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A Hybrid Simulation and the RAWEC Model for Performance Evaluation of Pharmacy Service Strategies

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ABSTRACT

Outpatient pharmacy operations frequently experience inefficiencies due to unpredictable demand, limited resources, and patient behaviors such as queue jockeying, resulting in extended wait times and reduced performance. This research introduces a hybrid framework that combines Discrete-Event Simulation (DES) with Multi-Criteria Decision-Making (MCDM) to assess and prioritize improvement strategies for complex systems. A discrete-event simulation model was created to replicate a multi-server pharmacy, incorporating realistic factors such as time-dependent patient arrivals, variable service durations, and explicit jockeying behavior. The model produced performance data for five strategies: base case, single queue, self-service kiosks, dynamic staffing, and restricted jockeying. The output metrics, including waiting time, queue length, staff utilization, throughput, and jockeying frequency, were organized into a decision matrix. The Ranking of Alternatives with Weights of Criterion (RAWEC) method, a contemporary multi-criteria decision-making technique utilizing a reward–punishment mechanism grounded in average performance, was subsequently employed to rank the strategies according to varying managerial weightings (patient-centric versus efficiency-centric). The findings indicate that the single queue strategy (A1) emerged as the optimal choice, attaining the highest rank in both patient-centric and efficiency-centric managerial frameworks. This suggests that the implementation of a single-line system is advantageous for both patient experience and operational efficiency, thereby removing the perceived trade-off between these objectives in this particular instance. The hybrid DES–RAWEC approach offers managers a robust, data-driven instrument for formulating strategic decisions that reconcile competing objectives within complex service environments, such as healthcare pharmacies.

1. Introduction

The management of healthcare systems presents a significant global challenge, influencing patient satisfaction, operational costs, and public health outcomes [1, 2]. Outpatient pharmacy

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services serve as a vital patient interaction point within this intricate ecosystem, frequently marked by erratic demand, constrained resources, and the possibility of extended waiting periods. Inefficiencies may result in patient dissatisfaction, staff burnout, and ineffective resource allocation [3].

A fundamental issue in pharmacy management is the classic queuing dilemma, characterized by stochastic patient arrivals and variable service times [4]. This challenge is frequently intensified by particular operational constraints and patient behaviors prevalent in numerous healthcare environments. Multi-server, multi-queue systems can result in queue jockeying, wherein patients switch lines dynamically in pursuit of expedited service [5]. This behavior, although rational from an individual standpoint, may heighten perceived chaos at the system level, diminish fairness, and complicate the evaluation of various management strategies. The evaluation goal is inherently multi-objective, necessitating a balance among minimizing patient wait times, maximizing staff utilization, achieving high throughput, and maintaining an orderly service environment—objectives that frequently conflict with one another [6].

To address these dynamic complexities, discrete-event simulation (DES) has emerged as a powerful analytical tool. DES allows researchers to create digital twins of complex systems, modeling the flow of entities (patients) through processes (pharmacy service) under conditions of uncertainty [7]. In healthcare, DES has been successfully applied to emergency departments, surgical suites, and clinic workflows to test "what-if" scenarios without disrupting real-world operations [8]. For pharmacy management, simulation models have been used to determine optimal staffing levels and layout designs, proving effective in predicting key performance metrics like waiting times and queue lengths [9, 10].

However, simulation alone provides a plethora of output metrics but does not prescribe an optimal solution when objectives conflict. This is the domain of Multi-Criteria Decision-Making (MCDM). MCDM methods provide a structured framework for evaluating alternatives based on several, often competing, criteria weighted by decision-maker preferences [11]. Techniques such as TOPSIS, VIKOR, and AHP have been widely used in healthcare and service operations to rank strategies, balancing factors like cost, quality, and efficiency [12].

Recognizing the strengths of both methodologies, scholars have increasingly advocated for a hybrid simulation-MCDM approach. The simulation model generates robust, data-driven performance data for each alternative strategy under uncertainty, which then serves as the input for an MCDM model to perform an integrated evaluation [13]. While this hybrid paradigm has been applied in fields like manufacturing and supply chain management, its application to healthcare service design, particularly in the context of outpatient pharmacies with unique behavioral factors like jockeying, remains underexplored.

Furthermore, within the MCDM field, new methods continue to be developed to improve consistency and reliability. The selection of the Ranking of Alternatives with Weights of Criterion (RAWEC) method for this research was motivated by its novel reward-punishment mechanism, which benchmarks alternative performance against the average for each criterion [14]. Unlike traditional methods such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) or VIsekrzterijumska Optimizacija i Kompromisno Resenje (VIKOR), which identify distances from ideal and anti-ideal solutions, RAWEC’s foundation in average performance offers a distinct form of normalization that intuitively rewards outperformance and penalizes underperformance. This characteristic enhances interpretability for decision-makers by directly highlighting which strategies are above or below "average" across diverse metrics. While its computational simplicity is comparable to other distance-based MCDM methods, its methodological contribution lies in this unique benchmarking approach, providing a robust and transparent alternative for ranking alternatives in the presence of conflicting objectives. A review of the literature reveals a gap in the application of this specific MCDM technique within a hybrid framework, especially in a healthcare context [15, 16]. No prior study has yet employed a hybrid DES-RAWEC model to solve pharmacy management problems.

This study aims to address this gap by developing a novel hybrid DES-RAWEC model to assess and rank improvement strategies for outpatient pharmacies. The model simulates various strategies, including staffing changes, technological integration, and queue management, under realistic conditions of patient movement and shift-based staffing. The performance outputs then ranked utilizing the RAWEC method according to varying managerial priorities, specifically patient-centric and efficiency-centric approaches. It presents a practical, data-driven decision-support framework for healthcare administrators and introduces a novel methodological application of an advanced MCDM technique within the simulation-optimization field.

2. Methodology

This study utilizes a two-phase hybrid methodology that combines DES with MCDM. The initial phase entails the creation of a computational DES model designed to replicate the intricate stochastic processes of an outpatient pharmacy and to produce reliable performance data for a series of proposed enhancement strategies. The second phase employs the RAWEC method to assess and rank these strategies according to the simulated outputs, integrating established managerial preferences. This integrative approach guarantees that the final ranking of alternatives is based on dynamic, data-driven performance metrics instead of static or subjective evaluations. Figure 1 demonstrates the suggested methodology.

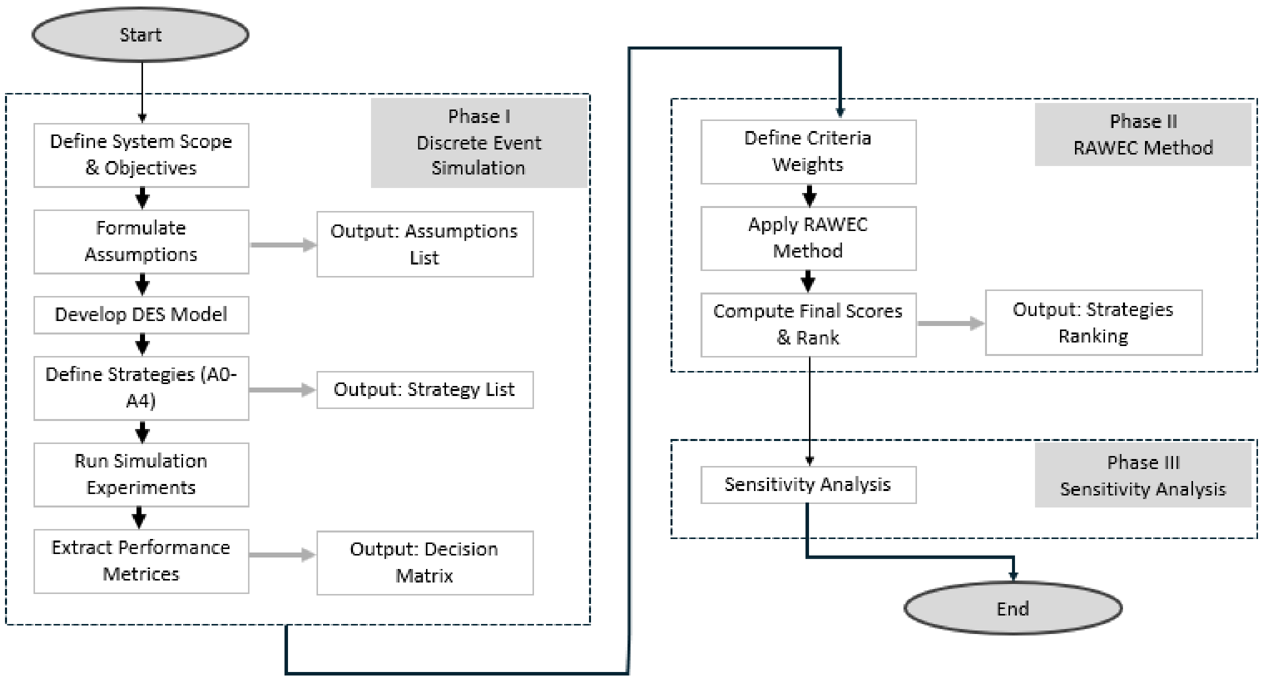

Fig. 1. Suggested methodology

The DES model was developed to illustrate a multi-server, multi-queue pharmacy system functioning continuously over a 24-hour timeframe. Stochastic elements were integrated using probability distributions to enhance realism. The inter-arrival times of patients were modeled through an exponential distribution, incorporating a time-dependent mean rate to account for variations in peak and off-peak demand periods. The service times for the prescription fulfillment process were modeled using a triangular distribution characterized by optimistic, most likely, and pessimistic duration estimates. A behavioral rule was established to model patient jockeying, allowing agents to switch to a shorter queue if it met a specified threshold.

Five unique operational strategies were developed and evaluated in comparison to a baseline scenario within the simulation framework. The strategies involved modifications to staffing levels, the introduction of self-service technology, the adoption of a single-queue (Management) system, and the enforcement of restrictions on queue jockeying. Each scenario was simulated over one week (168 hours), preceded by a 24-hour warm-up period to mitigate initial bias. The model recorded outputs for five essential performance indicators (KPIs): average patient waiting time, maximum queue length, pharmacist utilization rate, total patients served, and average frequency of jockeying per patient.

The simulated KPIs for each strategy were organized into a decision matrix, with rows representing alternatives and columns denoting performance criteria. The RAWEC method was chosen due to its innovative reward-punishment mechanism, which evaluates the performance of each alternative relative to the average value of all alternatives for each criterion. This mechanism allocates a reward value for performances exceeding the average and a punishment value for those falling short, thereby normalizing the data and highlighting both outperformance and underperformance across various metrics.

The RAWEC algorithm was executed according to a defined computational procedure, the logic of which can be summarized in the following pseudocode:

Input: A_i – Set of alternatives; C_j – Set of criteria; r_{ij} – Rating of alternative i on criterion j; w_j – Weight of criterion j

1. Construct decision matrix $R = [r_{ij}]$ of raw scores of alternative i under criterion j.
2. Normalize the decision matrix R to obtain benefit and cost-based scores n_{ij}:

- For benefit criteria (higher values preferred):

$$n_{ij} = \frac{x_{ij}}{\max\limits_{i} x_{ij}}, \text{ and } n'_{ij} = \frac{\min\limits_{i} x_{ij}}{x_{ij}} \quad (1)$$

- For cost criteria (lower values preferred):

$$\mathrm{c}n_{ij} = \frac{\min\limits_{i} x_{ij}}{x_{ij}}, \text{ and } n'_{ij} = \frac{x_{ij}}{\max\limits_{i} x_{ij}} \quad (2)$$

3. Compute weighted deviation scores:

$$v_i = \sum_{j=1}^{m} w_j.\left(1 - n_{ij}\right) \quad (3)$$

$$v'_i = \sum_{j=1}^{m} w_j.\left(1 - n'_{ij}\right) \quad (4)$$

4. Compute final ranking score Q_i for each alternative

$$Q_i = \frac{v'_i - v_i}{v'_i + v_i} \quad (5)$$

Output: Q_i – Overall score for each alternative; Ranking (descending order of Q_i).

To ensure the robustness of the findings, the model's validity was established through face validation with domain experts and by verifying that the base case simulation output aligned with known system behavior. Furthermore, a sensitivity analysis was conducted on the criterion weights used in the RAWEC model. This involved testing multiple weighting scenarios—specifically, a patient-centric weighting and an efficiency-centric weighting—to observe the stability of the strategy rankings and to provide policymakers with a range of recommendations based on differing organizational priorities.

3. Results

The Libyan healthcare system is characterized by a dual structure, comprising a public sector funded by the state and a rapidly growing private sector [17]. Public hospitals and clinics provide universal coverage but often suffer from resource constraints and overcrowding, while private facilities cater to patients seeking more immediate and often higher-quality care [18]. Both public and private institutions typically operate their own in-house pharmacies, which are critical for providing prescribed medications to patients. This study focuses on the private sector, specifically a large pharmacy in Misurata City—a major urban center with a competitive landscape of over 300 pharmacies. The subject of this case study is one of the largest and most frequented pharmacies in the city, making it an ideal candidate for analyzing operational efficiency and patient flow management due to its high patient volume and complex dynamics.

The simulation model was designed to accurately represent the 24/7 operational reality of the case study pharmacy. The scope was defined as a single pharmacy with four identical service counters, each staffed by a pharmacist. Patients arriving at the pharmacy select one of the four available queues upon entry. The model operates on a continuous basis, with staffing levels adjusted according to shift patterns to reflect realistic working hours and demand fluctuations, a common practice in such establishments.

Patient arrivals were modeled as a stochastic Poisson process, meaning inter-arrival times were exponentially distributed. To capture the pronounced variation in customer flow, a time-dependent arrival rate was implemented. During peak hours (09:00 to 17:00), the mean inter-arrival time was set to 2 minutes, reflecting high demand. For off-peak hours (17:00 to 09:00), the mean inter-arrival time was increased to 5 minutes. Service times were modeled using a Triangular distribution, defined by a minimum of 2 minutes, a mode of 5 minutes, and a maximum of 15 minutes, capturing the variability inherent in the prescription verification, payment, and dispensing process.

A critical behavioral assumption integrated into the model is patient-induced queue jockeying. This reflects the observed real-world phenomenon where customers, upon perceiving another queue to be moving faster, will switch lines to minimize their own waiting time. The model logic stipulated that a patient would jockey to a different queue if they perceived it to be shorter by at least two people. This rule was checked at regular intervals throughout a patient's waiting time, adding a layer of behavioral complexity that significantly impacts system performance metrics like average wait time and queue stability.

The model assumed that all pharmacists were identical in their service rate and efficiency. Furthermore, it was assumed that once a shift began, pharmacists were continuously available at their counters without breaks or interruptions until the end of their shift. While this simplifies variables like individual performance and scheduled breaks, it provides a clear baseline for measuring the impact of the strategic variables being tested, such as the number of staff and the introduction of new technology, on system-wide performance.

Performance metrics, including average waiting time, maximum queue length, pharmacist utilization, total patients served, and average jockeying per patient, were calculated exclusively for patients who completed the service process within the simulation run. To ensure statistical reliability and eliminate the bias of initial start-up conditions, the model was executed for a duration of 168 hours (7 days), with an initial 24-hour warm-up period, and results were averaged across multiple independent replications to account for stochastic variability and ensure robust conclusions.

Figure 2 illustrates an important patient-centric metric: the average duration of patient wait times. The findings indicate a notable difference in performance among the evaluated strategies. Strategy A1 (Single Queue) demonstrated the most significant enhancement, decreasing the average wait time to 15.1 minutes, approximately 33% lower than the Base Case (A0). In contrast, Strategy A4 (Restricted Jockeying) yielded the poorest performance, raising the average wait time to 25.8 minutes. The implementation of a single, shared queue is the most effective intervention for enhancing patient satisfaction by minimizing perceived wait times. In contrast, restricting patient movement without offering a more efficient alternative is detrimental.

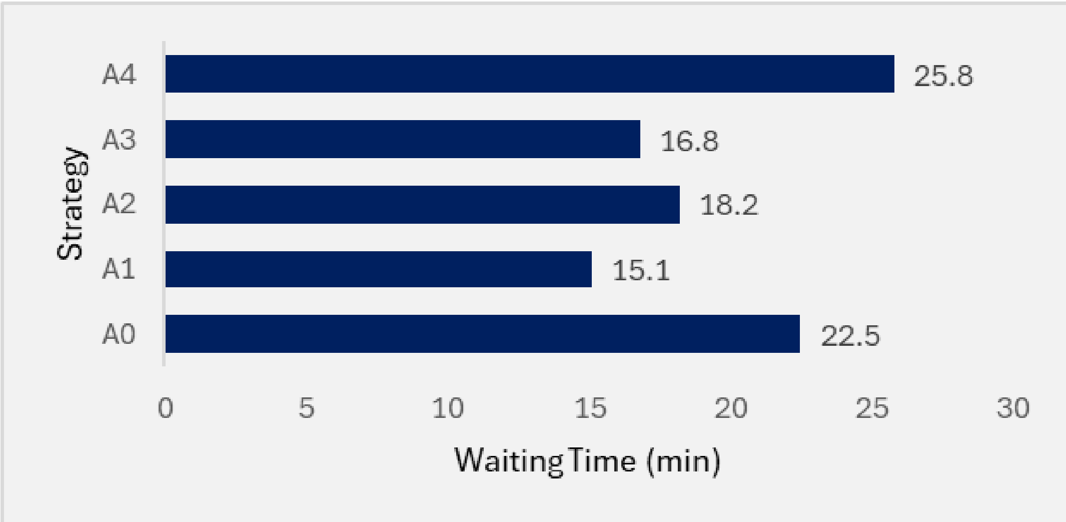

Fig. 2. Average duration of patient wait times

Figure 3 shows the essential trade-off between overall system throughput and staff utilization through a dual-axis chart. Strategy A2 (Self-Service Kiosks) attained the highest total output, serving 4,050 patients, through the optimization of the service process and the reduction of transaction times. In contrast, Strategy A4 (Restricted Jockeying) attained the highest pharmacist utilization rate at 79%, as the prevention of jockeying guarantees that staff remain engaged and are not left idle due to patients exiting their queue. This inverse relationship underscores a fundamental operational challenge: enhancing resource efficiency (utilization) does not inherently lead to increased total output (patients served). The optimal strategy is contingent upon whether the primary managerial goal is volume or cost-effectiveness.

Figure 4 illustrates the impact of each strategy on two key indicators of system order: the maximum queue length and the frequency of patient jockeying. Strategy A1 (Single Queue) demonstrates a dual advantage, achieving both the shortest maximum queue length (9 patients) and a near-total elimination of jockeying behavior (0.05 per patient). In contrast, the Base Case (A0) and Strategy A4 (Restricted Jockeying) resulted in the longest queues and higher levels of patient queue-switching, indicating poorer queue stability and a more chaotic service environment. This visualizes a core benefit of the single-queue system: it inherently organizes the service floor and eliminates the incentive for jockeying.

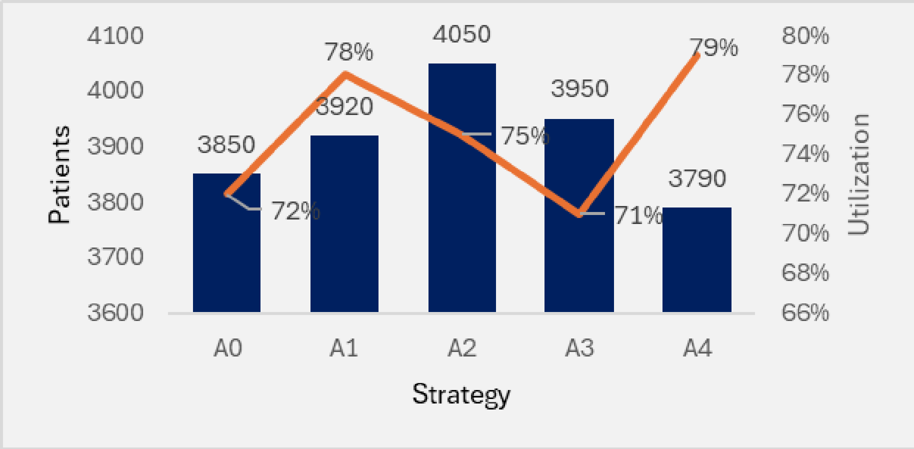

Fig. 3. Overall system throughput and staff utilization

Fig. 4. Overall system throughput and staff utilization

The RAWEC methodology was applied to simulated performance data, which was structured as an initial decision matrix (presented in Table 1). In this matrix, the rows represent the five operational strategies (A0: Base Case, A1: Single Queue, A2: Self-Service Kiosks, A3: Dynamic Staffing, A4: Restricted Jockeying), and the columns correspond to the five performance criteria. The nature of each criterion was defined as a priori for the RAWEC calculation: C1 (Average Waiting Time), C2 (Maximum Queue Length), and C5 (Average Jockeying) were classified as non-beneficial (cost) criteria, where lower values are preferable. Conversely, C3 (Pharmacist Utilization) and C4 (Total Patients Served) were classified as beneficial (benefit) criteria, where higher values indicate better performance. This initial matrix, populated with the raw output from the discrete-event simulation, served as the fundamental input for the subsequent RAWEC algorithm, which transforms these values through its unique reward-punishment normalization process based on the average performance of each criterion.

Table 1
Initial decision matrix

Alternative	C1	C2	C3	C4	C5
A0	22.5	18	72%	3850	1.8
A1	15.1	9	78%	3920	0.05
A2	18.2	14	75%	4050	1.6
A3	16.8	12	71%	3950	1.5
A4	25.8	20	79%	3790	0.1

After establishing the initial decision matrix, the core normalization procedure of the RAWEC algorithm was performed, resulting in the normalized decision matrix shown in Table 2. This matrix results from the method's distinct reward-punishment mechanism, which evaluates each performance value relative to the average value of its corresponding criterion. For beneficial criteria (C3, C4), values exceeding the average received a score greater than 1, whereas values falling below the average were assigned a score less than 1. In contrast, for non-beneficial criteria (C1, C2, C5), values below the average received rewards (>1), while values above the average faced penalties (<1).

Table 2
Normalized decision matrix

Benefit Normalization	C1	C2	C3	C4	C5
A0	0.671	0.5	0.911	0.951	0.028
A1	1	1	0.987	0.968	1
A2	0.83	0.643	0.949	1	0.031
A3	0.899	0.75	0.899	0.975	0.033
A4	0.585	0.45	1	0.936	0.5
Cost Normalization	C1	C2	C3	C4	C5
A0	0.872	0.9	0.986	0.984	1
A1	0.585	0.45	0.91	0.967	0.028
A2	0.705	0.7	0.947	0.936	0.889
A3	0.651	0.6	1	0.959	0.833
A4	1	1	0.899	1	0.056

The final ranking for the patient-centric weighting scenario is presented in Table 3. The results clearly indicate that Strategy A1 (Single Queue) is the optimal choice, achieving the highest Q_i score of 0.9665 and the number one rank. This superior performance is attributable to its exceptional results in patient-facing metrics such as waiting time and queue length, which were heavily weighted in this scenario. Strategy A3 (Dynamic Staffing) followed in second place (Q_i = 0.0758), offering a moderate but well-balanced improvement over the base case. Notably, the Base Case (A0) strategy was definitively ranked as the least effective option (Q_i = -0.6494), highlighting the significant potential for operational improvement through the implemented strategies.

Table 3
Final ranking order of strategic alternatives

Strategy	Description	v_{ij}	v'_{ij}	Q_i	Rank
A0	Base Case	0.352899	0.075026	-0.64935	5
A1	Single Queue	0.006714	0.394255	0.966513	1
A2	Self-Service Kiosks	0.247767	0.206679	-0.09041	3
A3	Dynamic Staffing	0.209013	0.243301	0.075806	2
A4	Dynamic Staffing	0.338227	0.109634	-0.51041	4

Under the efficiency-centric weighting scenario, which prioritized staff utilization and throughput, the RAWEC method produced a distinct ranking order, as shown in Table 4. While Strategy A1 (Single Queue) still emerged as the top-ranked alternative (Q_i = 0.8926), its lead over the other strategies is noticeably smaller compared to the first scenario. The results for Strategies A2 (Self-Service Kiosks) and A3 (Dynamic Staffing) are very close (Q_i = -0.0245, -0.0448 respectively), resulting in a second and third place rank. This suggests that for a decision-maker whose primary goal is cost efficiency and resource use, these three strategies (A1, A2, A3) are all relatively competitive, with the single queue maintaining a slight edge. The Base Case (A0) again consistently ranked as the worst alternative.

Table 4
Final ranking order of strategic alternatives

Strategy	Description	v_{ij}	v'_{ij}	Q_i	Rank
A0	Base Case	0.212178	0.045033	-0.64984	5
A1	Single Queue	0.013088	0.230745	0.892648	1
A2	Self-Service Kiosks	0.138471	0.131853	-0.02448	2
A3	Dynamic Staffing	0.140251	0.128227	-0.04478	3
A4	Dynamic Staffing	0.178995	0.087729	-0.34218	4

The comparative analysis of strategic rankings across the two weighting scenarios, as illustrated in Figure 5, highlights a significant finding: Strategy A1 (Single Queue) demonstrates superior robustness and performance, consistently achieving the top rank irrespective of managerial priorities. The stability of the rankings for the other strategies is significantly influenced by the weighting scheme employed. Strategy A3 (Dynamic Staffing) exhibits notable sensitivity, achieving a strong second position in the patient-centric scenario, yet dropping to third when prioritizing efficiency. In contrast, Strategy A2 (Self-Service Kiosks) demonstrates increased stability, shifting solely from third to second place across scenarios. This contrast highlights that although A1 serves as the optimal all-rounder, the selection between A2 and A3 depends on particular organizational objectives. The Base Case (A0) and Strategy A4 (Restricted Jockeying) consistently yield the lowest performance, indicating that any proposed intervention surpasses the status quo and that merely limiting patient flow without a structural solution proves ineffective.

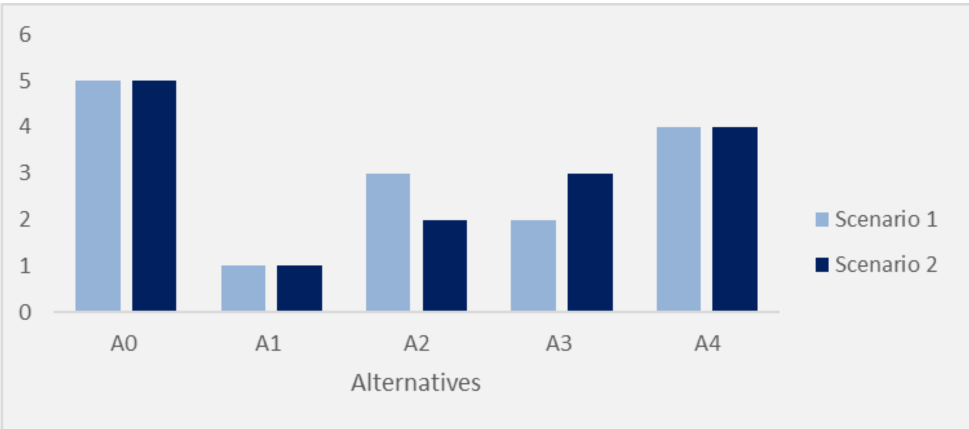

Fig. 5. Comparative analysis of strategic rankings across the two weighting scenarios

4. Managerial Implications

The consistent top ranking of the single-queue (A1) strategy offers a clear and actionable insight for pharmacy managers: consolidating multiple lines into a single, shared queue is a superior approach for enhancing both patient experience and operational efficiency. This strategy mitigates the perceived unfairness and chaos of multi-queue systems, reduces average wait times, and simplifies queue management. From a practical standpoint, implementation is often feasible with minimal physical reconfiguration and low capital investment, primarily involving floor markings and signage. However, managers should anticipate potential challenges, including the need for customer education to ensure compliance and the requirement for a coordinated payment and dispensing process to prevent bottlenecks at the service counters.

For policymakers and healthcare administrators in similar contexts, these findings suggest that operational policies should favor queue designs that promote fairness and reduce system randomness. Investing in structural solutions like a single queue is likely to yield greater returns than implementing restrictive measures that limit patient autonomy without improving underlying efficiency. The hybrid DES-RAWEC framework itself serves as a powerful decision-support tool, enabling managers to quantitatively evaluate the trade-offs of different strategies under their specific operational priorities before committing to real-world changes, thereby de-risking the implementation process.

5. Conclusions

This research developed a novel hybrid DES-RAWEC framework to evaluate pharmacy service strategies. The primary finding demonstrates that a single-queue system (A1) is the most robust and optimal strategy, consistently ranking first by significantly reducing patient wait times while maintaining high efficiency, irrespective of managerial weighting preferences. Strategies involving self-service kiosks (A2) and dynamic staffing (A3) showed context-dependent value, whereas the base case (A0) and restricted jockeying (A4) were consistently inferior.

A key limitation of this study is its reliance on simulation parameters and behavioral assumptions specific to the case study context, which may affect generalizability. Additionally, the model did not incorporate detailed financial data for a full cost-benefit analysis. Future research should, therefore, integrate exact cost parameters, validate the model in diverse healthcare settings such as emergency departments, and conduct a comparative analysis of the RAWEC method against other MCDM techniques to further elucidate its relative strengths and weaknesses in healthcare decision-making.

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Conflicts of Interest
Authors declare no conflict of interest in the publication of this research.

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