A Hybrid Generative AI and Optimization Approach for Resilient Emergency Department Layouts

Othman Manae, Khalil Bouramtane, Said Kharraja, Jamal Riffi, Omar El Beqqali

Abstract— **Effective spatial organization in hospital emergency departments (EDs) is critical for delivering timely patient care and minimizing operational inefficiencies. Instead of relying on human judgment or traditional optimization methods, which may not adapt well to changing healthcare systems, this work proposes a hybrid method of combining a large language model (LLM) with an optimized algorithm to automate and improve hospital department layouts. The framework incorporates key spatial and operational criteria, including patient flows between rooms, inter-room distances, room priority levels and the most important are the health crises constraints. The LLM acts as a constraint-aware symbolic generator used to initialize the optimization stage that produces clinically plausible room-function reassignments from a structured JSON representation of the layout, sanitary and operational constraints, and scientific knowledge retrieved via Retrieval-Augmented Generation (RAG). These LLM-generated proposals are then refined by Particle Swarm Optimization (PSO) and Simulated Annealing (SA), which optimize flow-weighted distance costs, reassignment penalties, room priorities, and feasibility requirements. Our contribution focuses on integrating LLM-based reasoning with optimization techniques to improve solutions to the healthcare facility layout problem (FLP). By comparing widely used optimization algorithms for healthcare facilities, we evaluate the effectiveness of our integrated approach. Our experimental results from our simulated ED with realistic hospital constraints indicate increased spatial and functional efficiency over the existing baseline layout. The simulated emergency department in this study is inspired by the organization of a hospital emergency unit in Roanne.**

Keywords: Emergency Department, Layout Optimization, Retrieval-Augmented Generation, Large Language Models, Particle Swarm Optimization, Simulated Annealing, Healthcare Planning, Facility Layout Problem

I. INTRODUCTION

The emergency department (ED) is the first point of access for patients requiring urgent medical care and is responsible for delivering timely, efficient, and continuous care (regardless of severity) [1]. The COVID-19 pandemic exposed vulnerabilities within hospital systems that forced these systems to combine under unprecedented pressures. Overcrowding and insufficient resources coupled with inflexible organizational designs led emergency departments to struggle in meeting evolving demand [2]. In many hospital systems, non-clinical spaces, such as offices or conference rooms, required urgent repurposing into temporary triage or treatment area [1]. Traditionally, hospital floor plan modifications and planning are based on manual experience, standardized rules, or traditional approaches to optimization [3]. While these methods can be useful in static conditions, they cannot be useful in dynamic reallocating space uses. There are possibilities with artificial intelligence (AI) to rethink space design for emergency departments. Generative models and Large Language Models (LLMs) can help generative develop automatic layout design about operational and clinical constraints [1] [2].

This topic is of primary importance during health crises conditions, when resources and space for treatment may be limited, patient conditions change quickly, and the time it takes to adjust space will not help situations that may require decisions regarding layout and patient flows at high demand [3].

The aim of this research study is to explore a hybrid approach to reconfigure ED layouts in times of health crises. A large language model (LLM) generates suggestions for functional reallocations based on initial proposals that consider constraints these are later optimized with algorithms to include factors, such as physical, logistical, and clinical constraints. In particular, two algorithms, simulated annealing (SA) and particle swarm optimization (PSO), are used to increase spatial efficiency and improve the flow of patients through the facility, with both being evaluated using an equal systematic comparison across each algorithm. The outcomes of this study show how LLM-based reasoning can be integrated with optimization methods for the design and reconfiguration of emergency spaces under high demand and critical health care situations, ultimately leading to data-supported, informed decision-making.

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II. LITERATURE REVIEW

The Healthcare Facility Layout Problem (FLP) is a major engineering problem faced by healthcare organizations today. FLPs aid in managing the flow of patients and the limitations of available space within a healthcare facility [4]. Early works on FLPs by Muther (1973) provided a foundation for developing many modern principles of spatial design [3]. More recently, advancements in the application of heuristic algorithms, process mining techniques, and bio-inspired techniques have been made, such as the use of Genetic Algorithms and Particle Swarm Optimization [5] [6]. PSO algorithms have demonstrated considerable improvements when applied to the layout of Emergency Departments by reducing the distance travelled by patients in real healthcare facilities [7]. Simulated Annealing algorithms escape local optima and also facilitate a better flow of operations [8].

Recent progress in generative AI has made it possible to automate parts or even the entirety of architectural design using either natural language descriptions or structured data [9]. Techniques such as Text2FloorEdit and GAN-based models [2] can now generate spatial layouts in real time. While these methods were first developed for residential and industrial environments, they can also be applied to healthcare settings. Moreover, Large Language Models (LLMs), particularly when combined with Retrieval-Augmented Generation (RAG), show great promise for hospital design. They can create spatial configurations that are both flexible and enriched with domain-specific knowledge [1].

Although hybrid AI approaches are increasingly being explored in areas such as optimization, autonomous driving, and logistics [10] [11] their use in healthcare layout design remains limited. Research has shown promising synergies between optimization techniques like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) and generative models such as Large Language Models (LLMs). However, when it comes to hospital design, these applications are still at an early stage of development [1].

Although significant progress has been made in ergonomics, generative models, and optimization techniques, their combined application for dynamic hospital space reallocation remains largely unexplored. Most existing generative approaches focus on residential layouts and rarely consider clinical constraints, while optimization methods are typically applied in static settings. To address this gap, this study proposes a hybrid framework combining Retrieval-Augmented Large Language Models with heuristic optimization to support resilient emergency department reconfiguration during crisis situations.

III. PROBLEMATIC

Hospitals are increasingly required to be responsive, flexible, and able to reorganize rapidly during emergencies, particularly in emergency departments. Recent worldwide health crises, such the COVID-19 pandemic has shown significant structural flaws in a number of healthcare systems [3]. So that what they give us a new vision about what a "Disease X" or future health crises can make as a shortcoming in emergency departments and the all organization. Some of the main challenges which have been highlighted by recent studies and on-field feedback.
Emergency departments rapidly become saturated in moments of crisis causing lengthy waiting times for patients and disorganized operational structures [12]. Hospitals often work on a basis of fixed organizational forms with standardized functions which is very unsuit-able for exceptional situations and to cope with these evolving circumstances such as pandemics [3]. The absence of tools for decision-making in the hospital context, especially as regards artificial intelligence to provide rapid realistic and context-adapted spatial reorganizations [13].

These points show there is great need for Methods that would automatically propose reorganization of hospital emergency departments developed over certain clinical situations. Also, the integration of spatial, functional and medical cases, and create approaches or algorithms that can quickly search complex solution spaces taking account of real hospital layouts and patient movements. To deal with these challenges, this study proposes a hybrid line of approach involving the joint use of two complementary technological solutions. A highly developed Large Language Model (LLM) whose skills have been greatly improved using a Retrieval-Augmented Generation (RAG) mechanism incurring symbolic proposals for functional organization of hospital spaces. Metaheuristic optimization algorithms, namely Particle Swarm Optimization (PSO) and Simulated Annealing (SA), which refine these symbolic proposals by explicitly accounting for fixed room geometries, spatial distances, clinical priorities, functional compatibilities, and capacity constraints inherent to hospital environments.

This dual approach overcomes the limitations of traditional methods, which are often too rigid or simplistic, while ensuring adaptable, realistic, and effective solutions particularly for emergency departments operating under crisis conditions such as pandemics.

IV. METHODOLOGY

A. Hybrid Generative Framework for Spatial Configuration

Advances in large language models (LLMs), such as GPT, LLaMA, and Gemma, have created new opportunities for the automatic generation of contextualized content in diverse application areas, including architecture, healthcare, and spatial optimization [14] [15] [16].

Retrieval-augmented generation (RAG): This is a method where retrieval techniques are used to augment the generative power of the LLM [17].
As represents figure 1, relevant scientific and technical documents are embedded and stored in a vector database to enable semantic retrieval. During inference, the most relevant content is combined with the user prompt to guide the LLM toward context-aware and healthcare-compliant spatial configuration proposals.

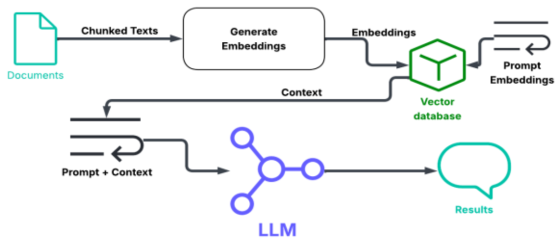

Figure 1. Figure representing the RAG process

B. RAG usage

The project attempts to create spatial layouts for emergency hospital units by taking into account both clinical and structural constraints, opting to utilize a RAG approach for the below reasons:

- It allows for recent scientific knowledge (for example, guidelines on COVID or disease X, principles of ergonomics, typology of hospital units) to be incorporated without completely finetuning the model.
- The prompts can be flexibly modified in real time to align with the characteristics of the layout being produced [17] [18].

C. Adopted configuration

To facilitate downstream optimization, as represented the layout was saved in the form of a JSON file as to each zone being encapsulated with attributes (name, priority, reassignable flag, position, and dimensions). As represented in figure 2, the experimental emergency department layout considered in this study is composed of 17 functional zones, among which a subset is marked as reassignable while the remaining zones are fixed due to clinical or architectural constraints.

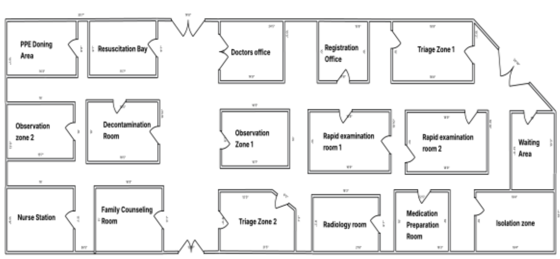

Figure 2. Initial layout of the emergency department showing functional zones.

In order to assist in computational optimization, the spatial configuration was encoded as a structured JSON schema, as represented table 1 in which each emergency-care zone was represented by first-order architectural and operational attributes (name, clinical priority, reassign ability, spatial location, and dimensions). This representation was consistent with present French architectural requirements for emergency departments [19].

In our framework, the JSON file serves as the machine-readable representation of the initial emergency department layout, from which both the LLM prompt and the optimization stage are initialized. Beyond their structured use in the JSON file, these attributes were also serialized into the LLM prompt in natural-language form, together with sanitary, operational, and functional compatibility constraints. This dual representation enabled the same layout description to support both symbolic generation by the LLM and numerical refinement by the optimization algorithms. By encoding the layout in this way, the proposed framework supports automated evaluation of spatial coherence, clinical prioritization, feasibility, and reconfigurability in the subsequent optimization stages.

TABLE I. ATTRIBUTES USED TO REPRESENT EMERGENCY DEPARTMENT FUNCTIONAL ZONES IN THE PROPOSED LAYOUT MODEL

Attributes	Description	Type
Name	The name of the area as it appears on the plan.	String
Priority	Its strategic importance in the care chain (high, medium, low).	Integer
Reassignable	Boolean indicator specifying whether the area can be reassigned to another function.	Boolean
Position	The position of the area on the two-dimensional plan.	list[float]
Dims	The size of the area on the two-dimensional plan.	list[float]

D. Response generation with LLM

With the relevant scientific context prepared, a LLaMA 3 model was used through Ollama to generate symbolic room reassignments for the emergency department.

In sanitary crisis contexts, the LLM can play an expert-like role at the initialization stage by leveraging contextual reasoning to generate clinically meaningful and crisis-aware reallocation proposals that guide the subsequent optimization process.

The LLM was used to produce semantically coherent candidate reallocations under structured prompt guidance. The ED layout was first encoded in JSON format, where each room was represented by its name, current function, priority, reassignable status, position, and dimensions. This information was injected into the prompt together with sanitary and operational constraints, scientific context retrieved through RAG, and explicit generation rules. In particular, the prompt instructed the model to preserve critical zones, respect crisis-related hospital constraints, avoid unrealistic reallocations, and propose only clinically justified changes. The logic of Equations (1)–(6) was not given to the LLM as an exact optimization program, but translated into symbolic instructions such as unique assignment, preservation of non-reassignable room functions, compatibility of room-function pairs, and minimization of unnecessary changes. Iterative prompting was used to progressively improve the relevance and feasibility of the generated layouts. Each generation produced a symbolic mapping from room names to new functions, which was stored in JSON format and then used as initialization input for PSO and SA, where the exact numerical optimization of flow-distance cost and reassignment penalties was performed.

E. Optimization and Refinement

While the initial configurations generated by the LLM are structurally coherent at a semantic level, they remain purely symbolic and are limited to functional reassignments without explicitly accounting for physical constraints. Therefore, Particle Swarm Optimization and Simulated Annealing are employed to refine these configurations by minimizing a flow-weighted distance cost, while penalizing excessive reassignments of high-priority clinical areas and enforcing capacity constraints. The resulting objective function integrates logistical flows, clinical priorities, and Euclidean distances between zones, enabling a physically consistent and operationally efficient refinement of the LLM generated proposals. Although the objective function is formulated as a quadratic assignment problem, heuristic methods (PSO and SA) operate on a compact mapping representation that implicitly encodes the decision variables.

The flow matrix between the different functional zones of the emergency department is represented in the following table. The numerical values range from 1-6, which indicate the average intensity of flow between each zone pair; where 6 expresses a very strong connection, and 1 a weak connection. This matrix illustrates both the spatial and functional relationships of the various areas within the emergency department.

Additionally, the Euclidean distance between zones was calculated from their 2D coordinates in the initial layout, ensuring that high-flow and high-priority rooms remained spatially close.

Priorities and flows were encoded in quantitative terms, and optimization sought a configuration that had minimal overall cost as defined by the objective function. The chosen parameters for PSO (inertia, cognitive/social coefficients) were based on past empirical evidence [20].

F. Objective Function

Sets

I = Set of hospital rooms or functional zones (indices i, j).

T = Set of possible clinical or logistical activities (e.g., triage, examination, observation, isolation, radiology, administrative, waiting, storage, etc.).

$A \subseteq I \times T$ = Set of allowed room–activity assignments (e.g., certain rooms cannot host "isolation" due to spatial constraints).

$I_{fix} \subseteq I$ = Subset of non reassignable rooms (fixed activity).

$I_{free} = I \setminus I_{fix}$ =Subset of reassignable rooms.

Constant parameters

$D_{ij} \geq 0$: Distance between rooms i and j.

$F_{ij} \geq 0$: Expected flow intensity between activity of room i and j.

$C_{tu} \geq 0$: Unit activity dependent transportation cost between functional types t and u, accounting for clinical affinity or incompatibility.

$t_i^0 \in T$: Initial activity type assigned to room i.

$\underline{K_t}, \overline{K_t}$: Lower and upper bounds on the number of rooms allocated to type t (capacity limits).

$\pi_i \in \{ \text{High}, \text{Medium}, \text{Low} \}$: Clinical/logistical priority level associated with room i.

$\omega_i \geq 0$: Cost weight for changing the activity of room i (based on its priority).

Decision variables

$\mathbf{x_{it}} = 1$ if room $\mathbf{i}$ is assigned to activity type t, 0 otherwise.

$\mathbf{y_i}$=1 if room $\mathbf{i}$ is reassigned ($t \neq t_i^0$), 0 otherwise.

Constraints

Unique assignment per room.

$$\sum_{t\in T} x_{it} = 1, \forall i \in I \tag{1}$$

Feasibility of assignments.

$$x_{it} \leq 1_{(i,t)\in A}, \forall i \in I, \forall t \in T \tag{2}$$

Fixed rooms.

If room i is fixed (non-reassignable), enforce:

$$x_{it_i^0} = 1, x_{it} = 0, \forall t \neq t_i^0 \tag{3}$$

Type capacities / priority targets.

$$\underline{K_t} \leq \sum_{i\in I} x_{it} \leq \overline{K_t}, \forall t \in T \tag{4}$$

Link reassignment indicator to assignment.

$$y_i \geq 1 - x_{it_i^0}, \forall i \in I \tag{5}$$

Constraints (1) enforce a unique assignment by ensuring that each room is allocated to exactly one functional activity.

Constraints (2) restrict assignments to feasible room activity pairs, preventing incompatible functions from being allocated to rooms that cannot support them due to spatial, technical, or clinical limitations.

Constraints (3) fix the activity of non-reassignable rooms, guaranteeing that critical or structurally constrained spaces preserve their original function throughout the optimization process.

Constraints (4) impose capacity bounds on each activity type, ensuring that the total number of rooms assigned to a given function remains within predefined minimum and maximum limits reflecting operational requirements.

Finally, constraints (5) link the reassignment indicator variable to the assignment decision, activating a penalty whenever a room is reassigned from its original activity. This mechanism allows the optimization process to discourage excessive or unnecessary changes, particularly in high-priority clinical areas, while still enabling flexibility where appropriate.

After modeling the key elements required for constructing the cost function, we now present its formulation and explain in detail the meaning of each term:

$$min \sum_{i,j\in I} \sum_{t,u\in T} F_{ij} D_{ij} C_{tu} x_{it} x_{ju} + \sum_{i\in I} \omega_i y_i \tag{6}$$

The proposed objective function (6) aims to minimize the total material handling cost (TMHC) [21] induced by interactions between functional zones of the emergency department. This formulation is inspired by the classical Facility Layout Problem (FLP) and the Quadratic Assignment Problem (QAP)[27], which are widely used to model flow–distance trade-offs in spatial layout optimization.

Binary decision variables x_{it} indicate whether room i is assigned to activity type t. The product $x_{it}x_{ju}$ therefore activates the interaction cost between rooms i and j when the corresponding activity types are selected, yielding a quadratic objective function consistent with QAP-based formulations of TMHC. In addition to the TMHC term, the objective function includes a reassignment penalty $\sum_{i \in I} \omega_i y_i$ where y_i indicates whether room i is reassigned and ω_i represents a priority dependent cost. This term discourages excessive or clinically disruptive reassignments.

In the end, the process enables generative AI and numerical optimization to enable more rapid reorganization of hospital spaces with constraints in mind. The initial model proposals, informed by contemporary scientific knowledge, optimize through PSO / SA into layouts that reflect clinical realties and crisis response, providing a clear advance in the state of the art for continuing hospital facility planning [22].

There's a general schema about the whole process:

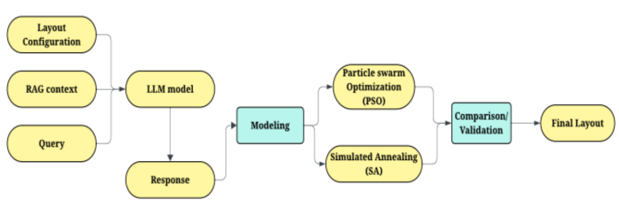

Figure 3. The project process diagram

V. Results

The proposed hybrid approach was evaluated through a set of experiments conducted on a small-to-medium emergency department layout instance. All experimentation conducted on all instances of Emergency Department Layout were done so at the local office work station, which had a Windows operating system environment with an AMD Ryzen 5 5000SERIES processor which had a maximum clock frequency of 3.30 GHz, 16GB of RAM and a NVIDIA GTX 1650 Video Graphics Processing Unit with 4GB of Video RAM. The Graphics Processing Units (GPU's) were used for the local execution of the Large Language Model (LLM) via the Ollama Framework while the optimization algorithms of Particle Swarm Optimization (PSO) and Simulated Annealing (SA) were executed on the CPU.

Symbolic functional reassignment proposals for the emergency department were generated by the LLaMA-3 model. The generated text was parsed so that it could be structured and included as part of the optimization framework. Next, Particle Swarm Optimization (PSO) and Simulated Annealing (SA) methods were used to minimize Total Material Handling Cost (TMHC) of the generated floorplans, while addressing clinical priorities and penalties associated with functional reassignments.

Table 2 compares standalone metaheuristics (SA, PSO), LLM-seeded optimization approaches (LLM+SA, LLM+PSO), using a TMHC-based total cost, the number of functional reassignments, the relative gap (%) with respect to the initial layout cost, and the computational time. The total cost reflects the flow–distance interaction and the reassignment penalty defined in the objective function [27] [26], while the number of changes quantifies organizational disruption, which is a critical constraint in hospital layout reconfiguration [3]. The gap (%) measures how well heuristic solutions are (or are not) related to the initial layout solution it represents, as defined by accepted standards for facility layout optimization [28].

Overall, the use of an LLM+SA approach resulted in the lowest total costs with fewer reassignments. Thus, an effective compromise between spatial efficiency and organizational stability was achieved using this method. On the other hand, pure SA remains competitive while PSO-based techniques execute more quickly but incur slightly higher total costs. These results highlight the usefulness of metaheuristic and LLM-seeded optimization methods for crisis-driven reconfiguration, where both solution quality and rapid decision support are important.

TABLE II. Comparison of optimization scenarios based on Total Cost, number of changes, %gap and execution time.

Scenario	Total Cost	%Gap vs Initial Layout	changes	Time (s)
LLM+SA	**25039.117**	**-11.11**	**4**	**29.80**
SA	25479.689	-9.54	5	0.52
LLM+PSO	25537.879	-9.34	5	29.93
PSO	25560.209	-9.26	5	0.44
Initial Layout (baseline)	28167.648	0.00	0	-

As illustrated in figure 4, the final layout introduces a limited number of targeted functional reassignments, highlighted in green, focusing on low-priority and reassignable zones while preserving critical clinical areas. These controlled changes reduce the total cost by improving proximity between highly connected units and achieve a balance between spatial optimization and organizational stability in time-sensitive crisis scenarios.

Figure 4. Final Layout of the emergency department showing functional zones

VI. CONCLUSION

In conclusion, this work proposed a hybrid generative and optimization-based framework for tackling the emergency department facility layout problem under crisis conditions. The LLM generates clinically meaningful functional reassignment proposals, which are then refined by optimization algorithms that account for inter-room distances, patient flows, clinical priorities, and reassignment penalties. Experimental results on a simulated emergency department layout inspired by a real hospital organization showed improved spatial and operational efficiency compared with the baseline layout, with LLM+SA achieving the best trade-off between total cost reduction and limited functional disruption. Although the current study was evaluated on a 17 room emergency department instance, the proposed framework is intended to scale to larger layouts because the JSON-based representation and symbolic generation stage are not tied to a fixed number of rooms or activities. In a real hospital decision-support setting, the framework could also be used as a human-in-the-loop tool, where hospital planners or clinical managers review, validate, or reject the generated reallocation proposals before implementation. Overall, these findings highlight the potential of combining generative AI with heuristic optimization as a practical decision-support tool for resilient hospital layout planning in time-sensitive and high-demand healthcare environments. Future work will focus on evaluating the quality and consistency of the LLM-generated proposals, extending the performance assessment through additional evaluation metrics, and validating the framework on multiple hospital layouts and problem instances.

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