A Comparative Performance Study of AHP and Fuzzy AHP Methods for Optimizing Drug assignment in Automated Drug Dispensing Systems

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Abstract: This paper uses the Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (FAHP) to optimize drug assignment in Free-Fall-Flow-Rack AS/RS Automated Drug Dispensing (ADD) systems. By prioritizing drug placement within ADD compartments, we develop a systematic approach to enhance dispensing efficiency. The results demonstrate that the AHP and FAHP models significantly reduce retrieval times, highlighting their effectiveness in improving the efficiency of these automated drug dispensing systems.

Keywords: Pharmacy automation, Automated Drug Dispensing systems (ADDs), Analytic Hierarchy Process (AHP), Fuzzy Analytic Hierarchy Process (FAHP), Decision-making frameworks, Assignment problem, Resource allocation

1. INTRODUCTION

Efficient and precise medication delivery is crucial for patient well-being in healthcare. Automated Drug Dispensing systems (ADDs) represent a significant advancement in this field, addressing challenges highlighted in studies (Weant et al., 2014). For instance, while ADDs can reduce pharmacist workforce needs, they may increase working hours due to more comprehensive workflows (Noparatayaporn et al., 2017). The integration of ADDs enhances transparency and accountability in drug distribution (Zheng et al., 2021), reduces nursing time with rapid access (Roman et al., 2016), and minimizes cross-infection risks by limiting direct contact between staff and patients (Craswell et al., 2020). With advancements in technology, traditional dispensing methods are evolving into smart pharmacies, utilizing automated systems to streamline processes (Yuan et al., 2023).

Effective drug assignment in automated dispensing systems (ADDs) presents several challenges. A critical issue is the need to minimize dispensing time while ensuring accurate drug distribution. Optimizing storage involves complex decisions about inventory allocation, retrieval paths, and compartment utilization. (Atmaca & Ozturk, 2013).

Better improvements and outcomes result from better resource allocation and utilization, However, determining the optimal placement involves complex decision-making processes influenced by various factors, including drug consumption patterns and co-usage frequencies. As such, there is a need for a systematic approach to prioritize drug placement within ADD compartments, considering both quantitative data and qualitative insights., which is achieved when the most important attributes and aspects are fulfilled first with least effort. One approach for better resource allocation is to prioritize service elements based on their importance and effects on overall efficiency. The Analytic Hierarchy Process (AHP) is an effective multi-criteria tool that uses hierarchical structures to represent a problem and then develop priorities for alternatives based on the judgment of the user (Saaty, 1977), AHP provides a systematic and simple-to-use procedure for ranking alternatives, including a numerical check for the consistency of final results. However, the inherent uncertainty and variability in the parameters involved can affect the decision-making process. To address these uncertainties, fuzzy set theory can be integrated with conventional AHP.

Fuzzy Analytic Hierarchy Process (FAHP) allows decision-makers to evaluate their preferences between attributes using linguistic values rather than precise numerical values (Kahraman, 2004). FAHP has been applied in various fields to solve decision-making problems and determine the best strategies for resource allocation (Singh & Dutta, 2015),(Ramanathan & Ganesh, 1995) and optimization Both AHP and FAHP offer robust frameworks for optimizing drug placement in ADD, ultimately aiming to reduce dispensing time.

This paper will follow an IMRAD structure for easy understanding. First, we'll explore into the existing literature to provide context. Next, we'll explain our methodology. Then, we'll present our findings, followed by a discussion to explore their meaning. Finally, we'll wrap up with a conclusion summarizing our key points.

2. LITERATURE REVIEW

Efficient medication management within healthcare facilities is critical for ensuring patient care, particularly with the integration of automated dispensing systems (ADDs). This literature review synthesizes various methodologies aimed at optimizing medication assignment within these systems, highlighting their strengths, challenges, and practical applications.

Traditional drug assignment methods in pharmacy settings typically involve class-based storage policies, where medications are categorized according to specific criteria. This system simplifies the process for pharmacists, who can easily locate drugs based on their classes.

Several strategies have been developed for storage location assignment within ADDs. Random storage involves allocating drugs to any available storage location, maximizing space utilization but potentially increasing retrieval times due to scattered storage. Conversely, dedicated storage assigns each drug to a fixed location, enhancing familiarity for users but often underutilizing space as some slots may remain empty. Class-based storage groups drugs with similar attributes or usage patterns, striking a balance between ease of retrieval and space utilization. Storage location based on full turnover places high-turnover drugs in more accessible locations, reducing retrieval times but requiring detailed usage data and frequent adjustments (Roodbergen & Vis, 2009), (Hausman et al., 1976).

Advancements in optimization techniques have further improved medication assignment in ADS. (Atmaca & Ozturk, 2013) introduced a comprehensive mathematical model aimed at minimizing factors such as inventory holding costs and retrieval times within a dedicated storage policy. This model is particularly effective in predefined storage environments but requires adaptations for larger, more complex scenarios. To address the limitations of mathematical modeling in larger solution spaces, the authors employed a simulated annealing (SA) algorithm. This metaheuristic technique dynamically adjusts parameters like temperature and iteration numbers, providing near-optimal solutions across diverse scenarios.

(Chaker & Khalid, 2020) proposed an innovative Sudoku-inspired approach to prevent similar drugs from being placed in neighboring compartments. This method effectively reduces errors due to drug similarities and optimizes storage assignments through strategic coding and placement. The simplicity and effectiveness of this approach make it particularly appealing, though further exploration is needed to assess its scalability in larger healthcare systems.

(Esmaili et al., 2018) presented two mixed integer programming (MIP) models focusing on minimizing retrieval efforts by medical staff. MIP1 operates under a position-free paradigm, while MIP2 addresses layout restrictions critical for minimizing dispensation errors. These models outperform heuristic methods and traditional models in various benchmarking analyses, offering robust solutions for complex layout considerations in ADS.

(Yuan et al., 2023) proposed a three-stage method involving statistical analysis, Jaccard similarity coefficient-based grouping, and optimal location assignment within groups. This approach minimizes cross-machine picking and enhances efficiency, as evidenced by real-world applications in hospitals like Changi General Hospital. The method's practical viability is highlighted by its ability to significantly reduce mean picking times and the number of cross-machine prescriptions.

(Hachemi & Alla, 2013) tackled the medication assignment problem using a controller synthesis approach based on Petri nets. This method models the system's parameters, such as the number of drawers, compartments, and medications, incorporating constraints based on medication similarities. The approach ensures safe allocations by enforcing incompatibility constraints through an augmented Petri net model.

In summary, while existing methodologies offer valuable solutions for drug assignment optimization, there remains a gap in integrating a comprehensive decision-making framework that considers multiple criteria systematically. This study aims to address this gap by applying AHP and FAHP to optimize drug placements in ADDs.

3. METHODOLOGY

3.1. ALYTICAL HIRARCHY PROCESS (AHP)

The analytical hierarchy process (Saaty, 1977) is a decision approach designed to aid in the solution of complex multiple criteria problems in a number of application domains. This method has been found to be an effective and practical approach that can consider complex and unstructured decisions (Partovi, 1994). The analytical hierarchy process (AHP) is proposed in this research in order to handle both tangible and intangible factors and sub-factors affecting vendor selection decisions. The selection of the methodology is based on the characteristics of the problem and the consideration of the advantages and drawbacks of other methodologies. The decision-maker judges the importance of each criterion in pairwise comparisons. The outcome of AHP is a prioritised ranking or weighting of each decision alternative.

The AHP procedure involves six essential steps (Lee et al., 2008):

a) *Define the unstructured problem*

In this step the unstructured problem and their characters should be recognized and the objectives and outcomes stated clearly.

b) *Developing the AHP hierarchy*

The decision problem is broken down into a hierarchy, consisting of the main objective, criteria (attribute layers), and alternatives. This hierarchical structure simplifies the complex problem, as shown in Figure 1.

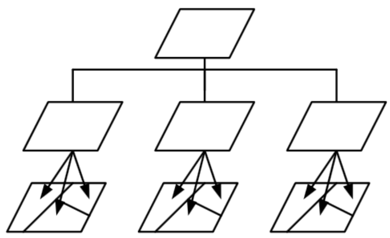

Figure 1 Hierarchical structure of decision problem

c) *Pairwise comparison*

Each element in the hierarchy is compared pairwise to determine their relative importance. This is done using a comparison matrix A (1):

$$A = \begin{pmatrix} 1 & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & 1 & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & 1 \end{pmatrix} \qquad (1)$$

Where A = comparison pairwise matrix,
$w_1, w_2, \ldots\ldots, w_n$ are weights of elements 1,2 …., and n.
The scale for these comparisons ranges from 1 (equal importance) to 9 (extreme importance), as outlined by (Saaty, 1977)

d) Estimate the relative weights

Methods like the eigenvalue method are used to calculate the relative weights of the elements in each pairwise comparison matrix. The relative weights W are derived from the following equation (2):

$$AW = \lambda_{max} IW \qquad (2)$$

Where $\lambda_{\max}$ is the largest eigenvalue of matrix A.

e) Check the consistency

To ensure the consistency of the judgments, the Consistency Index (CI) is calculated:

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (3)$$

This index is compared to the Random Index (RI) to calculate the Consistency Ratio (CR) (4). According to (Franek & Kresta, 2014), for a comparison matrix of dimension 3×3, the RI is equal to 0.58.

$$CR = \frac{CI}{RI} \qquad (4)$$

If CR is less than 0.1, the judgments are considered consistent.

f) Obtain the overall rating

The relative weights of decision elements are aggregated to get an overall rating for the alternatives:

$$W_i^S = \sum_{j=1}^{j=m} w_{ij}^S w_j^a \qquad ; i = 1, \ldots, n. \qquad (5)$$

Where W_i^S is the total weight of site i, w_{ij}^S is the weight of site i for attribute j, w_j^a is the weight of attribute j, m is the number of attributes, and n is the number of sites.

3.2. FUZZY ANALYTICAL HIERARCHY PROCESS (FAHP)

Fuzzy set theory is a mathematical framework designed to model the inherent fuzziness in human cognitive processes (Vahidnia et al., 2008). Unlike classical set theory, where elements have binary membership (either in or out), fuzzy set theory allows for gradual membership, characterized by a membership function $\mu_A(x)$. This function denotes the degree to which any element x in the domain X belongs to the fuzzy set A.

Definition 1: A fuzzy set A in a universe of discourse X is defined by its membership function $\mu_A(x)$, which assigns each element x a real number in the interval [0,1]. The value $\mu_A(x)$ represents the grade of membership of x in A.

Definition 2: A triangular fuzzy number (TFN) A is characterized by a triplet (l, m, u) as shown in Figure 2, where l is the lower bound, m is the mode, and u is the upper bound. The membership function $\mu_A(x)$ for a triangular fuzzy number is defined as:

$$\mu_A(x) \begin{cases} \frac{x - l}{m - l} & \text{if } l \le x \le m \\ \frac{u - x}{u - m} & \text{if } m \le x \le u \\ 0 & \text{Otherwise} \end{cases} \qquad (6)$$

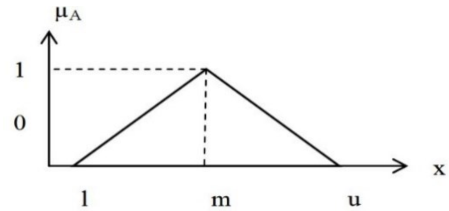

Figure 2 Triangular fuzzy number A

Triangular fuzzy membership functions are commonly used due to their simplicity and effectiveness in representing subjective and imprecise information (Xu & Chen, 2007).
To convert a TFN (l, m, u) to a crisp value, various methods can be employed, such as fuzzy extent analysis, center-of-area defuzzification, and the α-cut method. Which is often used due to its consideration of decision makers' attitudes to risk, converts fuzzy numbers into crisp values using the following formulas (7):

$$C_\lambda = \lambda \times \alpha Right + (1 - \lambda) \times \alpha Left \qquad (7)$$

where C_λ represents the average crisp value, and λ represents the degree of optimism, ranging between 0 and 1.
In traditional AHP, decision makers compare criteria using precise values, assuming certainty and confidence in their judgments. However, this is not always realistic, especially when dealing with complex and uncertain criteria. To address this, FAHP integrates fuzzy set theory with AHP, allowing decision makers to use linguistic variables rather than precise values (Mikhailov & Tsvetinov, 2004).
FAHP retains the same steps as conventional AHP but employs fuzzy membership values for comparisons.
The steps to construct FAHP models are similar to those in conventional AHP, with the main difference being the use of fuzzy membership values instead of crisp values for pairwise comparisons. These linguistic values are transformed into fuzzy membership functions to represent the inherent fuzziness and uncertainty. The fuzzy values obtained are then normalized to crisp values using the α-cut method as described previously.

By incorporating fuzzy set theory, FAHP effectively handles uncertainty and imprecision in decision making, providing a more robust framework for complex decision problems.

3.3. Application to Drug Assignment

3.3.1. Application of AHP

The AHP method is applied to optimize the placement of drugs in the Free-Fall-Flow-Rack Based Automated Drug Dispensing System by considering two main criteria: the monthly consumption (CM) and the co-use of drugs, from the second criteria we extract two criteria, the number of co-use instances, and the average co-use frequency, The objective is to minimize the dispensing time by optimally placing frequently used drugs closer to the drop-off station. The problem is defined as assigning each drug to a specific compartment within the ADD, the decision problem is broken down into a hierarchy in *Figure 3*.

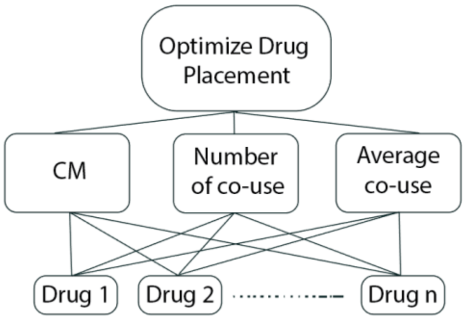

Figure 3 AHP Hierarchy Diagram

Each criterion is compared pairwise to determine their relative importance. A comparison matrix *A* is created where elements represent the relative importance of one criterion over another. Initially, the comparison matrix is provided as an input to evaluate the outcomes. The comparison matrix A is defined as follows:

$$A = \begin{pmatrix} 1 & a_{12} & a_{13} \\ a_{21} & 1 & a_{23} \\ a_{31} & a_{32} & 1 \end{pmatrix} \tag{8}$$

The matrix A is a 3x3 square matrix representing the importance of criterion i relative to criterion j. Consistency is then checked for multiple values using the eigenvalue method (2) and (3) as the judgment is derived from the data.

Normalization of the Criteria:
Normalization is performed to standardize the data for each criterion, ensuring comparability. The criteria are normalized using Min-Max normalization, which scales the values between 0 and 1.

$$C'_{ij} = \frac{C_{ij}}{max(C_i)} \tag{9}$$

where:

- C'_{ij} is the normalized value of criterion i for attribute j.
- C_{ij} is the original value of criterion i for attribute j.
- $\max(C_i)$ is the maximum value of criterion i across all attributes?

This normalization is applied to:

1) Number of Co-use.
2) Average co-use.
3) CM.

The score S_j for each drug j is calculated by combining the criteria weighted by their respective weights, from (5) we have:

$$S_j = W_1.C'_{1j} + W_2.C'_{2j} + W_3.C'_{3j} \tag{10}$$

Sorting Drugs Based on Scores:
Drugs are then sorted in descending order based on their scores. Higher scores indicate higher priority for placement, meaning that drugs with higher scores are placed in more accessible compartments.

3.3.2. Application of FAHP

The implementation of FAHP within the drug assignment system of ADD involves the following steps:

a) Define Fuzzy Variables and Membership Functions:
In the context of the drug placement system, the Mamdani fuzzy logic approach was chosen for several reasons, including interpretability, a rule-based system, handling uncertainty, and flexibility (Botta et al., 2008), the first step is to define fuzzy variables for CM and co-use frequency .These variables are characterized by membership functions that describe their linguistic terms, such as "Low," "Medium," and "High." For example, the frequency variable may have membership functions like "Low," "Medium," and "High," with corresponding triangular or trapezoidal shapes representing the degree of membership in each category Figure 4.

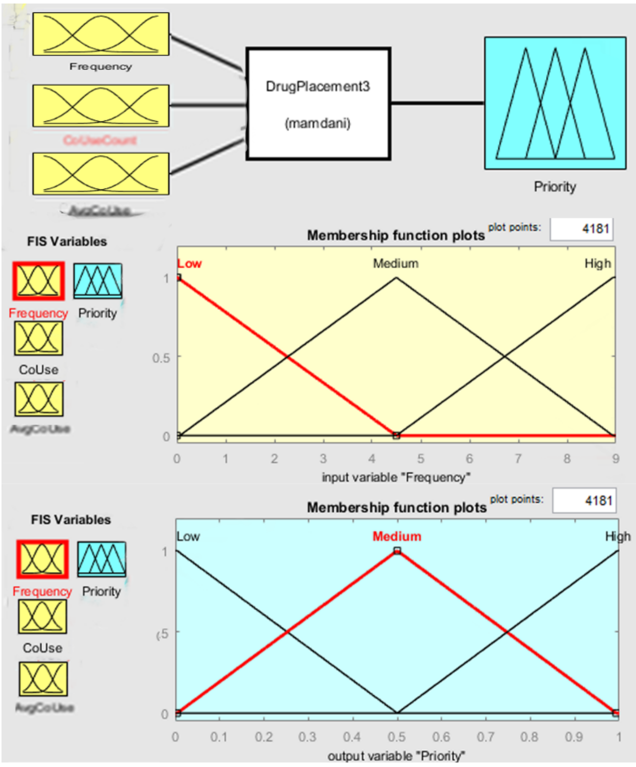

Figure 4 Mamdani fuzzy inference system

Using triangular or trapezoidal shapes to represent the degree of membership in each category offers a balance of simplicity, flexibility, effectiveness, and intuitiveness, making them well-suited for modeling uncertain or imprecise information in fuzzy logic systems like the one utilized in the drug placement system.

b) Define Fuzzy Logic System and Rules:
A fuzzy logic system (FLS) is then constructed using a fuzzy inference engine. This engine incorporates the defined fuzzy variables and membership functions to determine the priority of drug placement. Fuzzy rules, which encode expert knowledge or domain-specific insights, are established to govern the relationship between the input variables (CM, co-use count, and average co-use.) and the output variable (placement priority). These rules specify how the system should behave under different combinations of input values.
Each rule specifies a condition (combination of input variable states) and the corresponding output action (Priority level) (Figure 4 Mamdani fuzzy inference system.

c) Calculate Fuzzy Scores for Each Drug:
Using the constructed FLS, fuzzy scores are calculated for each drug based on its CM and co-use frequency (co-use count, and average co-use.) and. The FLS evaluates the input values for each drug and produces a corresponding output value representing the priority of placement. This process involves fuzzy inference, where the input values are fuzzified, rules are applied to determine the degree of activation, and the output is defuzzified to obtain a crisp score.
d) Sort Drugs Based on Scores:
The drugs are then sorted based on their fuzzy scores, with higher scores indicating higher priority for placement in the dispensing process.

3.3.3 Evaluation using Retrieval-Travel-Time in Free-Fall-Flow-Rack AS/RS:
The expected retrieval-travel-time is a crucial factor in optimizing the efficiency of an Automated Drug Dispensing (ADD) system. In this work, we evaluate the program in a specific type of ADD: The Automated Storage and Retrieval System (AS/RS) with Free-Fall-Flow-Rack (FF-Flow-Rack AS/RS) The retrieval-travel-time in the FF-Flow-Rack AS/RS includes two phases: the free fall of the product and the transport via conveyor (Figure 6).
Machine description: As illustrated in Figure 5, the FF-flow-rack AS/RS includes a deep rack with multiple sloping bins, using a gravitational conveyor with rolling wheels to slide products from storage to the picking side. Each bin contains segments with identical products placed consecutively. A pick-up station is on the storage face, and a drop-off station is on the retrieval face, connected by a transport conveyor. An operator or storage machine handles item storage(Metahri & Hachemi, 2018).
According to a comparative study by(Metahri & Hachemi, 2017), the FF-flow-rack improves throughput by up to 90%, reduces average retrieval-travel time by 38%.

For this purpose, the retrieval-travel-time model developed by (Metahri & Hachemi, 2018) can be effectively utilized. The model is given by the equation:

$$E(T'_g) = E(T'_v) + E(T'_h) = \frac{1}{2}V_c L' + \frac{2}{3}\sqrt{\frac{2H'}{g}} \qquad (11)$$

Provides a comprehensive method to estimate the retrieval time, where L' represents the length of the rack, H' represents the height of the rack, V_c represents the speed of the transport conveyor, and g represents the acceleration due to gravity $E(T'_v)$ and $E(T'_h)$ represents the mean of the vertical and horizontal travel time respectively Figure 6.
The model is based on key assumptions, including dedicated storage policies and uniform demand distributions, which are essential for accurately predicting retrieval times.
We suppose that the left side of the ADD is the closest to the Drop-Off station.

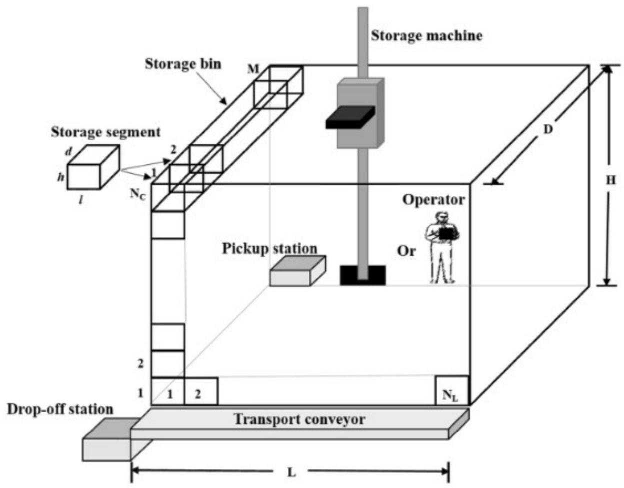

Figure 5 Typical configuration of FF-flow-rack AS/RS

4. RESULTS

4.1 Drug Placement Optimization Using AHP

The AHP method was applied to optimize the placement of drugs within a Free-Fall-Flow-Rack Based Automated Drug Dispensing System (ADD). This optimization considered three criteria: Monthly consumption (CM) and Co-Used frequency (the number of co-use instances, and the average co-use frequency). The goal was to minimize dispensing time by strategically placing frequently used drugs closer to the exit. Considering the co-use pattern of the drugs, an AHP algorithm was constructed to assign each drug to a specific compartment within the ADD.
As mentioned previously, the comparison matrix is provided as an input based on data-derived judgments. Once consistency is checked and accepted, the score is calculated, taking into account that the left side of the ADD is the closest to the drop-off station and the distance is calculated from the center of the compartment (Figure 6).
In applying this model to a practical scenario, consider an ADD system with compartments having dimensions (l, h, d) = (0.15 m;0.10 m; 0.10 m), The dimensions L' and H^'

represent the distances from a specific compartment to the point where all items converge for retrieval. An ADD machine with 5 rows and 7 columns was simulated to evaluate the program's performance. Utilizing the model (11) , retrieval times were computed based on various inputs. To assess efficiency, the AHP model's performance was juxtaposed with that of a randomized drug placement strategy and sequential drug positioning (initial positioning). Through a series of 10 simulated prescriptions, the retrieval times were meticulously recorded. A comprehensive table was crafted to present the retrieval times associated with each prescription, elucidating the impact of the AHP model compared with Sequential and random drug placement. Diverse comparison matrix values were employed to scrutinize outcomes and ascertain the most optimal configuration, as discerned from retrieval time analyses Table 1 and Table 2.

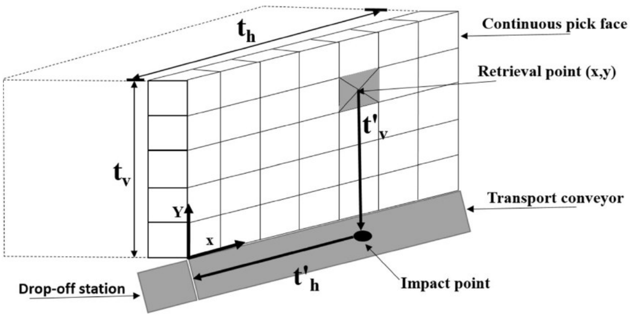

Figure 6 Depiction of the product movements in the retrieval face (continuous face)

Table 1 Drug Retrieval Time Random/Sequential Drug Placement

Prescription	Retrieval time (s)	
	Randomized Drug Positioning	Sequential Drug Positioning
1	1,4156	1,6130
2	1,6644	1,1906
3	1,3880	1,5298
4	1,5791	1,5791
5	0,9041	1,2144
6	1,1906	1,0798
7	1,6644	1,1906
8	1,7406	1,4394
9	1,6644	1,1906
10	1,3880	1,5298
Total	14,5992	13,5571

The tables Table 1 and Table 2 summarize the cumulative retrieval time for multiple prescriptions, with each prescription containing three different drugs. It includes retrieval times for optimized placements based on different AHP comparison matrices.

A_1, A_2, and A_3, the matrices are defined as follows:

$$A_1 = \begin{pmatrix} 1 & 2 & 2 \\ \frac{1}{2} & 1 & 1 \\ \frac{1}{2} & 1 & 1 \end{pmatrix} A_2 = \begin{pmatrix} 1 & 1 & \frac{1}{2} \\ 1 & 1 & \frac{1}{2} \\ 2 & 2 & 1 \end{pmatrix} A_3 = \begin{pmatrix} 1 & \frac{1}{2} & 2 \\ 2 & 1 & 4 \\ \frac{1}{2} & \frac{1}{4} & 1 \end{pmatrix}$$

Table 2 Drug Retrieval Time for AHP

Prescription	ADH results		
	A_1	A_2	A_3
1	1,2144	1,1630	0,9894
2	1,4156	1,4156	0,938
3	1,388	1,3048	1,2144
4	1,6406	1,5791	1,388
5	1,6644	1,6406	1,4394
6	0,9041	0,7644	1,0798
7	0,3144	0,4048	0,3144
8	1,6644	1,6406	1,4394
9	0,488	0,3144	0,4048
10	1,388	1,3048	1,2144
Total	12,0819	11,5321	10,4220

The results demonstrate the effectiveness of the AHP method in optimizing drug placement within the ADD system. The decreasing retrieval times from Random Placement to A_3 illustrate the progressive improvement in efficiency.
The AHP-based placements (A_1, A_2, A_3) significantly reduce retrieval times, with A_3 being the most efficient configuration for this dataset.

4.2 Drug Placement Optimization Using FAHP

As mentioned in the previous section, the FAHP method was implemented within the FF-Flow-Rack AS/RS to optimize drug placement. This approach utilized fuzzy logic to evaluate the three primary criteria, same as the AHP study, the objective was to reduce retrieval time by strategically positioning frequently used drugs closer to the exit.
The process began with defining fuzzy variables and membership functions using the Mamdani fuzzy logic approach, Membership functions for these variables were characterized by linguistic terms such as "Low," "Medium," and "High" (Figure 4)
Next, a fuzzy logic system (FLS) was constructed, incorporating the defined fuzzy variables and membership functions. 27 Fuzzy rules were established to determine the priority of drug placement based on these input variables. The FLS evaluated the input values for each drug and produced a crisp output value representing the priority of placement.
Fuzzy scores were then calculated for each drug using the constructed FLS. This involved the FLS evaluating the input values and producing corresponding output values that represented the priority of placement. The drugs were subsequently sorted based on their fuzzy scores, with higher scores indicating higher priority for placement.
The evaluation of the FAHP model was conducted using the same setup and data-set as described previously for the AHP

method. An Automated Drug Dispensing system (ADD) with 5 rows and 7 columns was simulated the retrieval times for 10 different prescriptions were recorded and are presented in Table 3.
The results demonstrate a significant improvement in drug retrieval times with the implementation of the FAHP method compared to both randomized and original placements (Table 1). FAHP consistently achieves lower retrieval times for each prescription, underscoring its effectiveness in optimizing drug placement. Specifically, the total retrieval time for FAHP (12.3451 seconds) stands out as notably lower than those for Random Placement (14.5992 seconds) and Original Placement (13.5571 seconds). This efficiency extends to individual prescriptions, with FAHP consistently outperforming both Random Placement and Sequential Drug Positioning.

Table 3 Drug Retrieval Time for FAHP method

prescription	FADH Retrieval time (s)
1	1,3880
2	0,6298
3	1,5298
4	1,4394
5	1,6644
6	0,9656
7	0,9041
8	1,6644
9	0,6298
10	1,5298
Total	12,3451

5.DISCUSSION

The results from the optimization of drug placement within the Free-Fall-Flow-Rack Based Automated Drug Dispensing System (ADD) using both the Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (FAHP) methods reveal insightful findings regarding efficiency and effectiveness.
The AHP method proved to be effective in optimizing drug placement by considering three main criteria The hierarchical structuring of the problem allowed for a systematic comparison of these criteria, leading to a prioritized ranking of drugs. However, AHP's reliance on precise numerical values for pairwise comparisons can be a limitation in scenarios where decision-makers face uncertainty or lack confidence in their judgments (lack real data-set). This limitation is addressed by the FAHP methodology, which integrates fuzzy set theory to handle imprecise information.
When comparing AHP and FAHP, it is evident that both methodologies offer substantial benefits over non-optimized placements. However, AHP consistently outperformed FAHP in terms of retrieval times, the variation in results across different AHP configurations (A_1, A_2, A_3) underscores the importance of selecting appropriate comparison matrices to achieve optimal placement.
FAHP holds a slight edge due to its ability to handle uncertainty and provide a more nuanced evaluation of criteria weights. This makes FAHP particularly useful in complex environments where precise data may not always be available.

6. CONCLUSION

In healthcare, the integration of ADDs represents a significant step forward in enhancing medication delivery efficiency and precision. This study addresses the challenges of optimizing drug placement within these systems by employing the AHP and its fuzzy extension FAHP.
The application of AHP and FAHP in optimizing drug placement within ADDs offers a comprehensive and effective approach to improving medication delivery in healthcare settings. The results demonstrate that both significantly reduce drug retrieval times compared to random and non-optimized placements, thereby enhancing the efficiency of the dispensing process
Future research could explore the integration of real-time data and machine learning algorithms with AHP and FAHP to further refine drug placement strategies. Additionally, investigating the scalability of these methodologies in larger and more complex dispensing systems could provide valuable insights into their applicability in diverse healthcare settings. The exploration of other fuzzy logic variants and multi-criteria decision-making techniques could also offer new avenues for improving the optimization process.

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