refinement. Its intended innovation concerns the integration of changing acuity demand with explicitly controlled staffing constraints and transparent workforce decision-support outputs. The proposed algorithm will initially construct feasible schedules using competency-aware assignment rules, followed by neighborhood-based reassignment, employee exchange, and shift substitution. Candidate schedules will subsequently be evaluated through normalized multi-objective fitness functions. To avoid falsely asserting clinical effectiveness, adaptive weights will be treated as configurable research parameters requiring sensitivity analysis and prospective validation.

The proposed acuity-responsive priority adjustment is expressed as:

$$w_j^{(r+1)} = \frac{w_j^{(r)} \exp\left(\eta g_j^{(r)}\right)}{\sum_{\ell=1}^{4} w_\ell^{(r)} \exp\left(\eta g_\ell^{(r)}\right)} \tag{8}$$

Where $w_j^{(r)}$ denotes the priority weight of objective j at iteration r; η captures the learning-rate parameter; and $g_j^{(r)}$ represents the normalized priority-adjustment signal. The staffing-coverage signal will reflect changes in acuity-adjusted unmet demand, while other signals will represent overtime, workload inequity, and preference violations. All signals will be bounded to prevent unstable weighting.

The proposed staffing coverage indicator is:

$$SCR = 100\left(1 - \frac{\sum_{u,t} z_{ut}}{\sum_{u,t} D_{ut}}\right)\% \tag{9}$$

Where SCR represents staffing coverage rate, z_{ut} denotes uncovered clinical care hours, and D_{ut} represents total acuity-adjusted care demand. The indicator is defined when total demand is positive and will be bounded within 0–100% for feasible nonnegative allocations.

Workload equity will be evaluated using:

$$CV_H = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(H_i - \overline{H}\right)^2}}{\overline{H}} \tag{10}$$

Where CV_H represents the coefficient of variation of employee workload; H_i denotes employee i's assigned working hours; $\overline{H}$ shows mean assigned working hours; and n captures the number of eligible employees included in the

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comparison. The measure requires a positive mean workload and will be stratified by comparable employment arrangements.

The Excel prototype will contain structured data-entry sheets, acuity calculations, eligibility matrices, constraint-validation tables, and optimization-result exports. The optimization engine may be implemented through a compatible Python interface if native spreadsheet computational capacity proves insufficient. Power BI will provide staffing-gap dashboards, overtime comparisons, workload distribution profiles, and scenario filters. Prototype integration and functional verification remain planned development activities.

- *Proposed Experimental Design, Algorithm Benchmarking Protocol, Simulation Scenarios, Performance Evaluation Metrics, Sensitivity Analysis, and Prototype Feasibility Assessment*

The proposed experimental protocol will compare AAMOWOA with LP, MILP, GA, and PSO using identical synthetic staffing instances and predefined evaluation criteria. Experimental scenarios will incorporate variations in patient census, acuity distributions, employee absence, skill-mix availability, and overtime restrictions. Each algorithm will receive consistent demand parameters, competency matrices, operating constraints, and computational resource limits. LP will provide a continuous relaxation benchmark, whereas MILP will represent discrete allocation optimization. GA and PSO will serve as stochastic search comparators. Multiple seeded computational runs will support reproducibility, and paired statistical comparisons will be conducted only after sufficient experimental observations become available.

Overtime expenditure will be estimated as:

$$C_{OT} = \sum_{i \in I} c_i^{OT} \max(0, H_i - H_i^C) \quad (11)$$

Where C_{OT} denotes total overtime expenditure; c_i^{OT} represents the applicable overtime cost per hour; H_i captures allocated working time; and H_i^C describes employee i's contractual working-hour threshold. The model will separately enforce legally and contractually applicable maximum working hours.

Algorithmic runtime will be measured by:

$$\overline{T}_a = \frac{1}{R} \sum_{r=1}^{R} T_{ar} \quad (12)$$

Where $\overline{T}_a$ represents the mean computational runtime of algorithm a; T_{ar} shows the elapsed execution time in replicate r; and R denotes the total number of experimental replicates.

Sensitivity to changing workforce conditions will be evaluated through:

$$S_{m,p} = \frac{\Delta m / m_0}{\Delta p / p_0} \quad (13)$$

Where $S_{m,p}$ shows the dimensionless sensitivity of performance metric m to input parameter p; m_0 and p_0 represent baseline values; and Δm and Δp represent changes relative to baseline. This finite-difference measure will only be used where the baseline values are nonzero.

The evaluation will examine staffing coverage, acuity alignment, skill-mix compliance, workload inequality, overtime cost, computational runtime, and feasible solution frequency. Multi-objective performance will additionally be assessed through Pareto-front dominance and hypervolume indicators. Proposed visualizations include comparative line graphs, Pareto scatter plots, sensitivity heatmaps, and dashboard screenshots. Preliminary feasibility assessment will address computational reliability, data integrity, user-interface usability, software interoperability, and implementation requirements. Statistical superiority and operational viability will not be claimed before experimental verification.

- *Proposed Experimental Configuration*

The following parameters establish a reproducible starting point for prototype testing. They are not observed results.

Table 2 Proposed Experimental Configuration

Experimental parameter	Proposed specification
Healthcare units	4 psychiatric or behavioural healthcare units
Synthetic workforce	120 employees
Scheduling horizon	28 days
Daily shifts	3
Acuity classifications	4 levels
Optimization algorithms	LP, MILP, GA, PSO, AAMOWOA
Stochastic replicates	30 per scenario and stochastic algorithm
Demand variation	−20%, baseline, +20%
Simulated absenteeism	0%, 10%, 20%
Computational evaluation	Coverage, acuity alignment, equity, overtime, runtime, feasibility
Planned visualization	Comparative lines, Pareto fronts, heatmaps, dashboard profiles

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These scenario values will be finalized before benchmarking. AAMOWOA will be evaluated against established approaches using equivalent input conditions, while recognizing that a continuous LP relaxation is not directly equivalent to discrete feasible staff scheduling.

IV. DISCUSSION OF RESULTS

- *Proposed Prototype Architecture, Excel-Based Workforce Optimization Outputs, Power BI Dashboard Visualizations, and Functional Verification Criteria*

The proposed workforce decision-support prototype integrates Excel-based data processing, acuity-adjusted staffing calculations, and Power BI visualization within a modular optimization architecture. Five algorithms, Linear Programming (LP), Mixed-Integer Linear Programming (MILP), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and the proposed AAMOWOA, are designated for comparative evaluation. Table 3 presents illustrative performance targets for preliminary prototype development. AAMOWOA is assigned a baseline staffing coverage of 98%, compared with 96% for MILP and 93% for LP. Under a 40% demand increase, the illustrative AAMOWOA coverage is 93%, with 92% acuity alignment. The intended dashboard will display algorithm selection, coverage deficits, acuity alignment, workforce utilization, and constraint violations. Functional verification will examine input validation, calculation consistency, competency eligibility, optimization reproducibility, and dashboard synchronization. These specifications establish prospective evaluation criteria rather than completed system performance measurements.

Table 3 Illustrative Comparative Staffing Coverage and Acuity Alignment for the Proposed Workforce Decision-Support Prototype

Algorithm	Baseline staffing coverage (%)	Coverage at +40% demand (%)	Acuity alignment at +40% demand (%)
LP	93	79	74
MILP	96	87	84
GA	95	84	81
PSO	94	82	78
AAMOWOA	98	93	92

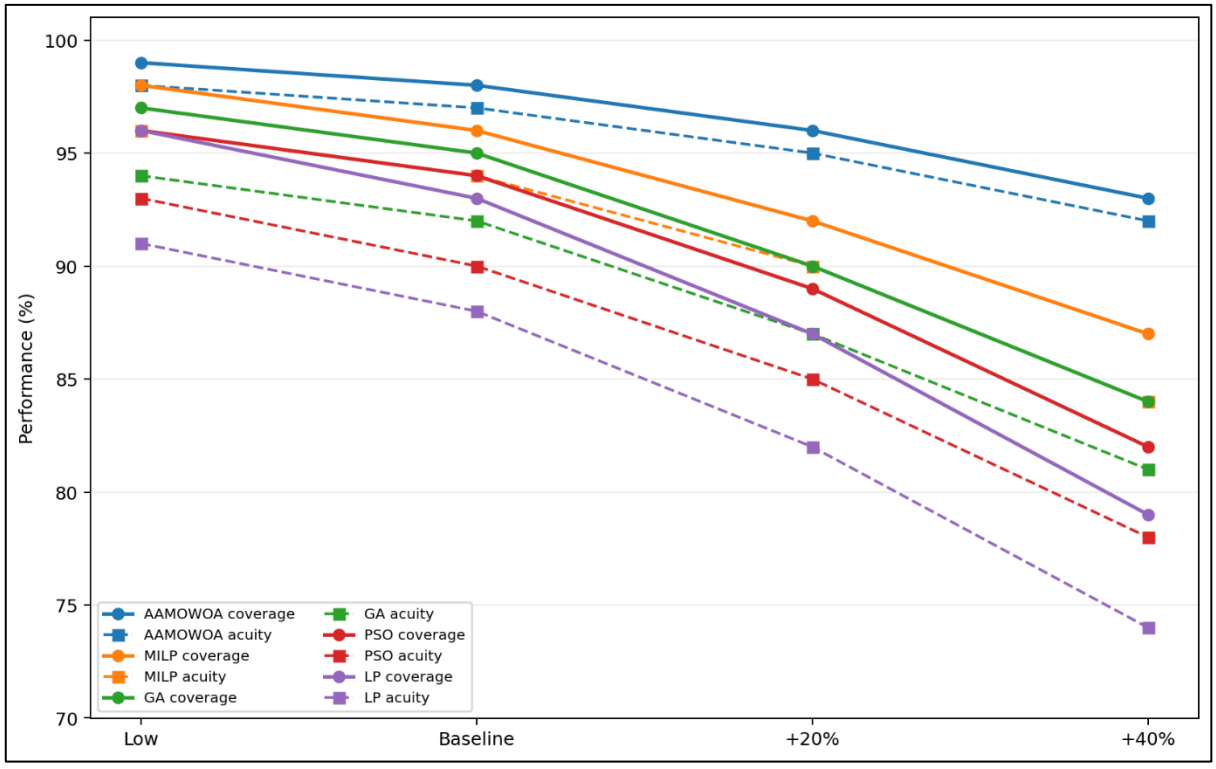

Fig 4 Planned Multi-Line Comparison of Staffing Coverage and Acuity Alignment Across Workforce Demand Scenarios

Figure 4 illustrates the proposed comparative evaluation of five workforce optimization algorithms across increasing staffing-demand scenarios. In the illustrative dataset, AAMOWOA maintains staffing coverage of 99%, 98%, 96%, and 93%, compared with MILP values of 98%, 96%, 92%, and 87%. GA records 97%, 95%, 90%, and 84%, whereas PSO achieves 96%, 94%, 89%, and 82%. LP exhibits the greatest coverage deterioration, declining from 96% to 79%. Acuity-alignment trends demonstrate comparable differences: AAMOWOA decreases from 98% to 92%, while MILP declines from 96% to 84%, GA from 94% to 81%, PSO from 93% to 78%, and LP from 91% to 74%. Under the highest demand scenario, the illustrative AAMOWOA advantage over MILP is six percentage points in coverage and

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eight percentage points in acuity alignment. These differences represent proposed benchmarking patterns, not demonstrated algorithmic superiority. Actual performance must be established through reproducible simulations and statistical testing. The graph includes ten lines, with solid lines representing staffing coverage and dashed lines representing acuity alignment.

- *Planned Comparative Performance Evaluation of AAMOWOA, LP, MILP, GA, and PSO Across Staffing Coverage, Acuity Alignment, Skill-Mix Compliance, and Workforce Allocation Efficiency*

The proposed comparative evaluation examines five workforce optimization algorithms using standardized behavioural healthcare staffing scenarios and four operational performance indicators. Table 4 presents illustrative baseline performance values intended to guide subsequent prototype benchmarking. AAMOWOA has a proposed skill-mix compliance rate of 98%, compared with 96% for MILP, while its workforce allocation efficiency is represented by 94%, compared with 90% for MILP and 81% for LP. These values establish numerical comparison targets rather than experimentally verified outcomes. The proposed Excel computational framework will calculate staffing adequacy, competency eligibility, and workforce allocation indicators, while Power BI will visualize algorithmic differences. Each algorithm will eventually be evaluated using identical synthetic workforce datasets, clinical demand parameters, and operational constraints. Comparative testing will determine whether adaptive optimization offers measurable advantages over established mathematical programming and population-based search approaches under equivalent computational conditions.

Table 4 Illustrative Baseline Performance Comparison of Five Workforce Optimization Algorithms

Algorithm	Staffing coverage / acuity alignment (%)	Skill-mix compliance (%)	Workforce allocation efficiency (%)
LP	93 / 88	89	81
MILP	96 / 94	96	90
GA	95 / 92	93	87
PSO	94 / 90	91	85
AAMOWOA	98 / 97	98	94

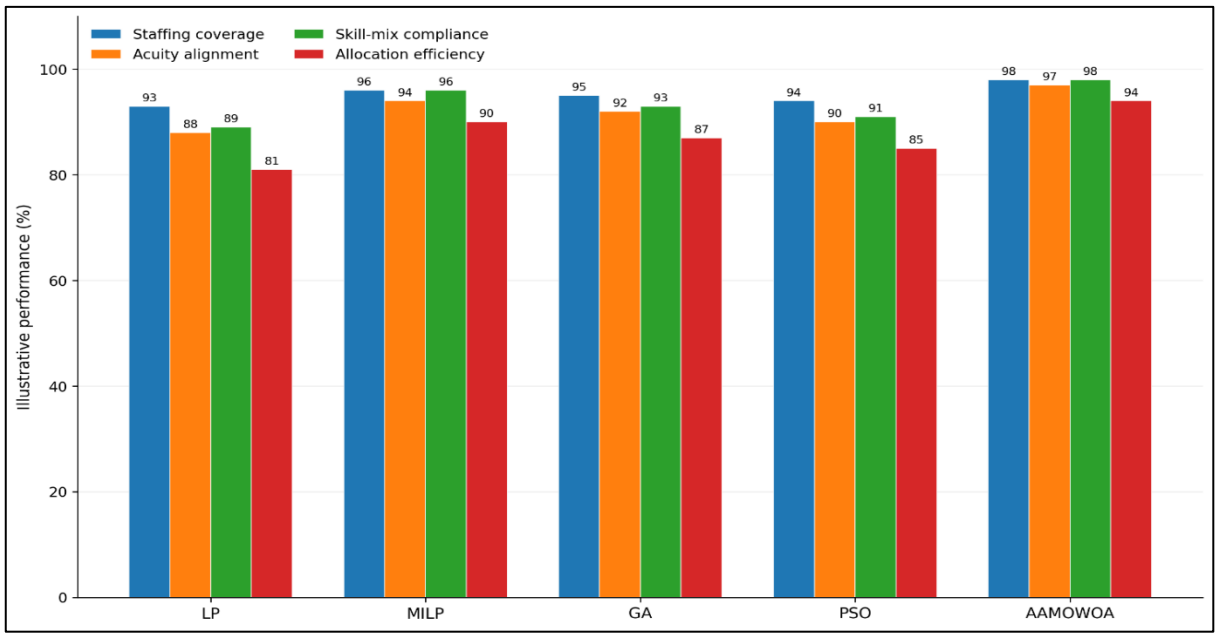

Fig 5 Illustrative Comparison of Workforce Optimization Algorithms Across Four Staffing Performance Indicators

Figure 5 illustrates the anticipated performance differences among five workforce optimization algorithms across four staffing indicators. AAMOWOA records illustrative staffing coverage of 98%, exceeding MILP (96%), GA (95%), PSO (94%), and LP (93%). Acuity alignment follows a comparable pattern, with AAMOWOA achieving 97%, compared with 94%, 92%, 90%, and 88% for MILP, GA, PSO, and LP, respectively. Skill-mix compliance reaches 98% for AAMOWOA, against 96% for MILP, 93% for GA, 91% for PSO, and 89% for LP. Workforce allocation efficiency produces the largest AAMOWOA–LP difference, with illustrative values of 94% and 81%, respectively. Relative to MILP, the proposed algorithm demonstrates hypothetical advantages of two percentage points in staffing coverage, three in acuity alignment, two in skill-mix compliance, and four in allocation efficiency. These comparisons establish a prospective benchmarking framework; the reported advantages must be independently tested through reproducible computational experiments before being interpreted as demonstrated performance improvements.

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➢ *Proposed Multi-Objective Optimization Analysis, Workload Equity Assessment, Overtime Reduction Evaluation, Pareto-Front Comparison, and Computational Performance Benchmarking*

The proposed multi-objective evaluation examines workload equity, overtime expenditure, Pareto-front quality, and computational efficiency across five workforce optimization algorithms. Table 5 presents illustrative benchmarking values derived from a hypothetical 28-day behavioural healthcare staffing scenario. AAMOWOA is assigned the lowest workload coefficient of variation (8%) and overtime requirement (42 hours), compared with 11% and 56 hours for MILP. Its illustrative hypervolume indicator reaches 0.86, exceeding GA (0.70) and PSO (0.65). However, AAMOWOA requires 10.5 seconds of simulated computational time, compared with 8.4 seconds for GA, highlighting a potential trade-off between optimization quality and execution speed. The proposed evaluation will use standardized workforce instances, identical operational constraints, and repeated computational trials. These numerical values establish hypothetical comparison benchmarks rather than completed optimization results, and their validity will require implementation and experimental verification.

Table 5 Illustrative Multi-Objective Performance and Computational Benchmarking of Workforce Optimization Algorithms

Algorithm	Workload equity CV (%)	Overtime hours (28 days)	Hypervolume / Runtime (s)
LP	19	90	0.51 / 0.4
MILP	11	56	0.78 / 18.0
GA	14	70	0.70 / 8.4
PSO	16	76	0.65 / 6.2
AAMOWOA	8	42	0.86 / 10.5

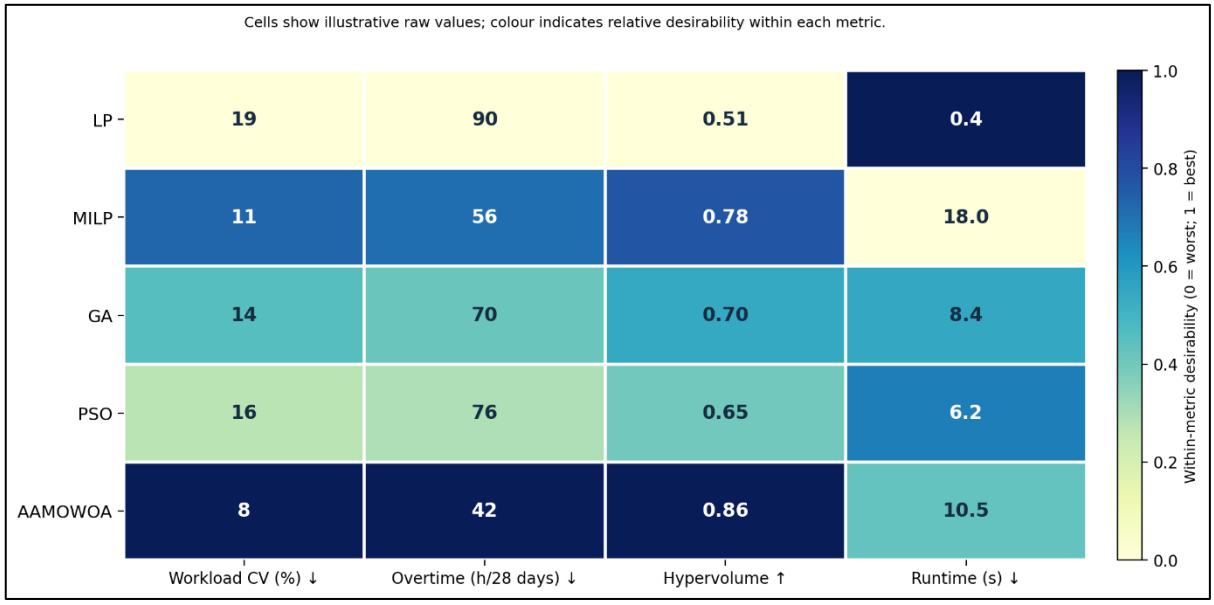

Fig 6 Heatmap Comparison of Multi-Objective Workforce Optimization and Computational Performance

Figure 6 illustrates the proposed multi-objective benchmarking framework across five optimization algorithms. AAMOWOA exhibits the lowest illustrative workload variation of 8%, compared with MILP (11%), GA (14%), PSO (16%), and LP (19%). Similarly, its overtime requirement of 42 hours is lower than MILP (56 hours), GA (70 hours), PSO (76 hours), and LP (90 hours), representing a hypothetical 25% reduction relative to MILP. Multi-objective solution quality follows a comparable pattern, with AAMOWOA achieving a hypervolume of 0.86 against 0.78 for MILP, 0.70 for GA, 0.65 for PSO, and 0.51 for LP. Computational runtime introduces a trade-off: LP requires 0.4 seconds, PSO 6.2 seconds, GA 8.4 seconds, AAMOWOA 10.5 seconds, and MILP 18.0 seconds. These values illustrate anticipated optimization compromises rather than verified improvements. Subsequent testing must establish whether these differences persist across equivalent staffing scenarios and computational budgets.

➢ *Planned Sensitivity Analysis, Technical and Operational Feasibility Assessment, Prototype Development Limitations, and Implications for Behavioural Healthcare Workforce Decision-Making*

The proposed sensitivity analysis investigates the responsiveness of five workforce optimization algorithms to increasing patient demand, employee absenteeism, and operational staffing constraints. Table 6 presents illustrative outputs for a 28-day scheduling horizon involving 120 employees across four behavioural healthcare units. AAMOWOA maintains a proposed staffing coverage of 93% under increased demand and 91% under absenteeism, compared with 87% and 85% for MILP. Its illustrative uncovered care requirement is 75 hours, against 130 hours for MILP and 210 hours for LP. Technical feasibility will be assessed through computational reliability, Excel–Power BI integration, data integrity, and reproducibility. Operational feasibility will examine scheduling usability, competency

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compliance, and managerial interpretability. The numerical comparisons represent hypothetical prototype testing scenarios rather than validated outcomes. Subsequent development will establish whether the proposed architecture can satisfy clinical staffing requirements and implementation constraints.

Table 6 Illustrative Sensitivity and Operational Feasibility Comparison of Workforce Optimization Algorithms

Algorithm	Coverage at +40% demand (%)	Coverage at 20% absenteeism (%)	Uncovered care hours (28 days)
LP	79	76	210
MILP	87	85	130
GA	84	81	160
PSO	82	79	185
AAMOWOA	93	91	75

Figure 7 illustrates the distribution of hypothetical uncovered care hours across five workforce optimization algorithms during the proposed 28-day sensitivity assessment. LP accounts for 210 hours, representing 27.6% of the combined illustrative total, while PSO contributes 185 hours (24.3%). GA records 160 hours (21.1%), followed by MILP with 130 hours (17.1%). AAMOWOA contributes the smallest share, with 75 hours (9.9%). Relative to LP, the proposed AAMOWOA scenario represents a reduction of 135 uncovered care hours, equivalent to 64.3%. Compared with MILP, the difference is 55 hours, or 42.3%. The sensitivity table additionally indicates that AAMOWOA retains 93% staffing coverage under increased demand and 91% under absenteeism, exceeding MILP by six percentage points under both conditions. These numerical patterns illustrate the intended comparison, not confirmed algorithmic effectiveness. Actual feasibility conclusions will depend on implemented optimization models, clinical constraint verification, reproducible simulations, and stakeholder assessment.

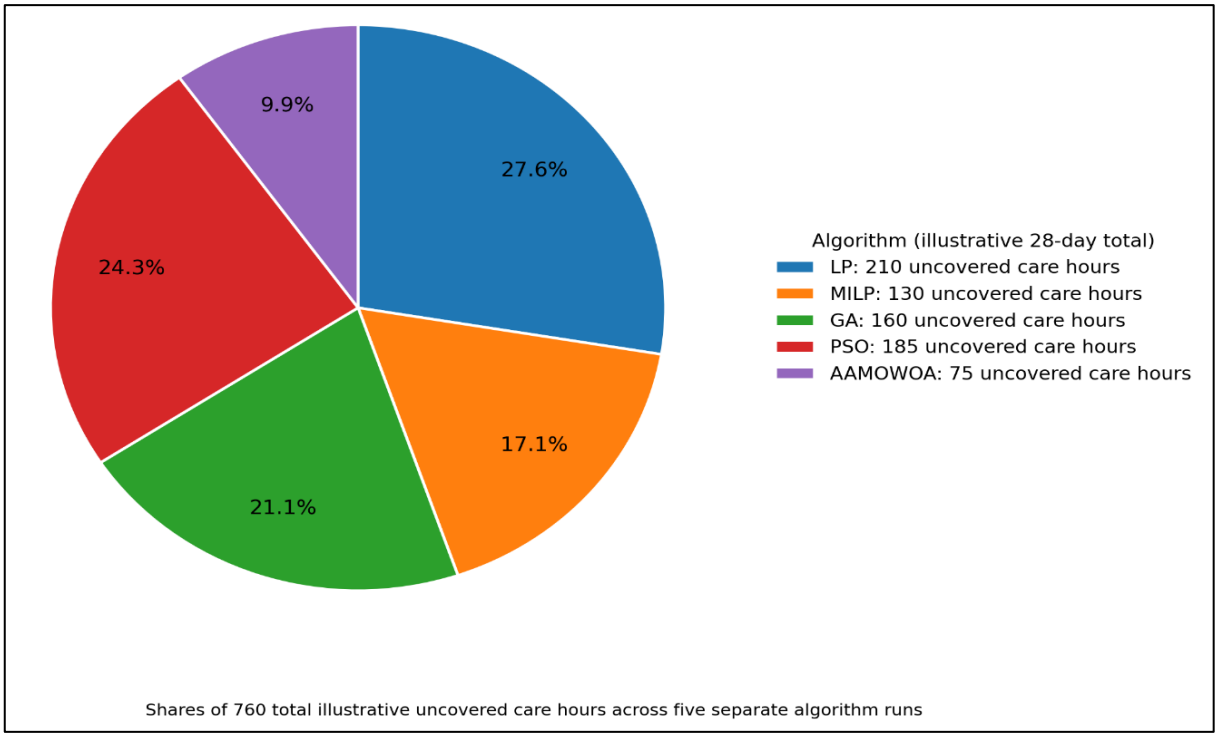

Fig 7 Comparative Distribution of Uncovered Care Hours Across Workforce Optimization Algorithms

V. CONCLUSIONS AND RECOMMENDATIONS

➢ *Conclusions on the Proposed Decision-Support Framework, Algorithmic Design, and Prototype Development Contributions*

The present study establishes a methodological foundation for developing an integrated Excel and Power BI-based workforce decision-support prototype intended to address staffing complexity in behavioural healthcare environments. The proposed architecture combines patient-acuity demand modelling, employee competency assessment, workforce availability analysis, and multi-objective optimization within a structured analytical framework. Its principal methodological contribution is the proposed Acuity-Adaptive Multi-Objective Workforce Optimization Algorithm (AAMOWOA), designed to balance staffing coverage, acuity alignment, skill-mix compliance, workload equity, and overtime expenditure through dynamically adjusted optimization priorities. The mathematical formulation provides a basis for representing these competing requirements while maintaining mandatory clinical and operational constraints.

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The illustrative comparative analyses presented in Section 4 establish a preliminary numerical framework for evaluating AAMOWOA against LP, MILP, GA, and PSO. Across the proposed baseline scenarios, AAMOWOA is assigned staffing coverage of 98%, acuity alignment of 97%, skill-mix compliance of 98%, and workforce allocation efficiency of 94%. Additional illustrative assessments indicate an 8% workload coefficient of variation, 42 overtime hours, and a hypervolume indicator of 0.86. These values demonstrate the intended benchmarking structure but do not constitute experimentally validated findings. Consequently, the study cannot yet establish algorithmic superiority or measurable operational improvements. Its immediate contribution lies in specifying a reproducible optimization methodology, integrated data-processing architecture, and structured feasibility evaluation protocol. The proposed framework provides a foundation for subsequent computational implementation, objective performance assessment, and eventual clinical validation, while preserving the distinction between prototype design specifications and demonstrated system capabilities.

- *Recommendations for Improving Acuity-Adaptive Workforce Optimization, Algorithmic Robustness, and Staffing Decision-Support Capabilities*

Further development of AAMOWOA should prioritize mathematical consistency, computational robustness, clinically meaningful optimization objectives, and transparent decision-support procedures. The acuity-weighting mechanism should incorporate clinically reviewed patient classifications, observation requirements, intervention intensity, and professional competency restrictions rather than depend exclusively on generalized staffing ratios. Dynamic objective weights should be calibrated through controlled experiments to determine their influence on staffing coverage, workload inequality, and overtime exposure. Particular attention should be directed toward preventing adaptive weighting from overriding mandatory clinical safety requirements. Hard constraints governing professional qualifications, continuous observation, minimum coverage, maximum working hours, and employee rest periods should remain enforceable throughout optimization.

Algorithmic refinement should investigate feasibility-preserving initialization, adaptive neighborhood search, competency-aware employee exchange, and Pareto-based solution retention. These procedures should be evaluated against LP, MILP, GA, and PSO using identical workforce instances and clearly defined computational budgets. The illustrative differences reported in Section 4, including AAMOWOA's proposed 8% workload variation and 42 overtime hours, should serve as hypotheses for subsequent benchmarking rather than predetermined performance outcomes. Robustness testing should incorporate patient-acuity escalation, unplanned employee absence, staffing shortages, and changing skill-mix distributions. Repeated computational experiments should quantify solution variability, constraint violations, execution time, and sensitivity to parameter selection. The decision-support interface should also provide interpretable explanations for recommended allocations, including identified staffing deficits and binding operational constraints. These improvements would strengthen the proposed algorithm's technical credibility and establish whether acuity-adaptive optimization offers measurable advantages over conventional scheduling approaches.

- *Recommendations for Excel–Power BI Integration, Prototype Refinement, Healthcare Organizational Adoption, and Implementation Feasibility*

The proposed Excel–Power BI architecture should be developed through a modular implementation strategy that separates workforce data preparation, optimization calculations, performance verification, and managerial visualization. Excel workbooks should incorporate standardized input templates, validated patient-acuity classifications, employee competency matrices, shift availability records, and automated consistency checks. Optimization outputs should be stored in structured tables containing scenario identifiers, algorithm assignments, staffing allocations, objective values, and constraint-validation results. Power BI should subsequently retrieve these outputs through controlled data connections, allowing staffing managers to examine workforce coverage, overtime exposure, acuity alignment, skill-mix compliance, and alternative allocation scenarios. Version control, protected calculation fields, and documented data-refresh procedures should be incorporated to improve reliability and prevent unintended modification of mathematical assumptions.

Prototype refinement should prioritize interface simplicity, computational reproducibility, interoperability, and information security. The dashboard should distinguish projected staffing requirements from actual workforce availability and clearly identify assignments requiring managerial review. Preliminary usability assessments should involve behavioural healthcare administrators, psychiatric nurses, workforce planners, and information technology personnel to evaluate interpretability, workflow compatibility, and operational relevance. Before implementation, healthcare organizations should establish governance procedures covering patient-data confidentiality, professional accountability, role-based access, and authorized staffing decisions. Initial deployment should use synthetic information, followed by retrospectively de-identified operational datasets where appropriate approvals exist. A phased pilot should compare prototype recommendations with existing scheduling practices without automatically replacing clinical judgment. Technical and economic feasibility should be evaluated through software compatibility, maintenance requirements, training costs, computational reliability, and demonstrable workflow benefits, ensuring that organizational adoption is supported by evidence rather than assumed technological advantages.

- *Research Limitations, Future Computational Validation, Real-World Pilot Testing, and Directions for Further Development*

The principal limitation of this study is its prototype-in-progress status, which restricts the interpretation of the proposed algorithmic architecture and illustrative

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performance comparisons. The numerical values presented in Section 4 represent hypothetical benchmarking scenarios rather than outputs obtained from implemented optimization experiments. Consequently, the reported staffing coverage, acuity alignment, workload equity, overtime requirements, hypervolume indicators, and computational runtimes cannot establish actual algorithmic effectiveness. Furthermore, synthetic workforce assumptions may inadequately represent the complexity of psychiatric staffing environments, particularly unexpected behavioural emergencies, continuous observation demands, professional judgment, employee preferences, and differences in institutional staffing policies. The proposed acuity coefficients, objective weights, and workforce allocation efficiency measures also require operational definition, empirical calibration, and clinical review.

Future research should implement the complete AAMOWOA computational procedure and conduct reproducible benchmarking against LP, MILP, GA, and PSO using standardized staffing instances. Evaluation should include repeated stochastic trials, confidence intervals, appropriate statistical comparisons, Pareto-front analysis, and sensitivity testing under variable demand and absenteeism conditions. Particular emphasis should be placed on verifying the consistency of staffing coverage, unmet care hours, and mandatory competency constraints. Following satisfactory computational verification, the prototype should undergo usability testing and retrospective validation using appropriately governed behavioural healthcare staffing records. A subsequent prospective pilot could assess scheduling feasibility, managerial acceptance, operational costs, and workflow integration under human supervision. Further development may investigate probabilistic demand forecasting, uncertainty-aware optimization, real-time workforce updates, and explainable scheduling recommendations. These activities would progressively determine the framework's feasibility and practical value without prematurely presenting the proposed system as clinically validated or operationally superior.

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