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PAPER

Design and Analysis of a Mobile Chatbot Application for Hospital Room Availability Using the Bryant Evaluation Method

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ABSTRACT

The availability of inpatient rooms plays a vital role in providing intensive medical care for patients. However, many hospitals still face challenges in managing and accessing real-time information on room availability. This information is critical for hospital operations, particularly during emergencies, patient surges, or public health crises. Unfortunately, most hospitals continue to rely on localized, manual, and non-integrated information systems, which hinder efficient data sharing across institutions. This study aims to analyze the effectiveness of the Bryant method in evaluating an integrated system for retrieving inpatient room availability across hospitals. The Bryant method serves as a prioritization framework that assigns weighted values to predetermined parameters. In this research, a WhatsApp-based chatbot application was developed to facilitate the retrieval of inpatient room information at RSIA Abby and MMC General Hospital in Lhokseumawe, Indonesia. The evaluation criteria based on the Bryant Method include disease type, proximity to nurses, number of patients or privacy level, proximity to the bathroom, and room lighting or window access. The system's performance test demonstrated a response time of approximately one second per chat interaction. User evaluation results revealed that 41.3% of respondents rated the chatbot as *highly appropriate* and 37% as *appropriate* in displaying real-time inpatient room availability for both hospitals. Additionally, 45.7% and 30.4% of respondents, respectively, rated the system's response speed as *highly appropriate* and *appropriate*, while 43.5% and 37% agreed that the chatbot effectively assisted in determining suitable inpatient room selections. These findings indicate that the integration of the Bryant Method within a mobile-based chatbot application can enhance hospital information accessibility and decision-making efficiency.

KEYWORDS

Bryant method, chatbot application, hospital information system, inpatient room availability, prioritization criteria

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1 INTRODUCTION

The availability of inpatient rooms is a critical component of hospital service management and patient care efficiency. The existence of inpatient rooms plays a central role in providing intensive treatment to patients, while timely and accurate information on bed occupancy not only improves patient admission processes but also supports optimal resource utilization, enhances referral coordination, and contributes to better overall patient satisfaction. In the context of Indonesia, many hospitals still rely on manual updates or isolated Hospital Information Systems (SIMRS) that lack real-time data synchronization between departments or institutions. These limitations often result in long waiting times, ineffective referrals, and suboptimal evaluations from the Indonesian National Health Insurance (BPJS).

Globally, several challenges are commonly encountered in the search for inpatient room availability information. Many hospitals or SIMRS platforms do not have real-time or accurate data, forcing users to come directly to the hospital [1]. Bed-tracking systems are often not integrated across wards, between hospitals, or across regions [2]. The slow and incomplete updating of inpatient room information creates obstacles in obtaining accurate data [3]. Furthermore, many hospitals operate at high occupancy rates, which causes system overloads when sudden surges in demand occur. The limited capacity of inpatient rooms also leads to delays, resulting in patients waiting for long periods or even being transferred to other hospitals [4], [5]. In addition, many hospital staff still use manual processes such as telephone inquiries or checking Excel files for inpatient room availability, which are time-consuming and prone to human error [6].

These information delays have significant impacts, including the slowdown of patient referral processes, decreased public satisfaction, and an overall decline in healthcare quality. Hospitals also often receive poor evaluations from BPJS due to delayed updates of inpatient room availability. In the era of digital transformation and the Fourth Industrial Revolution (Industry 4.0), technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI)-based chatbots present strategic opportunities to address these issues. Chatbots can provide fast, interactive, and automated information services to users without overburdening hospital staff. Nevertheless, the development of such systems requires comprehensive evaluation to ensure their effectiveness and integration capability within hospital networks.

Several studies have addressed the importance of efficient hospital bed management and the need for technological innovation in this area. Malekar [1] emphasized that understanding hospital bed availability is essential for optimizing patient care delivery, while Jones [2] proposed an analytical framework for hospital bed capacity planning. Mark et al. [3] examined how traditional bed tracking systems fail to meet the challenges of real-time information, whereas Bartlett et al. [4] and Emrick [5] focused on internal quality improvement without addressing patient accessibility. Shakil [6] designed a proactive bed management system but relied solely on manual web-based data inputs without AI integration.

Meanwhile, the integration of AI, IoT, and mobile chatbot systems offers new opportunities for digital transformation in hospital services. Leng et al. [7] proposed an IoT-based smart hospital framework, while Yanti et al. [10] and Setiawan et al. [11] implemented chatbot systems for healthcare communication and scheduling, though these were limited to single institutions. From a methodological perspective, the Bryant method has been widely used for prioritization and decision-making in other domains, such as telecommunication [8] and community health [9]. However, its application in hospital bed management remains unexplored—particularly when combined with intelligent chatbot systems and real-time SIMRS integration. The structured scoring and weighting framework of the Bryant method makes it suitable for evaluating multiple measurable criteria, including response speed, data accuracy, user satisfaction, ease of integration, and scalability.

To illustrate the novelty of this research, a comparative analysis between previous studies and the present work is summarized in Table 1.

Table 1. Analysis of research gap between previous studies and current study

Aspect	Description	Relevant References	Academic Relevance Explanation
Research Focus	Previous studies focused on patient administration systems and manual data management.	[1] Malekar (2024); [3] Tami L. Mark et al. (2019); [6] Shakil (2025)	These works discuss hospital bed management but are limited to administrative systems without chatbots or intelligent automation.
Technological Approach	Lack of real-time data integration with digital user interfaces.	[2] P. Jones (2024); [4] Bartlett et al. (2023); [7] Leng et al. (2022)	These studies emphasize capacity planning and IoT-based hospital design but do not implement real-time mobile/chatbot integration.
Analytical Objective	Analysis aimed at improving internal hospital processes.	[4] Bartlett et al. (2023); [5] Kelly Emrick (2024)	Prior studies focused on internal optimization rather than improving patient access to information.
Research Output	Web-based system designs with manual data entry.	[6] Shakil (2025); [3] Mark et al. (2019)	The Hospital Bed Management System proposed by Shakil (2025) remains web-based without AI or chatbot automation.
Technology and Integration	The classical Bryant method does not integrate IoT/chatbot or inter-institutional interoperability.	[8] Ghiffary and Adharani (2020); [9] Ahmad et al. (2022)	Both studies use the Bryant method in manual, non-integrated contexts, indicating room for technological innovation.
Scale and Inter-Institutional Scope	Prior research was limited to single institutions; this study spans multiple hospitals.	[10] Yanti et al. (2024); [11] Setiawan et al. (2023)	These studies applied chatbots to single hospitals, while the current study expands to cross-institutional SIMRS integration.

As presented in Table 1, previous studies [1–6, 8–11] mainly addressed hospital bed management through internal administrative or web-based solutions without real-time data exchange between institutions. Research by Malekar [1], Mark et al. [3], and Shakil [6] discussed hospital bed availability but did not include intelligent interaction layers. Leng et al. [7] and Bartlett et al. [4] introduced IoT-based architectures, yet they lacked mobile-based implementations. In terms of methodological contribution, Ahmad et al. [9] and Ghiffary and Adharani [8] utilized the Bryant method traditionally, without integrating it into intelligent digital environments. In contrast, this research introduces a modified Bryant method within a mobile-based chatbot system, enabling real-time inter-hospital interoperability and intelligent prioritization for inpatient room availability.

Therefore, this study aims to design, implement, and evaluate a mobile-based chatbot integrated with hospital databases using the Bryant prioritization method.

The main contribution of this research lies in the development of an intelligent chatbot system capable of retrieving inpatient room information in real time, while simultaneously integrating SIMRS data from multiple hospitals through an interoperable architecture. In addition, the study applies and modifies the Bryant method to enhance decision-making and prioritization processes within hospital information systems, thereby providing a novel and effective approach to digital hospital management.

2 RESEARCH METHODOLOGY

2.1 Data collection and requirement analysis

The first stage of this research focused on the identification of empirical needs through data collection at two pilot hospitals, RSIA Abby and RSU MMC. This phase aimed to capture real operational challenges in inpatient room management and translate them into measurable user requirements for system development. To achieve this, a mixed-method approach was applied, combining field observations, structured interviews, and user surveys to understand how patients, families, and hospital staff currently manage inpatient room information and what improvements they expect from an integrated hospital information system.

Field observations were conducted to examine the workflow of inpatient room allocation and the functionality of the existing SIMRS. The results indicated that most hospitals still rely on manual updates or isolated system modules to track room availability. Consequently, patients and families experience delays in obtaining real-time information, while hospital staff encounter difficulties in coordinating referrals and managing occupancy efficiently.

Interviews with administrative officers and nursing staff confirmed the absence of a centralized mechanism that connects room data with patient preferences. These findings established the empirical problem that guided the research design—namely, the need for a real-time, user-oriented, and data-driven hospital room recommendation system.

A structured questionnaire was distributed to 115 respondents, comprising patients, family members, and hospital staff, to identify and quantify user preferences related to inpatient room selection. The survey covered key factors such as cleanliness, facilities, cost sensitivity, lighting, and proximity to medical personnel.

The quantitative results are presented in Figures 1 and 2.

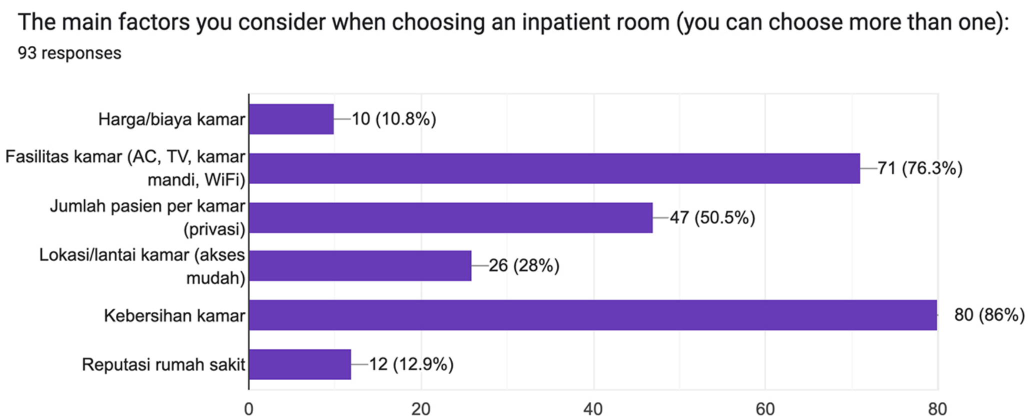

Fig. 1. Survey results on key factors for inpatient room selection

As shown in Figure 1, 86% of respondents identified *room cleanliness* as the most important factor when selecting an inpatient room, followed by 76% who emphasized the availability of *complete facilities*. In contrast, only 10.8% considered *cost* a primary determinant, suggesting that users prioritize comfort and service quality over financial aspects when choosing hospital rooms.

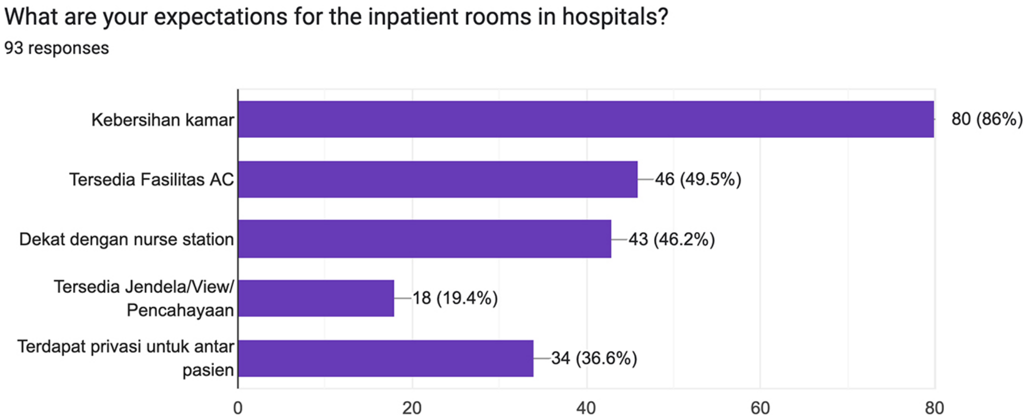

Fig. 2. Survey results on user expectations for inpatient room selection

According to Figure 2, 86% of respondents expected rooms with a high standard of cleanliness for both patients and accompanying family members. 46.2% highlighted the importance of proximity to the nurse station to ensure prompt response and care, while 19.4% preferred rooms with adequate natural lighting, windows, or outdoor views to enhance comfort and recovery atmosphere.

Based on the combined results of observations and survey responses, two user categories were identified:

1. General-care patients – those who do not require intensive medical supervision and can independently select their preferred rooms through the chatbot interface.
2. Special-care patients – those who require continuous monitoring (e.g., ICU, NICU, PICU, or isolation rooms), where room allocation is managed by hospital staff.

Accordingly, this study focused on general-care inpatients, who represent the majority of hospital admissions and are the primary beneficiaries of an automated room recommendation system.

The synthesis of survey and observational findings led to the selection of five key decision-making criteria, which became the main input variables for the Bryant method applied in this study:

1. Disease Type (Criticality of Illness) – determines patient eligibility for specific room categories.
2. Proximity to Nurse Station – represents accessibility and response efficiency.
3. Patient Privacy/Occupancy Ratio – indicates comfort level and the degree of room sharing.
4. Bathroom Accessibility – measures convenience and mobility for patients.
5. Lighting/Window Condition – relates to natural illumination, comfort, and psychological well-being.

Each variable was validated through expert consultations involving hospital administrators and nursing coordinators to ensure clinical relevance and compliance with hospital operational standards. The final selection of these five variables provided the empirical foundation for constructing the modified Bryant method framework.

2.2 Bryant method

The Bryant Method is a prioritization model that determines ranking by assigning scores to predefined parameters. Each criterion is rated, and the total score is obtained by multiplying or weighting the ratings according to importance. Traditionally, the method evaluates four factors: *Prevalence (P)*, *Seriousness (S)*, *Community Concern (C)*, and *Manageability (M)*, formulated as:

$$Total\ score = P \times S \times C \times M \tag{1}$$

where T denotes the total score of each alternative.

In this study, the Bryant method was modified to suit the context of inpatient room selection by replacing the four classical parameters with five key decision-making criteria.

Each criterion was rated on a 1–5 scale, where 1 represents *very low suitability* and 5 represents *very high suitability*. The weighting of each criterion was determined based on expert judgment from hospital staff and patient feedback, resulting in Table 2.

Table 2. Expert-determined weights for inpatient room selection criteria

Criterion	Weight
Disease Type	0.10
Nurse Proximity	0.25
Patient Privacy/Occupancy	0.30
Bathroom Accessibility	0.15
Lighting/Window	0.20

The total score for each room alternative (T_i) is calculated as:

$$T_i = \sum_{j=1}^{5} (w_j \times s_{ij})$$

Where w_j is the weight of each criterion and s_{ij} is the rating score of each room. This formula represents the decision-making logic that forms the basis for the system's recommendation algorithm.

2.3 Integrated system design

The integrated system was designed to connect the modified Bryant method with a mobile-based chatbot application linked to SIMRS. The main objective of this integration is to provide real-time information on inpatient room availability through an interactive WhatsApp interface. The system architecture combines algorithmic decision logic, data interoperability, and user-centered communication to ensure that hospital room recommendations are accurate, timely, and aligned with user preferences.

The overall system consists of four functional layers: (1) the User Interface Layer, (2) the Chatbot Engine Layer, (3) the Middleware API Layer, and (4) the Hospital Database Layer. The User Interface Layer provides the WhatsApp-based conversational interface that allows patients or their families to input room preferences and receive availability updates directly from the hospital system. The Chatbot Engine Layer, developed using Node.js, acts as the control center that handles conversation logic and executes the Bryant Method calculation. This layer integrates with the WhatsApp Business API to enable two-way real-time interaction between the system and users. The Middleware API Layer serves as a secure bridge between the chatbot and the hospital databases. It uses RESTful APIs and JSON-based data exchange to transmit queries, verify data, and standardize formats across different SIMRS systems. Finally, the Hospital Database Layer contains core hospital data, including room information, occupancy status, patient records, and facility attributes, which are synchronized periodically to ensure consistency and reliability of the information provided. The data flow and interaction between system components are illustrated in Figure 3.

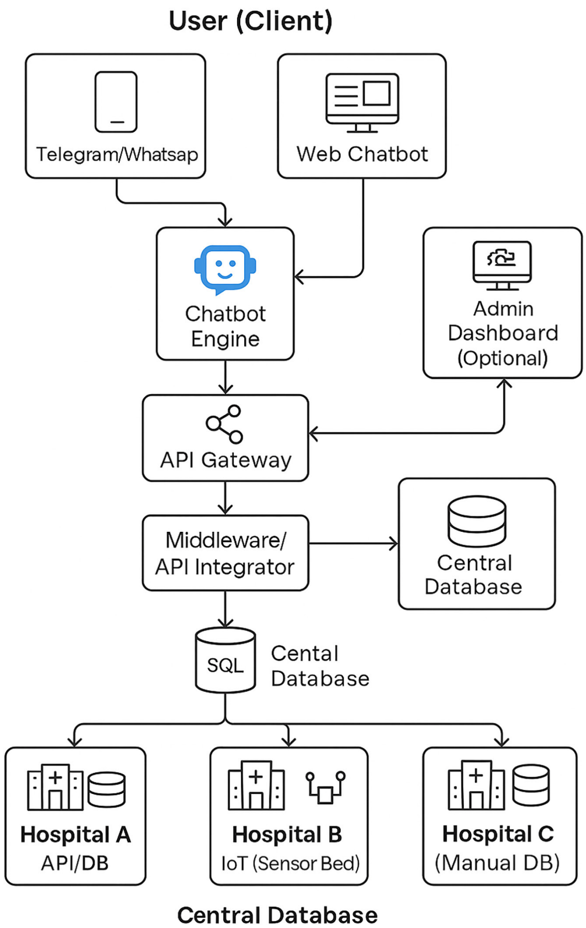

Fig. 3. System architecture of the integrated chatbot for hospital room availability

The data flow of the system begins when a user sends a query via WhatsApp. The chatbot engine interprets the user's request and forwards it through the middleware API to the connected hospital databases. Once the data are retrieved, the chatbot executes the Bryant Method to calculate the total score for each room alternative using the formula in equation 2, where w_j represents the weight of each criterion and s_{ij} denotes the corresponding rating score. The algorithm then ranks the room options according to their total scores, and the top recommendations are displayed instantly to the user through the WhatsApp interface. This process ensures a dynamic and data-driven response that reflects real-time hospital conditions and patient priorities.

The integrator synchronizes data from various hospital systems into a centralized SQL database, supporting three integration models: Hospital A: API-based SIMRS; Hospital B: IoT-based bed sensor system (automated updates); and Hospital C: Manual SIMRS entry (staff-updated).

All data are periodically synchronized and stored in the central SQL database. An optional Admin Dashboard provides monitoring, report generation, and analytic insights. This modular structure ensures scalability, secure data management, and real-time synchronization between chatbot interactions and SIMRS systems in multiple hospitals.

3 RESULTS AND ANALYSIS

3.1 Implementation and simulation of the Bryant method

The study began with the creation of a system flow to facilitate understanding of how the developed application operates. The overall process included defining the objectives, analyzing user requirements for inpatient room selection, designing the system architecture, collecting data for model development, and identifying the evaluation criteria used in the Bryant method. After the data collection and approval from the stakeholders (RSIA Abby and RSU MMC) regarding the selected evaluation parameters, the application development and integration process continued.

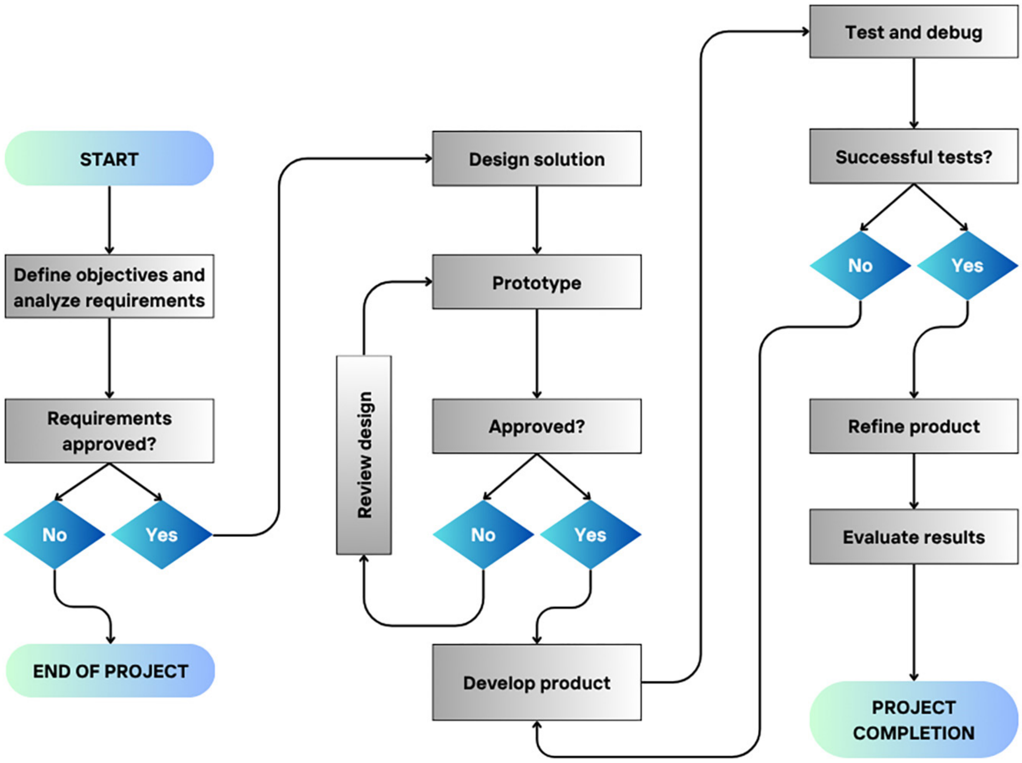

Fig. 4. System design workflow

As illustrated in Figure 4, the workflow begins with the formulation of objectives and requirement analysis, followed by system design and data collection.

The criteria identified from the analysis—disease type, nurse proximity, privacy, bathroom accessibility, and lighting—were applied within the modified Bryant method module integrated into the chatbot application.

After the integration was completed, a simulation of the Bryant calculation was conducted using six inpatient room alternatives (R-1 to R-6). Each criterion was evaluated according to field observations and expert consultations from RSIA Abby and RSU MMC. The weighted scores and total results are shown in Table 3.

Table 3. Simulation of the Bryant method calculation for inpatient room selection

Inpatient Criteria	Weight	R-1	R-2	R-3	R-4	R-5	R-6
Disease Type	0.10	5	5	5	5	5	5
Nurse Proximity	0.25	5	3	1	4	2	3
Number of Patients/Privacy	0.30	2	2	5	2	5	4
Bathroom Accessibility	0.15	3	4	4	3	4	4
Lighting/Window	0.20	1	4	4	4	3	2
Total Score	**1.00**	**3.00**	**3.25**	**3.65**	**3.15**	**3.90**	**3.75**

In this simulated case, six inpatient rooms were assessed based on the five criteria, with weights reflecting actual hospital conditions. For example, Room R-1 obtained a disease-type score of 5 and a nurse-proximity score of 5 because it is near the nurse station and suitable for general medical patients. However, it scored lower in privacy (2) and lighting (1), resulting in a total of 3.00—the lowest among all alternatives. The privacy criterion carried the highest weight (0.30), emphasizing users' preference for single-occupancy or VIP rooms. Consequently, Room R-5, which excelled in privacy and balanced accessibility, achieved the highest score (3.90) and is prioritized in the chatbot's recommendation display, while lower-ranked rooms such as R-1 are omitted.

The simulation results demonstrate that the modified Bryant Method effectively translates patient preferences and hospital constraints into quantifiable ranking values. These results are processed in real time by the chatbot engine, ensuring that patients receive accurate, data-driven room recommendations through the WhatsApp interface.

To support the computational process, a relational database schema was designed to store the data required for Bryant calculations and to facilitate integration with the chatbot system. The database architecture consists of five primary interconnected tables: Ward Table, with a one-to-many (1:M) relationship to the Room Table, representing hospital wards and rooms; Temporary Bryant Stage 1 and Stage 2 Tables, related in a 1:M relationship, serving as intermediate computation layers; Criteria Table, linked to Temporary Bryant Stage 2 and the Room Table in a many-to-one (M:1) relationship; Room Criteria Matrix Table, related to the Criteria Table in a one-to-many (1:M) relationship. These five interrelated tables store and process data for Bryant method calculations, enabling real-time recommendations for room availability to patients and families.

3.2 Chatbot WhatsApp development and interface implementation

The primary user interface in this research was developed using a WhatsApp-based chatbot, chosen for its wide accessibility and familiarity among both patients and hospital staff. This chatbot functions as an automated conversational platform integrated with the WhatsApp Business API, allowing two-way communication between users and the hospital information system without the need for direct human intervention. Through this integration, the chatbot can interpret user messages, retrieve relevant data from the hospital database, and present room recommendations that have been computed using the Bryant method.

The overall chatbot architecture integrates several core components working in coordination to ensure effective functionality [12]. The WhatsApp Business API [13] serves as the official interface responsible for sending and receiving messages securely within the application environment. Natural language processing (NLP) technology enables the system to recognize user intent and interpret the contextual meaning of queries, ensuring that responses remain relevant and adaptive to user input. The backend server, or bot engine, is responsible for executing decision logic, processing user data, and implementing the Bryant algorithm to generate ranked outputs. Meanwhile, the database or knowledge base stores conversation histories, user profiles, and computational results that support the chatbot's continuous learning and information retrieval processes [14].

From the user's perspective, interaction with the chatbot follows a simple, guided flow designed to replicate a natural conversation. The process begins with an initial greeting and user verification, followed by the selection of the patient's diagnosis or condition, and continues to the stage where users are asked to rank their preferred room facilities. After analyzing the responses, the chatbot automatically generates a list of recommended inpatient rooms ranked according to the results of the Bryant method calculation.

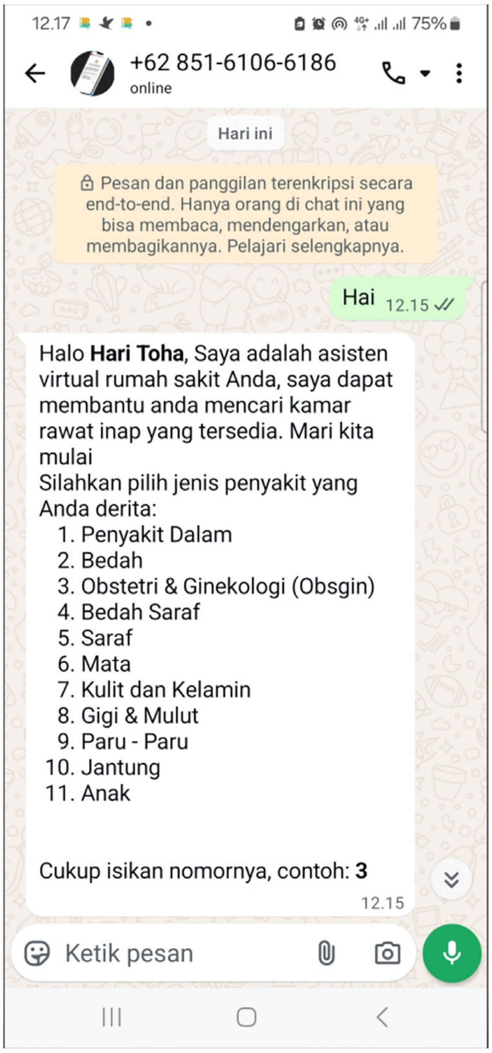

Fig. 5. Initial WhatsApp chatbot interface

As illustrated in Figure 5, users start by sending an initial greeting message, after which the system replies with a list of disease categories relevant to patient conditions. Once the diagnosis is selected, the chatbot proceeds to request room preference inputs from the user, as depicted in Figure 6.

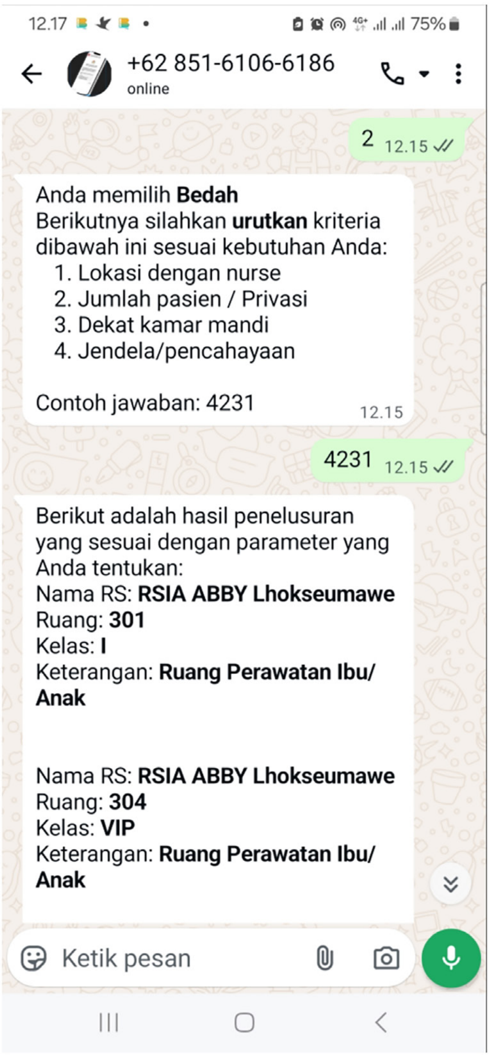

Fig. 6. Selection of inpatient room facilities

At this stage, users are instructed to assign priority levels to different room facilities by entering a numeric sequence (for example, "4231"), which represents their ranking for factors such as cleanliness, proximity to nurses, and lighting conditions. Based on these inputs, the chatbot processes the data and displays the available inpatient rooms in real time. Figure 7 shows an example of this output, where the system presents the room availability status and the corresponding recommendation score computed through the Bryant method algorithm.

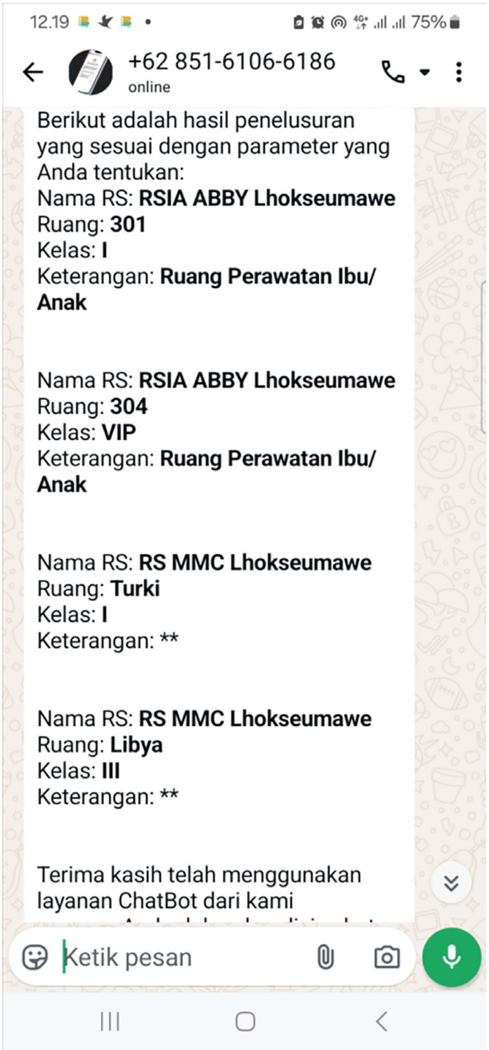

Fig. 7. Available room information display

This design approach ensures that patients and their families receive timely, accurate, and personalized information about available rooms through a familiar communication medium. At the same time, hospital administrators benefit from improved transparency and operational efficiency in room allocation, as the system automatically integrates user preferences with real-time data from the hospital information system.

3.3 Result visualization from Bryant calculation

The information displayed in the application corresponds directly to the results produced by the Bryant method, which has been fully integrated into the system. Within the web-based interface, users can view the detailed computation process and the ranking outcomes for each available inpatient room. The interface consists of two main sections that provide transparency in decision-making: the *Criteria Data View* and the *Bryant Method Calculation Output*.

In the Criteria Data View, the system presents the score for each evaluation criterion applied to the selected inpatient rooms. For instance, at RSIA Abby, Room 301 scored 5 for disease type, 3 for proximity to the nurse station, 2 for patient privacy, 4 for bathroom accessibility, and 4 for window or lighting quality. The VIP Room 304 at the same hospital achieved scores of 5, 1, 5, 4, and 4, respectively. Meanwhile, at RSU MMC, two available rooms—Turkey and Libya—were analyzed. Room Turkey received scores of 5 for disease type, 3 for nurse proximity, 5 for privacy, 1 for bathroom accessibility, and 3 for lighting. In contrast, Room Libya obtained scores of 5, 2, 3, 4, and 2 for the same set of criteria.

The system then applies the Bryant method to these criteria and calculates the total score for each room alternative. The results are summarized and visualized in Figure 8, which illustrates the ranking outcomes. The computation shows that Rooms 301 and 304 at RSIA Abby obtained the highest total score of 3.4. This value was derived by multiplying each criterion's score by its corresponding weight and summing the results. At RSU MMC, Room Turkey achieved a total score of 3.1, while Room Libya scored 3.0, confirming that the calculations align consistently with the Bryant method principles.

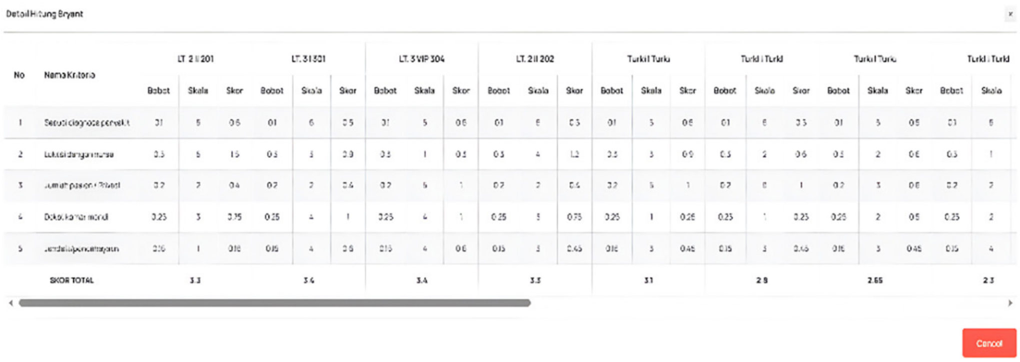

Fig. 8. Bryant method calculation results

The web-based system displaying these results is directly connected to the hospital's SIMRS database. The integration is facilitated through the *Matrix Setting* feature, which includes data columns such as room number, class, hospital name, and real-time room availability automatically retrieved from SIMRS. This synchronization ensures that every recommendation presented to users accurately reflects the current occupancy status in the hospital, thus enhancing the reliability and practicality of the decision-support system.

3.4 Response time testing

To evaluate the performance of the integrated chatbot system, a response time test was conducted to measure how quickly the application processed user requests and provided feedback. A total of 115 respondents interacted directly with the WhatsApp chatbot to simulate real user conditions. System logs from the WhatsApp Business API were analyzed to record message delivery and processing times.

The log data showed that 750 processes were initiated by users during the testing phase. Among them, 109 messages were categorized as "sending," 243 as "delivered," and 398 as "read." The "sending" category represents messages that failed to receive responses due to network disruptions or temporary server queue delays. The "delivered" messages indicated successful transmission and response, while the "read" category referred to messages that users viewed but did not continue interacting with—primarily due to a lack of familiarity with the chatbot's usage (see Figure 9).

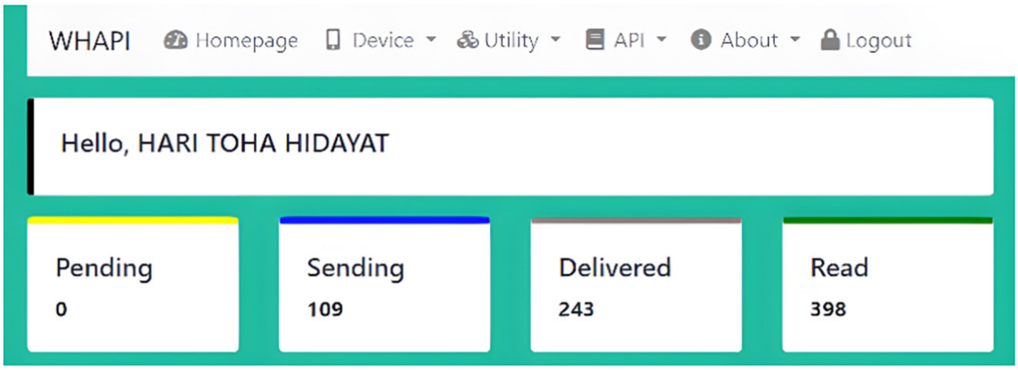

Fig. 9. Message delivery status during chatbot response testing

The chatbot's server activity was monitored in real time through the web-based dashboard, allowing developers to visualize message throughput and response latency.

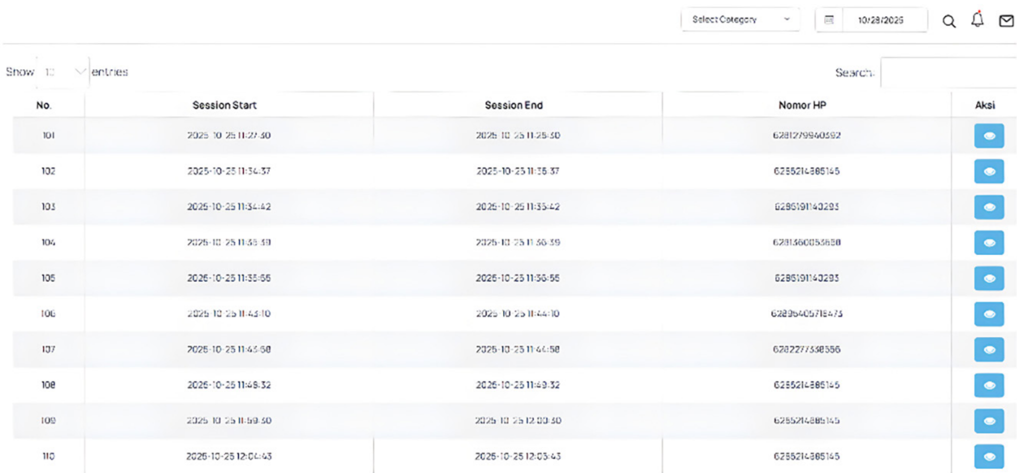

Fig. 10. System response time visualization

According to the analysis in Figure 10, the system achieved an average response time of approximately one second per message exchange. This indicates a high degree of responsiveness, with the chatbot successfully retrieving data from the hospital databases, applying the Bryant method computation, and returning ranked room recommendations in under three seconds. Such responsiveness aligns with usability standards for healthcare information systems, which recommend a maximum delay of five seconds for optimal user experience. The results confirm that the integration of the Bryant method within the WhatsApp chatbot operates efficiently under realistic network conditions.

3.5 Feasibility testing

A feasibility evaluation was carried out to determine the practicality and user acceptance of the developed chatbot system. The testing employed a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Forty-six respondents from RSIA Abby and RSU MMC participated in the evaluation, including hospital staff and patient representatives. The assessment focused on three main aspects of chatbot functionality: the accuracy of room availability information, response speed and relevance, and overall assistance in room selection.

a) The chatbot application displays room availability

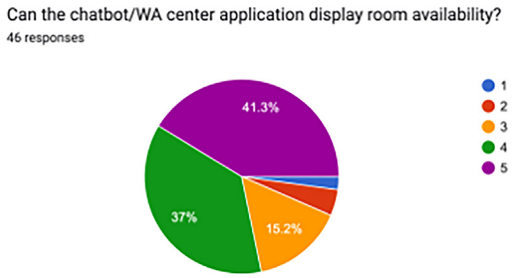

Fig. 11. Evaluation of the chatbot's room availability display

The survey showed that 41.3% of respondents strongly agreed and 37.0% agreed that the chatbot effectively displayed updated information about available inpatient rooms, indicating that data synchronization with SIMRS functioned correctly (see Figure 11).

b) The chatbot's response speed and relevance

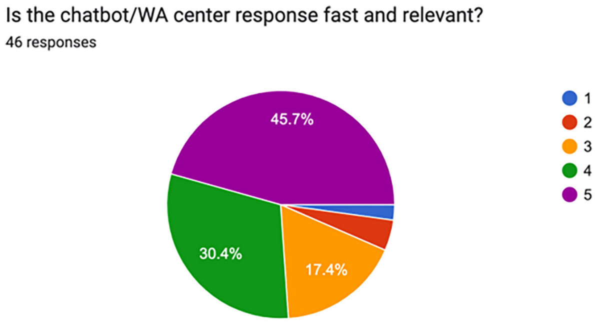

Fig. 12. Chatbot's fast and relevant response

In this aspect, 45.7% of respondents strongly agreed and 30.4% agreed that the chatbot provided fast and contextually relevant responses to their queries (see Figure 12). This finding aligns with the system's technical test results, which demonstrated a one-second average response delay.

c) The chatbot helps users select inpatient rooms quickly

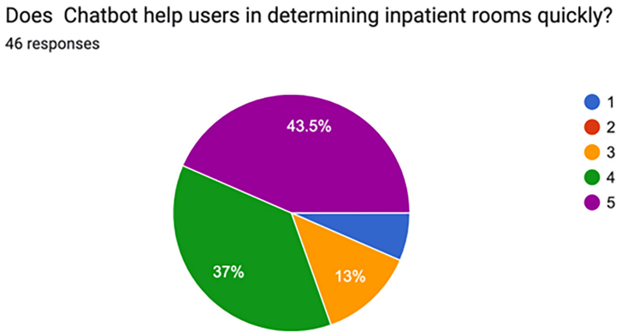

Fig. 13. Chatbot helps select inpatient rooms

Most users found the chatbot beneficial in simplifying the room selection process. Specifically, 43.5% of respondents strongly agreed and 37.0% agreed that the chatbot helped them identify suitable inpatient rooms efficiently, reducing the need for manual inquiries at the hospital front desk (see Figure 13).

Overall, the feasibility testing demonstrated positive user acceptance and satisfaction. Minor challenges were observed, including limited user familiarity with chatbot-based interfaces and occasional message delivery issues caused by unstable internet connections. However, these issues are technical in nature and can be resolved through user training and system optimization.

The findings suggest that the chatbot integrated with the Bryant Method can effectively improve hospital service accessibility and efficiency. The combination of automated data retrieval, intelligent prioritization, and real-time communication provides a reliable solution for managing inpatient room availability.

4 CONCLUSION

This study successfully developed a WhatsApp-based chatbot application to provide real-time information on inpatient room availability at RSIA Abby and RSU MMC in Lhokseumawe City. The system integrates the Bryant Method as a multi-criteria decision-making model to process and calculate weighted scores based on five evaluation parameters: disease type, proximity to nurse station, patient privacy/occupancy ratio, bathroom accessibility, and lighting quality. Each criterion was assigned a specific weight derived from expert judgment and user preference surveys, ensuring that the model reflects real-world clinical and user considerations.

Testing results demonstrated that the system operates efficiently, with an average response time of only one second per message, confirming the effectiveness of the chatbot engine and the robustness of the data-exchange architecture. The results of the application's automated Bryant computations were consistent with manual calculations, validating the accuracy of the algorithm's implementation. In both hospitals, the application successfully displayed two room options with the highest weighted scores, enabling patients and their families to make data-driven room selections quickly and conveniently.

User-feasibility evaluation further confirmed the practicality of the system. Approximately 41.3% of respondents strongly agreed and 37% agreed that the chatbot effectively displayed real-time room availability information. Regarding response performance, 45.7% of respondents strongly agreed and 30.4% agreed that the chatbot responded rapidly and provided relevant answers. Additionally, 43.5% strongly agreed and 37% agreed that the chatbot could assist them in efficiently selecting an appropriate inpatient room. These findings collectively demonstrate high system usability, accuracy, and reliability from the users' perspective.

In conclusion, the integration of the Bryant method within a WhatsApp-based chatbot framework has proven to be a practical and innovative approach for improving hospital information services. The developed system enables automatic decision-making, enhances transparency in room management, and provides patients with fast and personalized access to hospital resources. Future research may extend this framework by integrating additional parameters such as cost, treatment type, or patient satisfaction, and by expanding interoperability with other hospital information systems to support large-scale healthcare management networks.

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