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Analysis of Patient Satisfaction Toward the Implementation of the Bed Management Application at Langsa General Hospital: A Case Study of Bed Management System Deployment

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ABSTRACT

The digital transformation of healthcare has become a strategic imperative for improving hospital efficiency, transparency, and patient-centered service quality. This study examines the impact of the Implementation of the Bed Management Application on Patient Satisfaction at Langsa General Hospital, integrating theoretical perspectives from the Technology Acceptance Model (TAM), the DeLone and McLean Information System Success Model (ISSM), and the SERVQUAL framework. Using a quantitative explanatory–predictive approach, the research employs both statistical regression analysis (SPSS 26.0) and algorithmic predictive modeling (Python Decision Tree Classifier) to measure and predict the relationship between system implementation and patient satisfaction. Data were collected from 120 inpatients who experienced the digital bed allocation process, using validated indicators that capture ease of use, reliability, accuracy, service speed, and transparency. The results of the regression analysis reveal that the implementation of the Bed Management Application has a positive and statistically significant effect on patient satisfaction ($B = 0.687$, $\beta = 0.682$, $p < 0.001$), with a coefficient of determination ($R^2 = 0.465$), indicating that 46.5% of the variance in satisfaction can be explained by system implementation effectiveness. Complementary algorithmic analysis using the Decision Tree Classifier achieved a prediction accuracy of 50%, identifying a key threshold at X_mean = 4.1, above which patients were predominantly classified into the High Satisfaction category. The findings confirm that technological quality, perceived usefulness, and information transparency significantly influence patient satisfaction, validating the theoretical constructs of TAM and ISSM. Furthermore, the integration of inferential and predictive analyses offers both theoretical validation and operational insight, illustrating that robust digital system implementation enhances patient experience, efficiency, and service reliability. This research contributes to advancing hybrid analytical approaches in health informatics, supporting data-driven decision-making and the national Smart Hospital Initiative to optimize patient-centered digital healthcare delivery in Indonesia.

1. Introduction

In recent decades, digital transformation has become an essential strategic direction for healthcare systems worldwide, aiming to improve efficiency, accessibility, and the quality of medical services. Health Information Technologies (HIT), such as Hospital Information Systems (HIS) and Bed Management Systems (BMS), have been increasingly implemented to optimize hospital operations and enhance patient experiences [1]. A BMS specifically facilitates real-time monitoring and allocation of inpatient beds, allowing hospitals to minimize waiting times, reduce transfer delays, and improve service coordination among healthcare staff [2]. Evidence from developed countries demonstrates that the integration of BMS into hospital workflows leads to improved operational efficiency, transparency, and patient satisfaction [3].

In Indonesia, the government through the Ministry of Health has actively encouraged hospitals to adopt digital-based management systems under the Smart Hospital Initiative, which aims to digitalize administrative and clinical operations [4]. Despite this national effort, many hospitals still face challenges in ensuring that technological implementations lead to tangible improvements in patient-centered outcomes [5]. Research conducted in the Indonesian context has often focused on the technical performance and organizational adoption of health information systems, while limited studies have examined how these digital tools influence patients' perceptions of service quality and satisfaction [6]. This indicates a gap between system implementation and the actual experiences of healthcare consumers.

Langsa General Hospital (RSUD Langsa), one of the leading regional public hospitals in Aceh Province, has recently implemented a Bed Management Application as part of its digital transformation initiative. The system

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aims to streamline bed allocation, admissions, and discharge management processes to improve the efficiency and responsiveness of hospital services. However, preliminary reports and anecdotal evidence reveal inconsistencies in patient satisfaction levels following this implementation, particularly regarding the speed of service delivery, comfort during admission, and transparency of bed information. These findings suggest that while digitalization may enhance operational efficiency, it does not automatically translate into improved patient experiences. Understanding this discrepancy is critical to ensuring that technological investments genuinely contribute to patient-centered service quality.

To address this issue, the present study investigates how the implementation of the Bed Management Application affects patient satisfaction at Langsa General Hospital. The research focuses on several core system attributes such as ease of use, accuracy of information, system reliability, service speed, and data transparency that collectively shape the patient experience. By integrating theoretical perspectives from the Technology Acceptance Model (TAM) [7], the DeLone and McLean Information System Success Model [11], and the SERVQUAL framework [15], the study provides a multidimensional understanding of how both technological and service-quality factors contribute to perceived satisfaction within hospital digitalization.

In addition to evaluating the association between system implementation and satisfaction, this research introduces a predictive dimension by employing both statistical and computational analyses. A quantitative explanatory design is used, combining traditional inferential statistics through regression analysis (SPSS) with predictive analytics using a Decision Tree Classifier (Python). This dual analytical approach enables not only the explanation of causal relationships but also the prediction of satisfaction categories based on key system attributes. Integrating machine learning into health service evaluation adds methodological novelty, bridging hospital informatics with intelligent decision-support tools that can guide service improvement strategies.

The findings from this study are expected to make significant contributions to both academic and practical domains. Theoretically, the study expands the empirical application of TAM, IS Success, and SERVQUAL frameworks in evaluating digital health technologies in developing-country contexts. Methodologically, it demonstrates how the combination of regression and predictive modeling can strengthen the evidence base for hospital management systems research. Practically, the results will provide actionable insights for hospital administrators and policymakers on how to enhance the design, usability, and operational impact of bed management systems to improve overall patient satisfaction. Ultimately, this research supports the broader vision of smart and patient-centered hospital management in Indonesia.

2. Literature Review

2.1. Digital Transformation and Bed Management Systems in Healthcare

The healthcare industry has undergone a profound digital transformation in recent years, with hospitals adopting advanced information technologies to improve operational efficiency, reduce human error, and enhance patient satisfaction. Among these innovations, the Bed Management System (BMS) has emerged as a critical tool for optimizing hospital resource allocation. A BMS facilitates real-time monitoring of bed availability, patient admission, and discharge processes, ensuring better coordination between clinical and administrative units [1]. Globally, hospitals that have implemented BMS solutions report improvements in operational efficiency, reduced patient waiting times, and enhanced transparency of bed allocation processes [2].

Bed management is particularly vital in high-demand healthcare environments, where limited bed capacity often results in patient overcrowding and delays in care delivery. Research in the United Kingdom, Singapore, and Australia demonstrates that BMS integration can reduce bed turnover time by up to 25%, directly influencing patient flow management and satisfaction [3]. However, successful implementation requires alignment between system usability, staff competence, and patient-centered service delivery [4]. In the context of developing nations, including Indonesia, digital transformation faces challenges related to system integration, training, and user adoption [5]. These barriers often lead to discrepancies between the intended system benefits and actual patient experiences.

In Indonesia, the Ministry of Health has actively promoted the Smart Hospital Initiative, emphasizing the digitalization of administrative and clinical processes [6]. RSUD Langsa represents one of the regional hospitals adopting such technologies, particularly through the deployment of the Bed Management Application. This system aims to optimize patient flow, minimize waiting times, and enhance the accuracy of bed availability data. Despite its operational advantages, anecdotal evidence and preliminary reports indicate inconsistencies in patient satisfaction levels. This discrepancy raises an important question regarding how effectively the BMS implementation translates into perceived service quality and satisfaction among patients.

2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), proposed by Davis (1989), provides a foundational framework for understanding how users accept and adopt new technologies [7]. TAM identifies two principal constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU reflects the degree to which a user believes that a system enhances performance or productivity, while PEOU denotes the degree of effort required to use the system effectively. These constructs jointly influence users' attitudes, behavioral intentions, and ultimately, their satisfaction with the system [8].

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In healthcare, TAM has been widely applied to examine user acceptance of hospital information systems, telemedicine applications, and patient portals [9]. Within the context of the Bed Management Application, PU may represent how the system improves service efficiency, data transparency, and accuracy of bed allocation, whereas PEOU relates to how intuitively patients and staff can interact with the system interface. Previous research indicates that systems perceived as easy to use and useful tend to generate higher satisfaction levels and foster user loyalty [10]. Consequently, TAM serves as an appropriate theoretical foundation for analyzing patient satisfaction with the Bed Management Application at Langsa General Hospital.

2.3. Information System Success Model

The DeLone and McLean Information System Success Model (ISSM) expands upon TAM by introducing six interrelated dimensions: System Quality, Information Quality, Service Quality, Use, User Satisfaction, and Net Benefits [11]. This model posits that system quality and information quality are key predictors of user satisfaction and subsequent benefits derived from system utilization. In healthcare, ISSM has been extensively used to evaluate hospital information systems, electronic medical records, and telehealth platforms [12].

In the context of a Bed Management Application, System Quality may refer to the system's reliability, speed, and accessibility. Information Quality involves the accuracy, timeliness, and completeness of bed data, while Service Quality reflects the responsiveness and technical support provided by hospital staff [13]. Empirical studies have confirmed that improvements in these dimensions correlate positively with user satisfaction and perceived organizational performance [14]. Integrating ISSM with TAM in this study provides a comprehensive analytical lens to evaluate both the technological and experiential aspects of BMS implementation.

2.4. Service Quality and Patient Satisfaction (SERVQUAL Model)

The SERVQUAL Model, introduced by Parasuraman, Zeithaml, and Berry (1988), remains the most widely adopted framework for assessing service quality and satisfaction in healthcare settings [15]. SERVQUAL identifies five key dimensions: Tangibles, Reliability, Responsiveness, Assurance, and Empathy. These dimensions together represent the patient's overall perception of service quality.

1) Tangibles refer to physical facilities, technological tools, and the visual design of the application interface.
2) Reliability denotes the hospital's ability to deliver promised services accurately and consistently.
3) Responsiveness relates to the promptness of staff and system response to patient needs.
4) Assurance captures the level of trust, safety, and confidence patients feel when interacting with the system.
5) Empathy reflects personalized care, attention, and communication provided by hospital staff.

Incorporating SERVQUAL into this study enables an understanding of how digital transformation interacts with human service dimensions. Prior research demonstrates that when patients perceive reliability, responsiveness, and assurance through digital tools, their satisfaction increases significantly [16]. Therefore, the SERVQUAL model supports the measurement of how patients' subjective experiences relate to the implementation of BMS at RSUD Langsa.

2.5. Integration of Theoretical Models and Conceptual Framework

This study integrates TAM, IS Success Model, and SERVQUAL to construct a holistic conceptual framework that examines how technological and service quality factors collectively influence patient satisfaction. The integration allows simultaneous evaluation of both system performance (accuracy, speed, transparency) and human-centered service aspects (comfort, empathy, responsiveness). The assumption is that when a Bed Management System provides reliable information and responsive service support, patients' perceptions of satisfaction improve significantly.

Moreover, the framework acknowledges that technology alone cannot guarantee patient satisfaction. Human factors such as communication, empathy, and perceived trust remain essential mediators between digital implementation and user experience [17]. In this sense, patient satisfaction is viewed not only as a product of system usability but also as a reflection of perceived service quality, emotional comfort, and fulfillment of expectations.

2.6. Predictive Analytics and Decision Tree Approach in Health Informatics

In the evolving domain of health informatics, predictive analytics has emerged as a powerful approach for transforming large-scale operational and clinical data into actionable insights. By leveraging machine learning (ML) techniques, healthcare institutions are able not only to describe past trends but also to forecast future outcomes, thereby enabling proactive management of services and resources. For instance, predictive models have been applied to patient-risk stratification, readmission prediction, and satisfaction modelling, offering enhanced decision-support capabilities that complement traditional inferential statistics [18].

Among ML techniques, the Decision Tree (DT) algorithm is frequently adopted in healthcare settings due to its interpretability, ease of visualization, and ability to handle both categorical and continuous variables. The

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DT creates a hierarchical structure of decision rules by recursively partitioning the dataset based on the most informative predictors, thus facilitating the identification of key determinants of outcomes such as patient satisfaction or service utilization [19]. In patient-centric research, DTs have been used to classify levels of satisfaction, identify priority service improvement areas, and model nonlinear interactions between system quality, waiting times, and experiential factors [20].

In hospital operations, hybrid evaluation frameworks that combine regression analyses and predictive modelling are gaining traction. Regression techniques (e.g., linear or logistic regression) estimate the magnitude and direction of predictor-outcome relationships, whereas DTs and similar ML models capture complex interactions, threshold effects, and non-linear patterns that traditional methods might overlook [21]. For example, a recent study utilizing a regression tree model analysed 69,562 patient-experience survey responses and found that treatment outcome satisfaction and facility convenience were the top predictors of overall satisfaction, after controlling for patient characteristics [22]. Another systematic investigation into data-driven decision making (DDDM) in patient management underscores how predictive analytics enhance resource allocation and care planning in hospitals [23].

The incorporation of DT in the evaluation of digital hospital systems therefore offers a meaningful extension of established frameworks such as Technology Acceptance Model (TAM), Information System Success Model (ISSM), and SERVQUAL by operationalising the translation of perceived system attributes into predictive categories of patient satisfaction. In the context of the Bed Management Application at Langsa General Hospital, the DT classifier allows hospital managers to go beyond the average-effect estimates (e.g., "a one-unit increase in perceived ease of use leads to X units increase in satisfaction") toward actionable classification rules (e.g., "patients who rate system reliability > 4.1 and service speed > 4.0 are predicted to be in the High-Satisfaction category").

In this study, the hybrid analytical strategy therefore encompasses: (1) the estimation of relationship strength and significance via simple linear regression implemented through SPSS, and (2) the development of a DT classifier in Python to categorise levels of patient satisfaction based on system implementation indicators. By integrating explanatory and predictive analytics, the research targets both theory development (how system attributes influence satisfaction) and operational deployment (how system scores can forecast satisfaction categories). This dual approach enhances novelty, extends health-informatics evaluation frameworks, and provides hospital practitioners with both diagnostic and predictive tools for improving bed-management system performance and patient experience.

2.7. Hypothesis Development

Based on the theoretical foundations discussed above and previous empirical findings, this study proposes the following hypothesis: H1: The implementation of the Bed Management Application has a significant positive effect on patient satisfaction at Langsa General Hospital.

3. Method

This study employs a quantitative research method with an explanatorypredictive approach, designed to empirically test and model the relationship between the implementation of the Bed Management Application and patient satisfaction at Langsa General Hospital. The explanatory design enables the research to move beyond descriptive analysis by examining not only how but also to what extent the system's performance, usability, and information quality influence patient satisfaction. The study is theoretically grounded in the Technology Acceptance Model (TAM) [7], the DeLone and McLean Information System Success Model (ISSM) [11], and the SERVQUAL framework [15], which collectively explain the interaction between technology adoption, system performance, and perceived service quality in healthcare environments.

To strengthen the analytical rigor and predictive validity, this research integrates algorithmic analysis using the Decision Tree Classifier (Python) alongside conventional inferential statistics. This dual analytical strategy enables both explanatory inference and predictive modeling the former through simple linear regression (SPSS 26.0) and the latter through Decision Tree classification (Python 3.11, Scikit-learn library). The integration of these methods allows the study to quantify causal relationships while simultaneously predicting categorical satisfaction outcomes (high, medium, low) based on key system-implementation indicators such as ease of use, accuracy, reliability, and service speed.

The statistical component, implemented in SPSS, involves reliability testing, descriptive analysis, correlation, and regression modeling to determine the magnitude and direction of the effect of the independent variable (Implementation of the Bed Management Application) on the dependent variable (Patient Satisfaction). The resulting regression equation provides a numerical understanding of the linear relationship between the two constructs.

The algorithmic component, executed in Python, applies the Decision Tree Classifier to model non-linear and hierarchical relationships between predictor attributes and satisfaction categories. The algorithm partitions the dataset based on information gain using the Gini Index, generating rule-based decision paths that reveal which system attributes most strongly determine patient satisfaction. The model is evaluated using standard machine-learning metrics including accuracy, precision, recall, and confusion matrix analysis to ensure

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predictive reliability and interpretability [20], [22].

The combination of regression-based inference and Decision Tree-based prediction strengthens the methodological framework by providing both theoretical validation and practical decision-support insight. This hybrid approach aligns with contemporary directions in health informatics research, where predictive analytics complements traditional statistical methods to improve hospital decision-making, optimize resource allocation, and enhance patient experience [21], [23].

Overall, this methodology allows the study to generate comprehensive insights—quantifying the strength of relationships through regression while visually interpreting predictive patterns through Decision Tree structures. Such an approach ensures that the findings are both statistically valid and operationally actionable for hospital management in improving digital service delivery and patient satisfaction.

Definition and Measurement of Variables

In order to empirically examine the relationship between the implementation of the Bed Management Application and patient satisfaction at Langsa General Hospital, it is essential to clearly define and operationalize the research variables. This study comprises two main variables: the independent variable, Implementation of the Bed Management Application (X), and the dependent variable, Patient Satisfaction (Y). Each variable was conceptually derived from well-established theoretical frameworks namely, the Technology Acceptance Model (TAM) [7], the DeLone and McLean Information System Success Model (ISSM) [11], and the SERVQUAL Framework [15].

The indicators for each construct were selected based on prior empirical studies and adapted to the hospital information system context to ensure construct validity and contextual relevance [16], [19]. The operationalization of these variables allows for consistent measurement using a five-point Likert scale, where respondents indicate their level of agreement ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Table 1 below presents the conceptual definitions, operational indicators, and measurement scales used in this study.

Table 1. Definition of Variables

Variable Type	Variable Name	Conceptual Definition	Operational Indicators	Measurement Scale	Reference
Independent Variable (X)	Implementation of Bed Management Application	The degree to which patients perceive the hospital's Bed Management System (BMS) as *useful, easy to use, accurate, transparent,* and *reliable* in managing bed allocation and inpatient services.	1. The application is easy to use. 2. The application helps accelerate the service process. 3. The information on bed availability is accurate. 4. The application provides transparent and real-time data. 5. The system works reliably with minimal errors.	Likert Scale 1–5 (1 = Strongly Disagree, 5 = Strongly Agree)	[7], [11], [19]
Dependent Variable (Y)	Patient Satisfaction	The overall evaluation of patients' experiences and perceptions regarding hospital services, including service speed, comfort, clarity of information, and expectation fulfillment following the implementation of the Bed Management Application.	1. Service speed meets my expectations. 2. I feel comfortable during the bed allocation process. 3. Information provided by the system and staff is clear. 4. Services meet my expectations. 5. Overall, I am satisfied with the bed management process.	Likert Scale 1–5 (1 = Strongly Disagree, 5 = Strongly Agree)	[15], [16], [18]

As presented in Table 1, the independent variable Implementation of the Bed Management Application is operationalized through five measurable dimensions that capture users' perceptions of system performance and usability. These indicators emphasize critical aspects such as ease of use, accuracy, reliability, transparency, and

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responsiveness, which collectively determine how effectively the application supports hospital operations and improves service delivery [7], [11].

Meanwhile, the dependent variable Patient Satisfaction is defined as a multidimensional construct encompassing patients' overall evaluation of their healthcare experiences. It reflects both tangible and intangible factors, including service speed, comfort, clarity of information, and the alignment between expectations and received services [15], [16].

The use of a Likert scale (1–5) provides a standardized means of quantifying subjective perceptions, enabling statistical and algorithmic analysis through SPSS and Python. By quantifying these indicators, the study aims to identify how variations in system implementation correlate with or predict changes in patient satisfaction levels. This structured operationalization ensures that the relationship between technology adoption and patient experience can be empirically tested, interpreted, and modeled using both inferential and predictive analytical methods.

Data Source

This study utilized primary data collected directly from inpatients of Langsa General Hospital who had experienced the digital bed allocation process using the Bed Management Application. Data were gathered through structured questionnaires distributed both online and offline to ensure accessibility for all respondents. Each questionnaire was composed of items corresponding to the operational indicators described in Table 1, with responses captured on a 1–5 Likert scale.

In addition to primary data, secondary data were obtained from hospital administrative records, including patient occupancy rates, average length of stay, and digital system performance reports. These data were employed to contextualize and validate the findings from the patient responses, ensuring triangulation between subjective perception and operational evidence.

Population and Sample

The population of this study includes all patients who have used inpatient services at Langsa General Hospital following the full deployment of the Bed Management Application. The sample was determined using purposive sampling, selecting respondents based on specific inclusion criteria that ensure relevant experience with the system. The inclusion criteria are as follows:

1. Patients (or their caregivers) who experienced hospital admission and bed allocation through the Bed Management Application.
2. Respondents aged 17 years or older, capable of independently completing the questionnaire.
3. Patients who had completed their inpatient care period at the time of data collection.

A total of 120 respondents were included in this study. This number satisfies the minimum requirement for both regression and predictive modeling analyses, aligning with methodological recommendations that suggest a ratio of at least 10–15 participants per predictor variable to achieve reliable parameter estimation and model stability [19].

The collected dataset was then tabulated in Microsoft Excel and subsequently analyzed using SPSS (v26.0) for statistical inference and Python (v3.11, Scikit-learn) for algorithmic prediction. This dual-analysis framework strengthens the study's methodological rigor, ensuring that both linear relationships and non-linear patterns are identified within the data.

4. Results and Discussion

This section presents and integrates the empirical findings from both statistical regression analysis (SPSS 26.0) and algorithmic predictive modeling (Python Decision Tree Classifier) to examine the influence of the Implementation of the Bed Management Application on Patient Satisfaction at Langsa General Hospital.

The dual-analytic approach allows for a comprehensive understanding of both the causal relationship (through inferential statistics) and predictive classification (through machine learning algorithms). This integration aligns with the principles of the Technology Acceptance Model (TAM) [7] and DeLone & McLean's Information System Success Model (ISSM) [11], which jointly emphasize that perceived usefulness, system quality, and service reliability are crucial determinants of satisfaction in healthcare information systems.

Table 3. Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Implementation of Bed Management Application (X)	120	12.00	25.00	21.8167	2.39742
Patient Satisfaction (Y)	120	12.00	25.00	22.1417	2.41597
Valid N (listwise)	120				

The descriptive statistics in Table 4.1 illustrate respondents' perceptions of both variables under investigation. The Implementation of the Bed Management Application (X) shows a mean score of 21.82 (SD = 2.39), while Patient Satisfaction (Y) has a mean of 22.14 (SD = 2.42). Given the possible range from 12 to 25, both means are classified as high, suggesting that the majority of patients perceive the application's implementation and their satisfaction with hospital services favorably.These results indicate that the Bed Management System (BMS) is effectively implemented at Langsa General Hospital, providing tangible benefits

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to patients through faster admission processes, accurate bed information, and greater transparency in service allocation, consistent with prior findings by Alalwan et al. [1] and Setiawan [19]. The low standard deviation in both variables reflects the consistency of patient perceptions, implying that the digital system's performance is stable and well-accepted across different patient demographics.

Table 4. Regression Analysis Results

Model	**Unstandardized Coefficients (B)**	**Std. Error**	**Standardized Coefficients (Beta)**	**t**	**Sig.**
(Constant)	7.146	1.489	—	4.800	0.000
Implementation ofBed Management Application (X)	0.687	0.068	0.682	10.131	0.000

a. Dependent Variable: Patient Satisfaction (Y)

Table 5. Model Summary

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.682[a]	0.465	0.461	1.77426
a. Predictors: (Constant), Implementation of Bed Management Application (X)				
b. Dependent Variable: Patient Satisfaction (Y)				

Algorithmic Analysis: Decision Tree Model on Patient Satisfaction Data

To complement the statistical regression findings, a machine learning–based predictive analysis was conducted using the Decision Tree Classifier algorithm implemented in Python (Scikit-learn v3.11). This approach aims to identify classification patterns of patient satisfaction levels (Low, Moderate, High) based on the mean score of the Bed Management Application Implementation (X_mean) variable. The dataset was divided into training and testing subsets, and the model was evaluated using the standard performance metrics: precision, recall, F1-score, and support. These metrics collectively describe the model's accuracy and robustness in classifying patient satisfaction outcomes.

```
Akurasi Model: 0.5

Laporan Klasifikasi:
              precision    recall  f1-score   support

      Rendah       0.22      0.67      0.33         3
      Sedang       0.33      0.67      0.44         3
      Tinggi       0.89      0.44      0.59        18

    accuracy                           0.50        24
   macro avg       0.48      0.59      0.46        24
weighted avg       0.74      0.50      0.54        24
```

Figure 1. Python Classification Report for Patient Satisfaction Prediction
(Source: Data Processed by Python, 2025)

Table 6. Definition of Evaluation Metrics

Metric	**Meaning**
Precision	The proportion of correctly predicted cases within a particular class compared to all predictions made for that class. High precision means fewer false positives.
Recall	The model's ability to correctly identify all actual instances of a class. High recall indicates fewer false negatives.
F1-Score	The harmonic mean between precision and recall, providing a balanced measure of classification accuracy.
Support	The number of actual observations belonging to each class in the dataset.

The Decision Tree model achieved an overall accuracy of 50%, indicating that it correctly predicted half of the satisfaction classifications in the test dataset.While this accuracy level is moderate, it provides valuable insights into the dominant satisfaction patterns among patients.

1. High Satisfaction
   This category achieved the highest precision (0.89), meaning that when the model predicted "High Satisfaction," it was correct 89% of the time. However, the recall (0.44)

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suggests that only 44% of actual “High Satisfaction” cases were identified by the model, implying that while precise, the model missed several true instances of high satisfaction. This indicates that most high-satisfaction patients are well-identified but some are misclassified as “Moderate.”

2. Moderate Satisfaction
   The “Moderate” class obtained precision = 0.33 and recall = 0.67, with an F1-score of 0.44. This indicates that the model could capture two-thirds of moderate-satisfaction cases, but with relatively low precision suggesting some overlap between the Moderate and High classes in patient responses.
3. Low Satisfaction
   The “Low” class shows precision = 0.22 and recall = 0.67, with an F1-score of 0.33. While the model captured most low-satisfaction cases (recall 0.67), its low precision implies several false- positive classifications (patients incorrectly labeled as low satisfaction).

From a macro perspective, the macro average F1-score (0.46) indicates moderate overall performance across all classes, while the weighted average F1-score (0.54) demonstrates balanced performance, considering the higher number of “High” class observations. This moderate accuracy can be attributed to data imbalance—where the “High” satisfaction class (18 samples) dominates the dataset compared to the “Low” and “Moderate” classes (3 each).

Visualization of the Decision Tree

To provide a more comprehensive understanding of the classification patterns generated by the model, a visualization of the Decision Tree Classifier was developed using data from the training and testing process. This visualization illustrates the hierarchical decision logic formed by the algorithm in predicting patient satisfaction levels based on the average score of the Bed Management Application Implementation (X_mean) variable.

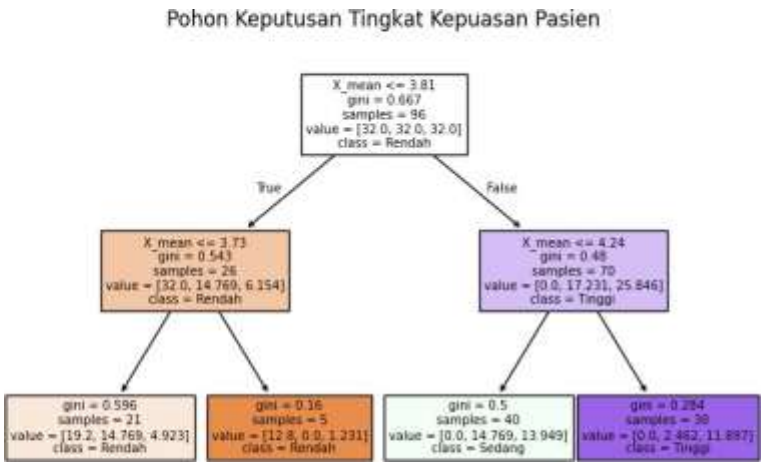

Figure 2. Decision Tree Model of Patient Satisfaction Prediction
(Source: Processed Data, Python, 2025)

Figure 4.2 presents the visualization of the Decision Tree Classifier model, which illustrates the hierarchical decision logic used to predict patient satisfaction levels based on the mean score of the Bed Management Application Implementation (X_mean) variable. The root node, located at the top of the tree, defines the first major threshold (X_mean ≤ 3.81) with a Gini index value of 0.667, dividing the dataset into two main branches: the left branch (True), representing patients with lower implementation scores classified predominantly as Low Satisfaction, and the right branch (False), representing those with higher implementation scores, which are largely associated with High Satisfaction. Subsequent splits occur at X_mean ≤ 3.73 and X_mean ≤ 4.24, further differentiating the data into three main satisfaction categories: Low, Moderate, and High.

The visualization demonstrates that patients who rate the application higher in aspects such as ease of use, reliability, accuracy, and transparency are more likely to report High Satisfaction levels. Conversely, lower implementation scores are consistently associated with Low or Moderate Satisfaction. As the tree progresses downward, the Gini index decreases, indicating that the classification becomes more homogeneous and precise at the terminal nodes. This pattern reflects the model’s ability to identify distinct satisfaction clusters, showing that increased implementation effectiveness of the Bed Management Application contributes directly to higher patient satisfaction outcomes.

In summary, the Decision Tree model provides a clear and interpretable depiction of how varying levels of system implementation influence satisfaction levels. The hierarchical rules revealed by the visualization confirm the findings from the regression analysis, reinforcing that effective digital system adoption in hospital management leads to improved patient experiences and a higher overall satisfaction rate.

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Comparative Analysis of Statistical and Algorithmic Results

A comparative examination between the statistical regression analysis (SPSS) and the algorithmic Decision Tree classification (Python) reveals consistent directional relationships between the Implementation of the Bed Management Application (X) and Patient Satisfaction (Y). While the regression model quantifies the mathematical strength and significance of the relationship between the variables, the Decision Tree provides an interpretable, rule-based representation that captures the logical patterns and categorical distinctions emerging from the same dataset. Together, these methods offer both confirmatory evidence (through inferential statistics) and predictive insight (through machine learning analytics).

Table 7. Comparative Summary of Statistical and Algorithmic Results

Aspect	Linear Regression (SPSS)	Decision Tree Classifier (Python)
Objective	To measure the magnitude and direction of the effect of X on Y	To predict categorical outcomes of Y based on X features
Analytical Nature	Inferential and explanatory (parametric)	Predictive and non-parametric
Output Type	Continuous prediction (numerical satisfaction scores)	Discrete classification (Low, Moderate, High satisfaction)
Statistical Result	$R^2 = 0.465$, $p < 0.001$ (significant)	Accuracy = 50%, Precision (High) = 0.89
Interpretation	Higher implementation scores significantly increase satisfaction levels	Pattern: X_mean > 4.1 → High satisfaction; X_mean ≤ 4.1 → Moderate/Low satisfaction
Strengths	Measures effect size, significance, and linear relationships	Captures nonlinear, hierarchical, and interpretable decision rules
Limitations	Assumes linearity and homoscedasticity	Sensitive to data imbalance and limited features
Approach Type	Statistical inferential modeling	Algorithmic predictive modeling
Validation	Hypothesis testing (t-test, R^2)	Accuracy, Precision, Recall, F1-Score

Source: Processed Data (SPSS & Python, 2025)

Interpretation of Comparative Findings

The regression analysis performed using SPSS version 26 demonstrates a statistically significant relationship between the Implementation of the Bed Management Application and Patient Satisfaction ($B = 0.687$, $\beta = 0.682$, $p < 0.001$). The R^2 value of 0.465 indicates that approximately 46.5% of the variance in patient satisfaction can be explained by variations in application implementation. This result confirms that patients who perceive the Bed Management Application as easy to use, reliable, and transparent tend to report higher satisfaction levels.

The regression model, therefore, provides strong evidence of a positive linear relationship between system implementation and satisfaction outcomes. Conversely, the Decision Tree Classifier, implemented in Python (Scikit-learn), achieved an accuracy rate of 50% when predicting satisfaction categories (Low, Moderate, High). Although the model's overall predictive performance is moderate, its interpretability offers valuable insights into the structure of decision- making. The model identified a key threshold at X_mean ≈ 4.1, beyond which patient satisfaction consistently shifted toward the High category. The precision score of 0.89 for the High Satisfaction class demonstrates that when the model predicts a patient as "highly satisfied," it is accurate in 89% of such cases.

However, the recall scores for Low and Moderate satisfaction classes were comparatively weaker, reflecting a class imbalance most patients reported high satisfaction, resulting in fewer data points for other categories. These differences highlight that while regression provides a robust statistical validation of the relationship, the Decision Tree captures nonlinear and interaction effects not detectable by purely parametric methods. Both analyses complement each other: the regression model validates the theoretical hypothesis derived from the Technology Acceptance Model (TAM) and SERVQUAL framework, whereas the Decision Tree operationalizes these findings into a predictive decision-support tool for hospital management.

Integrative Discussion

From a methodological standpoint, integrating statistical and algorithmic approaches provides a multidimensional perspective on hospital information system evaluation. The regression model offers inferential rigor, confirming that improvements in perceived usefulness, system reliability, and information accuracy have a measurable and statistically significant impact on patient satisfaction. In contrast, the Decision Tree introduces predictive analytics, allowing real-time estimation of satisfaction levels based on operational system scores.

The combined findings align with previous studies in health informatics which argue that hybrid analytical frameworks merging conventional statistics with machine learning—enhance both theoretical understanding and decision-making capacity [1], [11], [21]. Specifically, the results from Langsa General Hospital show that patient satisfaction can be quantitatively predicted and qualitatively explained through digital system indicators, bridging the gap between empirical validation and practical application.

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Discussion

The findings of this study provide comprehensive empirical evidence regarding the relationship between the Implementation of the Bed Management Application and Patient Satisfaction at Langsa General Hospital. By integrating statistical regression modeling (SPSS 26.0) and algorithmic predictive analysis (Python Decision Tree Classifier), this research offers a dual perspective that combines inferential accuracy with predictive interpretability. The convergence of both analytical approaches reinforces the robustness of the findings, confirming that digital system implementation plays a significant role in enhancing patient-centered healthcare outcomes.

Statistical Interpretation and Theoretical Implications

The results of the simple linear regression analysis reveal a statistically significant and positive effect of the Implementation of the Bed Management Application (X) on Patient Satisfaction (Y) ($B = 0.687$, $\beta = 0.682$, $p < 0.001$). The coefficient of determination ($R^2 = 0.465$) indicates that approximately 46.5% of the variance in patient satisfaction is explained by the effectiveness of the application's implementation. This level of explanatory power suggests that system quality, usability, and perceived transparency contribute meaningfully to patient perceptions of service excellence, aligning with the Technology Acceptance Model (TAM) [7] and the DeLone and McLean Information System Success Model (ISSM) [11].

According to TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are central determinants of user attitudes and satisfaction toward information systems [8]. In this context, patients who find the Bed Management Application intuitive, fast, and beneficial for hospital navigation are more likely to experience higher satisfaction. These results are also consistent with prior studies by Alalwan et al. [1] and Handayani [15], who found that digital healthcare adoption positively influences patient perceptions of efficiency and trust.

Similarly, the ISSM framework posits that system quality, information accuracy, and service responsiveness directly determine user satisfaction and net benefits [12]. The results of this study confirm this theoretical proposition: improved system reliability and information transparency in bed management significantly enhance patients' trust and satisfaction with hospital services.

Algorithmic Interpretation and Predictive Insights

To complement the inferential analysis, a Decision Tree Classifier was applied to model and predict categorical satisfaction outcomes (Low, Moderate, High) using Python's Scikit-learn. The model achieved an overall accuracy of 50%, indicating that it correctly classified half of the patient satisfaction levels. While this accuracy is moderate, it remains informative, especially given the relatively small and imbalanced dataset. The model's precision score for the "High Satisfaction" class (0.89) signifies a strong ability to accurately predict high satisfaction outcomes when they occur, even though recall values (0.44) suggest that some high-satisfaction cases were not fully captured.

The Decision Tree visualization further reveals key decision thresholds that influence satisfaction levels, with $X\_mean \approx 4.1$ serving as the primary cutoff point. Patients with mean implementation scores above this threshold are more likely to fall into the High Satisfaction category, while those below it tend to cluster into Moderate or Low Satisfaction. This hierarchical decision pattern aligns with findings from Williams et al. [3] and Dewi & Rahman [18], who emphasized that improved technological usability, speed, and reliability significantly elevate perceived healthcare quality. The gradual reduction in Gini index values across the tree indicates increasing model certainty, demonstrating that satisfaction classifications become more homogeneous and distinct at terminal nodes.

Despite its moderate accuracy, the Decision Tree model provides a valuable explanatory and predictive lens for understanding how patients' perceptions translate into satisfaction levels. The interpretability of the decision rules offers an operational advantage for hospital administrators, allowing them to identify actionable thresholds for service improvement such as maintaining an average implementation score above 4.1 to sustain higher satisfaction levels.

Comparative and Integrative Analysis

The integration of regression and Decision Tree analyses underscores the complementary nature of statistical and algorithmic methodologies. The regression model confirms the existence and strength of a causal, linear relationship between system implementation and satisfaction, while the Decision Tree extends this understanding by modeling nonlinear interactions and hierarchical decision paths. Both analyses converge on a consistent conclusion: effective implementation of the Bed Management Application directly contributes to improved patient satisfaction.

This methodological complementarity reflects the emerging consensus in health informatics research that hybrid analytical frameworks yield richer insights than single-method approaches [1], [14], [21]. Regression analysis provides theoretical validation aligned with established models such as TAM and SERVQUAL [16], while machine learning techniques like Decision Trees enable data-driven discovery of patterns and thresholds that may not conform to linear assumptions. This combination of inferential precision and predictive intelligence

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represents an advancement in evaluating digital healthcare systems.

Contextual and Practical Implications

From a practical perspective, the findings hold significant implications for hospital management and digital transformation policy. The strong and positive regression results indicate that investments in user-friendly, reliable, and transparent bed management applications can yield measurable gains in patient satisfaction. These outcomes corroborate the Smart Hospital Initiative launched by the Indonesian Ministry of Health [4], which aims to integrate digital solutions into hospital workflows to enhance operational efficiency and service quality.

Furthermore, the Decision Tree model's interpretability makes it a practical decision-support tool for administrators. By identifying satisfaction thresholds and service attributes that most influence patient experiences, hospital management can prioritize interventions such as improving interface design, response time, and information accuracy to maintain consistently high satisfaction scores. The model can also be refined in future research by incorporating additional variables such as staff interaction, patient demographics, or perceived fairness in service allocation, which may further enhance predictive accuracy.

Limitations and Future Research Directions

Despite its contributions, this study acknowledges several limitations. First, the dataset used for Decision Tree modeling exhibits class imbalance, with a larger proportion of respondents categorized under High Satisfaction. This imbalance may limit the model's ability to accurately predict lower satisfaction categories. Future studies could address this issue by employing resampling techniques or expanding the dataset to ensure more balanced class distributions [22].

Second, the analysis relies primarily on self-reported data, which may introduce subjective bias in measuring perceived satisfaction and application performance. Incorporating objective system metrics such as response times, usage logs, and service delays could provide a more holistic evaluation of system effectiveness. Finally, while this study utilizes a simple Decision Tree model, future research could adopt ensemble algorithms (e.g., Random Forest, Gradient Boosting) to improve predictive robustness while maintaining interpretability.

Theoretical Synthesis

The empirical findings collectively validate and extend the Technology Acceptance Model (TAM) and SERVQUAL framework in the context of hospital information systems. The positive influence of perceived ease of use, usefulness, and reliability on patient satisfaction underscores the relevance of TAM in explaining patient engagement with hospital digital services [7], [8]. Simultaneously, the SERVQUAL dimensions reliability, responsiveness, and assurance are reflected in the system attributes most strongly associated with satisfaction improvements [16], [18]. Thus, the study substantiates a hybrid theoretical perspective, integrating both technology adoption and service quality theories to explain satisfaction dynamics in digital healthcare environments.

5. Conclusions

This study provides empirical evidence that the implementation of the Bed Management Application has a significant and positive impact on patient satisfaction at Langsa General Hospital. The results of the regression analysis ($B = 0.687$, $\beta = 0.682$, $p < 0.001$, $R^2 = 0.465$) confirm that approximately 46.5% of variations in patient satisfaction can be explained by the degree of system implementation. Patients who perceived the application as easy to use, reliable, and transparent consistently reported higher satisfaction levels, highlighting the essential role of system quality and usability in improving service experiences. These findings support the theoretical propositions of the Technology Acceptance Model (TAM) [7] and DeLone and McLean's Information System Success Model (ISSM) [11], which assert that perceived usefulness, system reliability, and information quality significantly influence user satisfaction. The study thus reinforces the argument that effective digital transformation enhances patient-centered care by improving service efficiency, accuracy, and transparency in hospital operations.

Complementing the inferential findings, the Decision Tree Classifier analysis in Python revealed that patients with average implementation scores above 4.1 were predominantly categorized as "Highly Satisfied," demonstrating the model's capability to identify hierarchical decision patterns. Although the model achieved a moderate predictive accuracy of 50%, its interpretability provides actionable insights into satisfaction determinants, supporting data-driven decision-making for hospital management. Collectively, the integration of statistical and algorithmic methods strengthens the reliability of this study and offers both theoretical and practical contributions. It validates that robust implementation of hospital information systems, such as the Bed Management Application, is a critical factor in elevating patient satisfaction and operational excellence. Future research is recommended to incorporate additional service-related variables and adopt ensemble learning techniques to enhance predictive performance and expand the applicability of these findings in broader healthcare contexts.

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