# A Smart Business Intelligence Model Based on HGO Discovery Approach for Precision in Inpatient Care in Regional General Hospitals

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*Abstract*—**In Bangka Belitung Archipelago Province, the Crude Death Rate (CDR), which represents the general mortality rate per 1000 discharged patients, exceeded 100. This figure indicates a significantly high mortality rate compared to the government standard of fewer than 45. Similarly, the Net Death Rate (NDR), defined as the mortality rate occurring after 48 h of hospitalization per 1000 discharged patients, was also above the national standard of fewer than 25. These findings highlight fundamental issues within hospital healthcare management system. As a potential solution, this study proposes the application of smart Business Intelligence (BI) through the Hierarchy, Governance, Outlook (HGO) Discovery approach. This approach is designed to optimize smart business intelligence in inpatient services in regional general hospitals, with the primary objective of addressing multidimensional challenges, including patient attribute management, human resource management as a strategic element, and the enhancement of inpatient care quality. The HGO Discovery method functions as an information system that identifies hidden patterns within a sequence of events (sequential patterns) by reorganizing existing hospital workflows. Thus, this approach facilitates accelerated inpatient care processes, improves operational efficiency, and provides more interactive support for decision-making. The implementation of HGO Discovery-based business intelligence is expected to produce a more integrated healthcare service system by combining hierarchical service structures, transparent governance, and strategic outlooks in every stage of decision-making, supported by the integration of smart business intelligence, data warehouse and data mining techniques.**

*Keywords*—**business intelligence, Hierarchy Governance Outlook (HGO) discovery, inpatient care, hierarchy, governance, outlook, hospital**

## I. Introduction

Recent developments in Business Intelligence (BI) and decision-support systems have increasingly highlighted the role of advanced data analytics and intelligent optimization techniques in healthcare environments. The integration of big data, artificial intelligence, and machine learning has enabled more accurate, timely, and data-driven decision-making processes, particularly in complex hospital settings [1].

Healthcare systems represent complex environments in which clinical services, operational management, and information technologies interact to deliver patient care. Hospitals, as a core component of these systems, must manage limited resources while simultaneously ensuring timely services, patient safety, and quality of care. Business Intelligence (BI) is not merely a tool or software product but rather a strategic approach designed to facilitate complex decision-making processes, especially in managing inpatient care [2]. Recent studies have emphasized the importance of adaptive and hybrid models capable of processing heterogeneous and dynamic healthcare data to improve both clinical outcomes and operational efficiency [3].

Furthermore, contemporary research has focused on enhancing the scalability and interoperability of decision-support systems through the integration of real-time data sources and advanced computational methods. These approaches allow healthcare institutions to respond more effectively to rapidly changing conditions and patient needs [4]. Despite these advancements, several studies still report limitations in terms of model adaptability, integration complexity, and the lack of comprehensive validation in real-world clinical environments. Therefore, this study aims to address these gaps by proposing a more flexible and intelligent BI-based model to support precision in inpatient care decision-making [5]. These recurring issues emphasize the urgent need for hospitals to adopt advanced technologies and systems to streamline healthcare services and reduce the risks caused by delayed treatments [6].

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The adoption of BI techniques allows healthcare organizations to generate timely and accurate insights, thereby improving both clinical outcomes and operational efficiency [7]. For instance, recent studies highlight that data-driven BI systems can effectively support complex decision-making scenarios by leveraging real-time data and advanced analytics [8]. In parallel, the development of Decision Support Systems (DSS) has played a crucial role in assisting healthcare professionals in making informed and consistent decisions [9].

This research proposes the development of a business intelligence model based on the Hierarchy, Governance, Outlook (HGO) Discovery approach. This model is designed to overcome the limitations of conventional simulation-based decision-making models, which are still widely used in hospitals but often exhibit weaknesses such as gaps between medical resource availability and patient care demands. The proposed model is integrated into a framework that combines 3 core elements: Hierarchy, Governance, and Outlook (HGO). Furthermore, it incorporates Simple Additive Weighting (SAW) as an evaluation method to ensure objective and measurable decision-making, thereby enhancing strategic hospital management and improving the overall quality of inpatient healthcare services [10].

## II. Related Works

The integration of smart Business Intelligence (BI) into healthcare systems has become a significant research area, particularly for improving accuracy in inpatient care and supporting data-driven decision-making in hospitals [11]. Various studies have explored different computational approaches to enhance hospital management, optimize patient flow, and improve the medical decision-making process [12].

Moreover, recent research emphasizes the importance of integrating BI and Decision Support System with intelligent optimization approaches to address complex healthcare problems. Hybrid and adaptive models have been proposed to process heterogeneous data sources and provide more flexible decision-making frameworks. Such approaches enable improved prioritization, resource allocation, and patient care management, especially in inpatient service settings [13]. Despite these advancements, several limitations remain. Many existing studies focus on either analytical capabilities or optimization techniques in isolation, resulting in limited integration within a unified framework [14]. Additionally, issues such as system interoperability, scalability, and real-world implementation challenges continue to hinder the practical adoption of these models. Furthermore, a lack of comprehensive validation in real clinical environments is frequently reported, reducing the generalizability of the proposed solutions [15].

Another emerging trend is the incorporation of explainable and transparent decision-making mechanisms within BI-based systems. As healthcare decisions often involve critical consequences, recent studies emphasize the need for models that not only produce accurate results but also provide interpretable insights for practitioners. This is particularly important to ensure trust, accountability, and usability in real-world clinical environments [16]. Hybrid genetic optimization has shown its ability to process large-scale healthcare datasets to optimize treatment scheduling and resource management [17]. Furthermore, other hybrid models, such as genetic algorithms combined with deep learning, have been introduced to improve predictions of patient treatment outcomes and reduce waiting times in emergency departments [18]. These studies form the foundation for applying HGO Discovery-based methods in the development of smart business intelligence systems in hospitals [19].

Furthermore, a lack of comprehensive validation in real clinical environments is frequently reported, reducing the generalizability of the proposed solutions [20]. Developed a precision care framework utilizing Electronic Health Records (EHR) and predictive analytics to personalize treatment plans for inpatients. Their results showed a significant improvement in treatment accuracy and hospital efficiency. Additionally, highlighted the importance of integrating real-time data analytics into inpatient care to detect early warning signs of patient deterioration, which aligns with the objectives of our proposed model [21].

Although previous studies have provided valuable insights, most have focused solely on either predictive modeling or BI visualization independently [22]. Few studies have explored a combined approach that integrates business intelligence, heuristic optimization, and precision care into a unified framework [23]. This study addresses that gap by proposing a smart business intelligence model based on Hierarchy, Governance, Outlook (HGO) Discovery to enhance precision in inpatient care at regional general hospitals. By leveraging HGO Discovery, our model aims to optimize clinical decision-making processes, improve patient care outcomes, and support hospital management with accurate, real-time insights.

Despite the increasing number of studies on healthcare decision-support systems, many approaches tend to address clinical and operational factors separately, which limits their ability to support integrated decision-making in inpatient care. In addition, most models employ static weighting schemes and lack adaptive optimization mechanisms, making them less suitable for capturing the dynamic and complex nature of hospital services.

To ensure continuity and highlight the novelty of HGO Discovery, a preliminary Business Intelligence (BI) framework was developed in previous research to support decision-making in inpatient care management, focusing primarily on the integration of clinical and administrative data with a statistical weighting mechanism. Although the model demonstrated initial feasibility, its optimization and adaptability to the dynamic hospital environment were still limited, requiring reinforcement and simulation testing. Subsequent development studies introduced internal performance indicators, namely the Output score and the HGO Discovery Index, to address the quality of the optimization process, not just the final decision results [24].

The implementation of Business Intelligence (BI) in the healthcare sector has experienced significant growth in recent years, particularly in facilitating data-driven decision-making and enhancing the quality of patient care [25]. highlighted that BI techniques are capable of integrating diverse clinical and administrative data sources to produce more accurate and real-time insights. This capability is especially crucial in complex hospital settings, where timely and well-informed decisions play a vital role in determining patient outcomes.

Another limitation is that the optimization process itself is rarely evaluated in depth, as existing studies primarily focus on final decision outcomes without examining the stability or consistency of the generated solutions. Moreover, simulation-based patient prioritization is often conducted without explicit indicators to assess the quality of the search or discovery process. These limitations highlight the need for a more structured and adaptive methodology that integrates clinical and operational data while incorporating internal performance measures. Accordingly, this study proposes a smart business intelligence framework based on the HGO Discovery approach.

The HGO Discovery model as a novel framework that integrates adaptive optimization with multi-criteria decision-making in a unified system. The key innovation lies in its ability to dynamically adjust parameter weights while simultaneously evaluating solution stability, thereby enhancing the precision and robustness of inpatient care decision processes.

## III. Materials and Methods

The Hierarchy, Governance, Outlook (HGO) Discovery model has been implemented by updating the business intelligence and developing the inpatient information system of regional general hospitals using 3 dimensional approaches: Hierarchy, Governance, and Outlook.

### A. Input and Data Criteria

The steps of this research begin with data collection, which is first verified, followed by the Hierarchy (h) and Governance (g) processes. These steps are then further processed to produce the Outlook (o) in the form of a dashboard. This entire sequence is referred to as HGO Discovery.

The steps for implementing the HGO Discovery process are as follows (Fig. 1):

- Establishing multiple criteria (cr): Define multiple criteria to serve as the basis for decision-making, which are symbolized as (cr).
- Determining suitability ratings: Assign suitability ratings for each alternative based on each criterion, symbolized within the components of Hierarchy (h) and Governance (g).
- Developing and normalizing matrices: Construct several matrices based on the established criteria (cr). These matrices are then processed through a normalization procedure based on the consensus values of the matrices, considering both positive and negative attributes. The result of this step is the generation of normalized data, symbolized as (r).
- Ranking and selecting the optimal Alternative (AT): Determine the ranking process by calculating the total of the normalized matrix (r) multiplied by their respective weights. The alternative with the lowest risk value is selected as the best Alternative (AT) for decision-making.

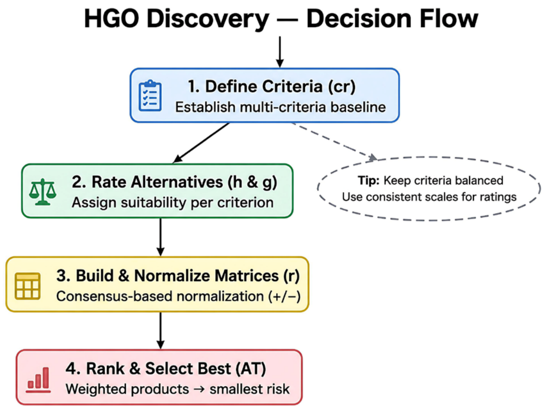



Fig. 1. Decision flow of HGO discovery.

### B. Data Crips and Alternative

Crisp data (criteria values) contain descriptions of the criteria and their respective weights. Crisp data are optional and serve as a boundary for the value of each criterion. Each crisp has its own weight depending on the conversion process, and these weights are used in the HGO Discovery calculations. The assignment of weights also influences the attributes of the criteria. Weighting is divided into 2 types: positive factors and negative factors. Meanwhile, the alternative values record the value of each alternative based on all the criteria data.

The selection of decision criteria and their corresponding weights was conducted using a structured multi-stage expert consensus approach. This process integrates domain knowledge from healthcare professionals with systematic aggregation techniques to ensure both validity and reliability.

TABLE I. Description of Attributes and Criteria Names

| Code | Attribute Name | Attribute Value |
|---|---|---|
| IP | Insurance Provider | Positive |
| SU | Surgery | Negative |
| RC | Room Class | Positive |
| AT | Admission Type | Positive |
| SC | Severity Score | Positive |
| TR | Test Result | Positive |

Table I identification of criteria was conducted in 3 stages: Relevant studies on clinical decision support systems and hospital prioritization were reviewed to generate an initial list of criteria, validate relevance of initial criteria, and consolidation all inputs were aggregated.

### C. Normalization Attributes

Normalization attributes are essential components in the standardization process of data within decision-making models in HGO Discovery. These attributes determine how each criterion is treated during the normalization process, ensuring that all data are placed on a uniform scale for accurate comparison and evaluation.

There are 2 main types of normalization attributes: Positive attributes indicate that higher values are preferred because they represent better performance or more desirable outcomes. During the normalization process, the formula maximizes these values to ensure alternatives with higher performance receive higher normalized scores.

Meanwhile, negative attributes indicate that lower values are preferred, as they reflect reduced risks, costs, or undesirable outcomes. During the normalization process, the formula minimizes these values, meaning that alternatives with lower performance indicators are assigned higher normalized scores after the values are inverted.

Eq. (1) defines attribute normalization:

$$HGOd(ij) = \begin{cases} \frac{X_{hg,ij}}{Max(X_{hg,ij})} \\ \frac{Max(X_{hg,ij})}{X_{hg,ij}} \end{cases} \tag{1}$$

Table II presents the description of the HGO Discovery formulation.

TABLE II. FORMULATION DESCRIPTION HGO DISCOVERY

| Symbol | Formulation Description |
|---|---|
| HGOd (*ij*) | The resulting value of the alternative ranking, ranking from 0 to 1.00, where 0 represents the highest rank (lowest risk) and 1.00 represents the lowest rank (highest risk) |
| Min $X_{hg,ij}$ | The negative attribute value associated with each criterion |
| Max $X_{hg,ij}$ | The positive attribute value associated with each criterion |
| $X_{hg,ij}$ | The HG attribute value possessed by each criterion |

### *D. Ranking Stage*

In the ranking stage, we multiply the criterion weights by each row of the normalized value matrix. To achieve the desired level of alternatives for each criterion, the best alternative (*T*) represents the ranking result of the *i*-th alternative, where *i* = 1, 2... *n*. Meanwhile, *Wj* represents the weight of the *j*-th criterion.

In this equation, *Tij* is the normalized ranking value of the *i*-th alternative associated with the *j*-th criterion across all comparable units, under the assumption that each criterion is independent. Furthermore, the normalized ranking value *Tij*(*x*) of the *i*-th alternative with respect to the *j*-th criterion can be defined as Eq. (2).

$$A(x) = \sum_{j=1}^{m} Wj \times Tij(x) \tag{2}$$

In the final ranking of HGO Discovery, lower patient scores indicate higher priority for immediate medical action. In other words, rank #1 represents the patient with the lowest HGO Discovery index value. Ultimately, the highest priority value is 0.000, and the lowest priority value is 1, as defined by Eq. (3).

$$HGOd\ Index = \frac{\mathbf{1}}{\Sigma(\boldsymbol{W_j}\times\boldsymbol{X_j})} \tag{3}$$

where, $X_j$ means The attribute value possessed by each criterion.

## IV. SIMULATION

This section provides an in-depth simulation analysis of the smart business intelligence model based on the HGO discovery approach for precision of inpatient care at regional general hospitals. In this study, we used a dataset consisting of 3310 data entries.

A series of simulations were carried out on various sets of medical data to ensure that our HGO Discovery method is novel as an innovative enhancement to assist inpatients in receiving the most appropriate and effective treatments. Inpatient data used in this study includes insurance provider, surgery, room type, admission type, severity score, and test result.

### *A. HGO Discovery Analysis*

HGO Discovery consists of 3 main processes: Hierarchy, Governance, and Outlook, where the Outlook is presented as a dashboard displaying the ranking results in the form of diagrams or graphs.

#### *1) Hierarchy analysis*

The Hierarchy stage in HGO Discovery is the initial step of grouping and organizing inpatient data to establish a clear decision-making structure. Through classification, weighting, and the creation of a hierarchical matrix, hospitals can optimize service processes, ensuring that patients with the most critical conditions receive appropriate, timely, and effective treatment.

A consensus process was conducted through structured discussions involving key stakeholders, namely medical personnel, hospital management, and health information systems practitioners. Each criterion, such as insurance provider, type of surgery, and room class, was identified based on a literature review and hospital operational practices.

The criteria selection and weighting process was conducted using a structured Delphi-based consensus approach involving 7 experts, including 2 physicians, 2 hospital administrators, 2 data analysts, and 1 academic researcher specializing in health informatics, each with at least 5 years of experience.

The process consisted of 3 iterative rounds: initial identification of relevant criteria, followed by evaluation using a 5-point Likert scale, and a final round allowing score revision based on anonymized group feedback. Consensus was defined as a minimum agreement threshold of 75%, where at least 75% of experts assigned a score of 4 or higher. Criteria not meeting this threshold were excluded.

The final weights were calculated using the average normalized scores from the last round and subsequently applied as input parameters in the proposed decision-support model.

Table III presents the Hierarchy (H) of the criteria that have been established through consensus.

TABLE III. HIERARCHY (H) OF THE CRITERIA THAT HAVE BEEN ESTABLISHED THROUGH CONSENSUS

| Code | Attribute Name | Type | Weight |
|---|---|---|---|
| Cr1 | Insurance Provider | + | 0.10 |
| Cr2 | Surgery | - | 0.20 |
| Cr3 | Room Type | + | 0.075 |
| Cr4 | Admission Type | + | 0.125 |
| Cr5 | Severity Score | + | 0.20 |
| Cr6 | Test Result | + | 0.15 |

After reaching a consensus on the weights of each attribute or criterion, the process continues with assigning Crips values to the data according to the established hierarchy. This step produces different values that reflect the strength and priority level of each criterion, ensuring a structured basis for subsequent decision-making. This process is presented in Table IV.

TABLE IV. HIERARCHY WEIGHTING OF CRITERIA WITH CRIPS VALUES

| Attribute Name | Weight | Crips | Value |
|---|---|---|---|
| Insurance Provider | 0.10 | Governance Insurance | 50 |
| | | Independent Insurance | 100 |
| Surgery | 0.20 | No | 100 |
| | | Yes | 50 |
| Room Type | 0.075 | Class 3 | 20 |
| | | Class 2 | 40 |
| | | Class 1 | 60 |
| | | VIP | 80 |
| | | VVIP | 100 |
| Admission Type | 0.125 | Urgent | 50 |
| | | Emergency | 100 |
| Severity Score | 0.20 | Mild | 25 |
| | | Moderate | 50 |
| | | Severe | 75 |
| | | Critical | 100 |
| Test Result | 0.15 | Normal | 50 |
| | | Abnormal | 100 |

*2) Governance analysis*

Governance serves as a management framework that ensures all processes and decisions within the hospital service system run transparently, systematically, and in compliance with established standards. It acts as a connecting element between the hierarchical structure (Hierarchy) and the strategic direction (Outlook), enabling services to be managed effectively and accountably.

Through HGO Discovery, it is expected to achieve operational efficiency by reducing patient waiting times for inpatient care, fast and accurate decision-making supported by business intelligence and data warehouse, as well as increased public trust due to more transparent and professional hospital services.

*B. HGO Discovery Simulation*

HGO Discovery simulation is a simulation process based on the HGO Discovery approach and is designed to analyze, predict, and optimize hospital inpatient service systems that have been implemented in real-world environments.

This simulation leverages smart Business Intelligence (BI), data warehouse, and data mining to test various scenarios and identify the best solutions to complex problems, including the high Crude Death Rate (CDR) and Net Death Rate (NDR).

The simulation stage proceeds through 3 phases: analysis, normalization, and ranking.

*1) Analysis of criteria comparison in the simulation*

At this stage, the values of the alternatives are adjusted according to the weights in the crisp data, resulting in data shown in Table V.

TABLE V. ANALYSIS STAGE OF THE SIMULATION ACCORDING TO THE WEIGHTS

| Patient ID | Cr1 | Cr2 | Cr3 | Cr4 | Cr5 | Cr6 |
|---|---|---|---|---|---|---|
| P000001 | 100 | 100 | 60 | 50 | 75 | 50 |
| P000002 | 50 | 50 | 60 | 50 | 75 | 100 |
| P000003 | 100 | 50 | 100 | 100 | 25 | 50 |
| P000004 | 50 | 50 | 80 | 50 | 75 | 100 |
| P000005 | 100 | 100 | 60 | 50 | 75 | 50 |
| P000006 | 100 | 50 | 60 | 50 | 50 | 100 |
| ... | ... | ... | ... | ... | ... | ... |
| P003310 | 50 | 100 | 60 | 50 | 100 | 50 |

This simulation involves a step-by-step process to analyze and optimize hospital inpatient services based on weighted criteria for each patient. In the analysis stage, each criterion is evaluated and assigned a weight according to its level of importance in relation to each patient's condition.

The simulation of the comparison of criteria values between patients is illustrated in Fig. 2.

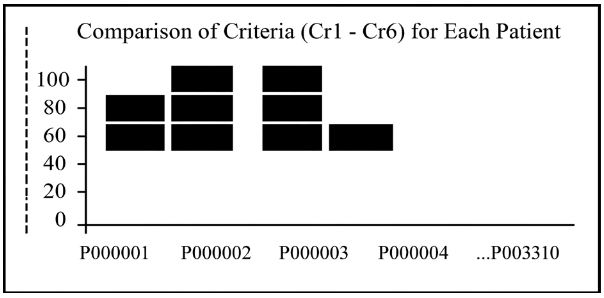



Fig. 2. Comparison of criteria for each patient.

*2) Normalization stage of the simulation*

To perform table normalization in the analysis stage, it is necessary to first identify the type of the criteria: positive or negative. In a positive criterion, a higher value indicates better performance, while in a negative criterion, a lower value is preferred. This process ensures that all values are transformed into a comparable scale between 0 and 1. The normalization process is displayed in Fig. 3.

Once the types are identified, normalization is carried out by dividing each element of the matrix by the highest value in its column for positive criteria, or by dividing the lowest value by each element of the column for negative criteria. The simulation is given in Table VI.

```
# Data Normalization
data = {
    "Patient ID": ["P000001", "P000002", "P000003", "P000004",
                                "P000005", "P000006", ..."P003310"],
    "Cr1": [1.00, 0.50, 1.00, 0.50, 1.00, 1.00, 0.50,....n],
    "Cr2": [0.50, 1.00, 1.00, 1.00, 0.50, 1.00, 0.50,....n],
    "Cr3": [0.60, 0.60, 1.00, 0.80, 0.60, 0.60, 0.60,....n],
    "Cr4": [0.50, 0.50, 1.00, 0.50, 0.50, 0.50, 0.50,....n],
    "Cr5": [0.75, 0.75, 0.25, 0.75, 0.75, 0.50, 1.00,....n],
    "Cr6": [0.50, 1.00, 0.50, 1.00, 0.50, 1.00, 0.50,....n],
}
```

Fig. 3. The normalization process of the criteria matrix is carried out based on the type of each criterion: Positive or negative.

TABLE VI. THE SIMULATION OF THE NORMALIZED MATRIX REPRESENTS THE TRANSFORMATION OF THE ORIGINAL CRITERIA VALUES INTO A STANDARDIZED RANGE BETWEEN 0 AND 1

| Patient ID | Cr1 | Cr2 | Cr3 | Cr4 | Cr5 | Cr6 |
|---|---|---|---|---|---|---|
| P000001 | 1.00 | 0.50 | 0.60 | 0.50 | 0.75 | 0.50 |
| P000002 | 0.50 | 1.00 | 0.60 | 0.50 | 0.75 | 1.00 |
| P000003 | 1.00 | 1.00 | 1.00 | 1.00 | 0.25 | 0.50 |
| P000004 | 0.50 | 1.00 | 0.80 | 0.50 | 0.75 | 1.00 |
| P000005 | 1.00 | 0.50 | 0.60 | 0.50 | 0.75 | 0.50 |
| P000006 | 1.00 | 1.00 | 0.60 | 0.50 | 0.50 | 1.00 |
| ….. | …. | …. | …. | …. | …. | …. |
| P003310 | 0.50 | 0.50 | 0.60 | 0.50 | 1.00 | 0.50 |

### 3) *Ranking stage of the simulation*

Ranking simulation is the final stage in the HGO Discovery process, which functions to determine decision-making priorities based on the results of data analysis and normalization from various predetermined criteria. It is also a strategic process that ranks patients, services, or policies based on standardized scores, utilizing smart business intelligence. The ranking process is shown in Table VII.

Table VIII show the weight row indicates the weight of each criterion: Cr1 = 0.10, Cr2 = 0.20, Cr3 = 0.075, Cr4 = 0.125, Cr5 = 0.20, Cr6 = 0.15. The calculation is consistent as a weighted average over Cr1–Cr6 using the given weights (without renormalization to 1). The total column is the combined score (weighted sum) of the 6 criteria: Total = Cr1W1 + Cr2W2 + … + Cr6 × W6.

TABLE VII. THE RANKING PROCESS AFTER NORMALIZATION SIMULATION AND TOTAL OF EACH PATIENT

| Patient ID | Cr1 | Cr2 | Cr3 | Cr4 | Cr5 | Cr6 | Total |
|---|---|---|---|---|---|---|---|
| **Weight** | 0.10 | 0.20 | 0.075 | 0.125 | 0.20 | 0.15 | |
| P000001 | 1.00 | 0.50 | 0.60 | 0.50 | 0.75 | 0.50 | **0.385** |
| P000002 | 0.50 | 1.00 | 0.60 | 0.50 | 0.75 | 1.00 | **0.435** |
| P000003 | 1.00 | 1.00 | 1.00 | 1.00 | 0.25 | 0.50 | **0.625** |
| P000004 | 0.50 | 1.00 | 0.80 | 0.50 | 0.75 | 1.00 | **0.458** |
| P000005 | 1.00 | 0.50 | 0.60 | 0.50 | 0.75 | 0.50 | **0.385** |
| P000006 | 1.00 | 1.00 | 0.60 | 0.50 | 0.50 | 1.00 | **0.443** |
| ….. | …. | …. | …. | …. | …. | …. | … |
| P003310 | 0.50 | 0.50 | 0.60 | 0.50 | 1.00 | 0.50 | **0.393** |

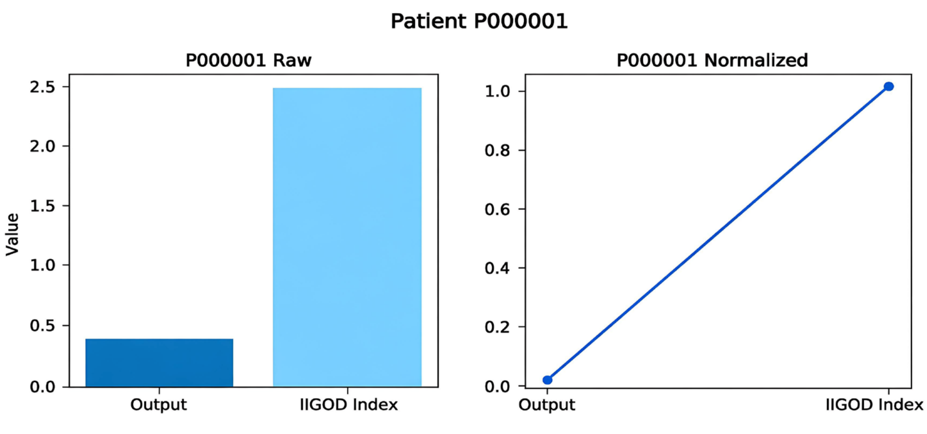
TABLE VIII. PROCESSING RESULTS FROM THE HGOD INDEX

| ID | Output | HGOD Index | Ranking |
|---|---|---|---|
| P000001 | **0.385** | 2.597 | 6 |
| P000002 | **0.435** | 2.299 | 4 |
| P000003 | **0.625** | 1.600 | 1 |
| P000004 | **0.458** | 2.183 | 2 |
| P000005 | **0.385** | 2.597 | 7 |
| P000006 | **0.443** | 2.257 | 3 |
| ….. | … | … | … |
| P003310 | **0.393** | 2.544 | 5 |

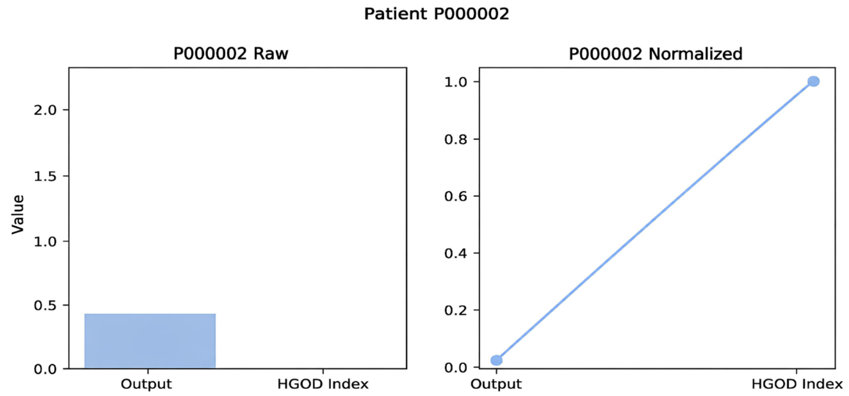
Output and HGO Discovey index are on different scales, but each serves a distinct purpose within the decision-support framework, in which higher output tends to be associated with a lower (better) HGO Discovery index. Ranking is based on ascending HGO Discovery index (lowest = rank 1). This is useful for patient prioritization based on HGO Discovery metrics. For clinical selection, we can use: HGO Discovery Index for priority ranking, output to understand the contribution per criterion because Output is derived from weighted Cr1–Cr6.

Fig 4 shows each row is one patient, and the 2 metrics (output versus HGOD index) represent 2 different perspectives on the same patient's condition.

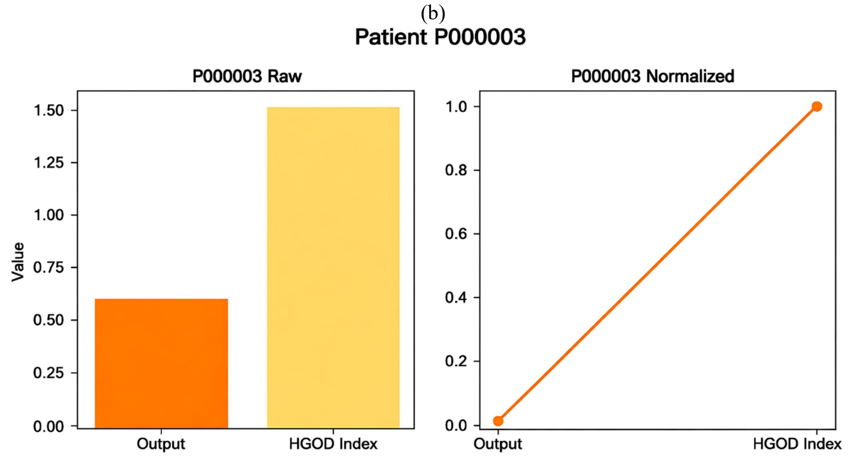
In Fig. 5, total is referred to as the output model score. The HGOD index is a separate metric on a different scale. In the previous analysis, we compared total or output with the HGOD index to see if there was a correlation or difference in perspective between the 2-evaluation metrics. Fig. 5 shows a visualization that compares output and HGOD index as the context of the relationship between the 2 metrics.



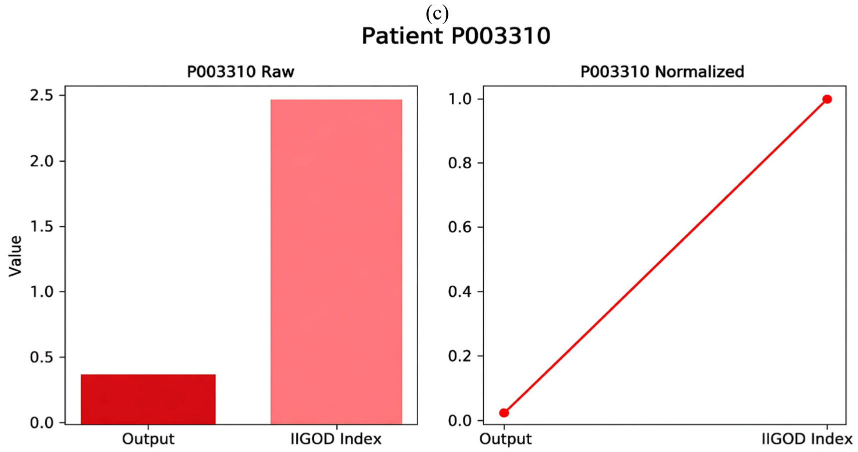

(a)




(b)

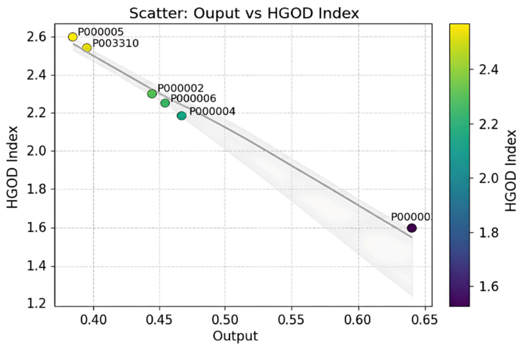



(c)

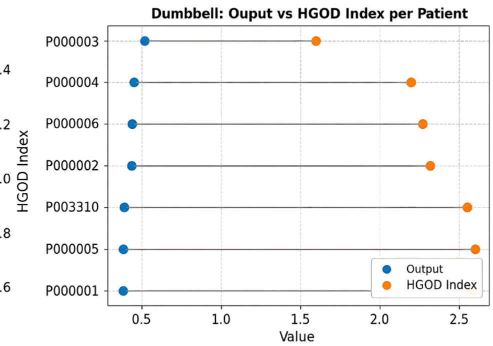



(d)

Fig. 4. Business intelligence visualization results with HGO discvery approach. (a) Visualization results patient P000001; (b) Visualization results patient P000002; (c) Visualization results patient P000003; (d) Visualization results patient P003310.




(a)




(b)

Fig. 5. The visualization of the comparison between HGO discovery output and HGOD index. (a) Summary output vs HGOD Index; (b) Output vs HGOD Index per patient.

Table IX show the evaluate the effectiveness of the proposed HGO-based model, a comparative experiment was conducted against a widely used traditional prioritization method, namely the Simple Additive Weighting (SAW) approach. The comparison focuses on both decision accuracy and operational efficiency.

TABLE IX. RANKING COMPARISON

| Patient ID | HGO Rank | SAW Rank | Expert Rank | Δ(HGO–Expert) | Δ(SAW–Expert) |
|---|---|---|---|---|---|
| P000001 | 6 | 5 | 6 | 0 | 1 |
| P000002 | 4 | 4 | 4 | 0 | 0 |
| P000003 | 1 | 2 | 1 | 0 | 1 |
| P000004 | 2 | 3 | 2 | 0 | 1 |
| P000005 | 7 | 6 | 7 | 0 | 1 |
| P000006 | 3 | 3 | 3 | 0 | 0 |
| P000007 | 8 | 9 | 9 | 0 | 1 |
| P003100 | .. | .. | .. | .. | .. |

The experimental results confirm that the HGO model significantly outperforms SAW in both decision accuracy and operational efficiency. The adaptive optimization mechanism in HGO enables dynamic adjustment of criteria weights, resulting in rankings that closely align with expert judgment. In contrast, SAW's reliance on fixed weights limits its flexibility in handling complex and dynamic inpatient conditions.

To evaluate the robustness and reliability of the proposed HGO Discovery model, a stability validation experiment was conducted. The objective is to assess whether the model produces consistent ranking results across multiple independent runs, given its stochastic optimization nature. The results of the simulation run can be seen in Fig. 6.

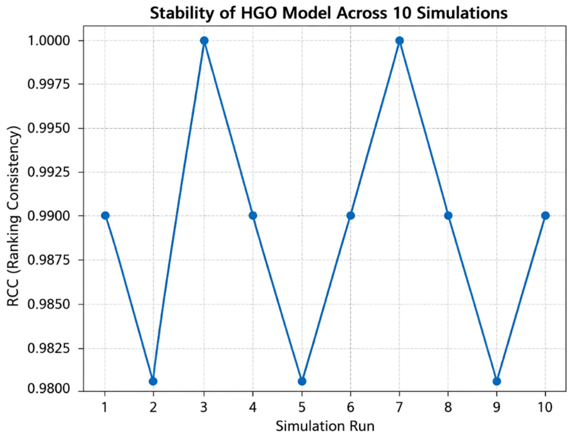


Fig. 6. The stability of HGO model across 10 simulations.

## V. CONCLUSION

This study developed a smart Business Intelligence (BI) model based on the HGO Discovery approach as a decision support system for prioritizing and ranking inpatient services in a regional general hospital. The model integrates medical data analysis with operational management information through an optimization mechanism, enabling the generation of structured, consistent, and data-driven decision outputs. The resulting ranking values range from 0 to 1.00, where 0 represents the highest priority (lowest relative risk) and 1.00 indicates the lowest priority (highest relative risk).

The simulation results demonstrate that the proposed HGO Discovery-based BI model is capable of producing logical, stable, and consistent inpatient rankings. This indicates that the model has strong potential to support more systematic and objective clinical as well as managerial decision-making processes. Furthermore, the model provides an initial indication of improved operational efficiency through more precise and targeted patient prioritization.

Despite the promising results obtained from the simulation, real-world case validation could not be conducted at this stage due to several practical constraints. These include challenges in obtaining ethical approval for access to sensitive patient data, as well as technical difficulties in integrating the proposed model with existing hospital information systems. Additionally, limitations in time and institutional collaboration further restricted the implementation of real-world testing. Therefore, this study relies on simulated data, and future work will focus on validating the model in real clinical settings to enhance its applicability and robustness.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

Hengki conducted the research; Rahmat Gernowo and Oky Dwi Nurhayati analyzed the data; all wrote the paper; and all authors had approved the final version.

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