

Effect of Monitoring & Evaluation Practices on the Public Program Performance and Efficiency: A Case of the Patient Voice Program at Masaka Hospital

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Abstract: This study examined the effect of Monitoring and Evaluation (M&E) practices on public program performance and efficiency, focusing on the Patient Voice Program (PVP) at Masaka Hospital in Kigali, Rwanda. Specifically, the study assessed the effects of M&E planning, data analysis and reporting, data quality assurance, and staff capacity on the performance and efficiency of the Patient Voice Program. The study was guided by the Donabedian model of healthcare quality, the resource-based view (RBV) theory, and systems theory. A mixed-methods research design was adopted, integrating quantitative and qualitative approaches. Target population comprised 195 respondents, including hospital staff, management personnel, support staff, and program stakeholders involved in implementing the Patient Voice Program. A census approach was employed whereby all members of the population participated in the study. Data were collected using structured questionnaires, semi-structured interviews, and documentary review. Quantitative data were analyzed using descriptive statistics, Spearman correlation, and hierarchical multiple regression using the Statistical Package for Social Sciences (SPSS), while qualitative data were analyzed thematically. The measurement model satisfied the recommended reliability and validity criteria, with Cronbach's alpha and Composite Reliability (CR) values exceeding 0.70, Average Variance Extracted (AVE) values exceeding 0.50, and discriminant validity confirmed using the Fornell-Larcker criterion. The hierarchical regression model explained 72.5% of the variation in public program performance and efficiency ($R^2 = 0.725$; Adjusted $R^2 = 0.718$), indicating substantial explanatory power. The overall regression model was statistically significant ($F = 99.877$, $p < 0.001$). The findings revealed that M&E Planning was the strongest predictor of public program performance and efficiency ($\beta = 0.872$, $B = 3.600$, $p < 0.001$). Data Analysis and Reporting ($\beta = 0.032$, $B = 0.148$, $p < 0.001$), Data Quality Assurance ($\beta = 0.014$, $B = 0.014$, $p = 0.004$), Program Responsiveness ($\beta = 0.057$, $B = 0.031$, $p = 0.002$), and Staff Capacity ($B = 1.616$, $p < 0.001$) also had statistically significant positive effects on program performance and efficiency. Furthermore, all post-estimation diagnostic tests, including assessments of normality, multicollinearity, heteroscedasticity, autocorrelation, influential observations, and model specification, confirmed that the regression model satisfied the required assumptions and was appropriate for statistical inference.

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I. INTRODUCTION

Monitoring and Evaluation (M&E) has therefore evolved from a reporting function into a strategic management tool that supports evidence-based decision-making, accountability, and continuous quality improvement (World Health Organization [WHO], 2024). Within healthcare, M&E enables institutions to systematically collect, analyze, and utilize performance information to improve service delivery, resource utilization, patient safety, and

overall health outcomes. Donabedian's Quality of Care Model further explains that healthcare quality is achieved when organizational structures and service delivery processes are continuously monitored to improve patient outcomes (Ameh *et al.*, 2022).

Many countries have strengthened patient feedback systems as part of broader healthcare reforms. Digital reporting platforms, patient satisfaction surveys, complaint

management systems, and citizen engagement mechanisms are increasingly being integrated into national health information systems to improve accountability and responsiveness. Evidence from the WHO (2024) indicates that health systems that routinely incorporate patient feedback into planning and decision-making demonstrate higher levels of service quality, organizational learning, and public trust. Although many low- and middle-income countries continue to face challenges related to limited digital infrastructure, workforce capacity, and data utilization, recent studies show that structured patient feedback systems significantly improve service responsiveness and programme effectiveness when supported by strong monitoring and evaluation practices (Mwangi *et al.*, 2023; OECD, 2024).

Rwanda has emerged as one of Africa's leading countries in implementing results-based health sector reforms. The country's healthcare transformation is guided by Vision 2050, which aims to build a high-quality, citizen-centred health system, and the Health Sector Strategic Plan V (HSSP V 2024-2029), which emphasises Universal Health Coverage (UHC), digital health transformation, accountability, and continuous performance monitoring (Ministry of Health, 2024). Through these reforms, Rwanda has strengthened the Health Management Information System (HMIS), expanded digital health technologies, and institutionalized monitoring and evaluation as a core component of healthcare governance. These initiatives are intended to ensure that health services remain responsive to citizens' needs while improving efficiency, transparency, and quality of care.

Rwanda Biomedical Centre (RBC) introduced the Patient Voice Program (PVP) to strengthen patient participation in healthcare delivery. The programme provides structured channels through which patients can express their experiences, complaints, compliments, and suggestions using digital platforms, exit interviews, suggestion boxes, and satisfaction surveys. Information collected through the programme is analysed and communicated to hospital management to support evidence-based decision-making and continuous service improvement (Rwanda Biomedical Centre, 2024). The Patient Voice Program therefore represents one of Rwanda's practical strategies for operationalising patient-centred care while supporting national commitments to Universal Health Coverage and Vision 2050.

➤ Problem Statement

The challenge is particularly evident at Masaka Hospital. According to the Masaka Hospital Annual Report (2024), average outpatient waiting times exceed 90 minutes, almost double the national benchmark of 45 minutes. Similarly, while approximately 85% of patient complaints are formally recorded, only 52% are resolved within the recommended seven-day period, leaving nearly one out of every two complaints unresolved beyond the expected timeframe. Delayed complaint resolution contributes to prolonged waiting times, repeated patient visits, increased staff workload, inefficient utilisation of hospital resources, and declining patient confidence in public healthcare services. These operational inefficiencies ultimately reduce programme effectiveness by delaying evidence-based

management decisions and limiting opportunities for continuous quality improvement. Institutional assessments further indicate that only 58% of personnel responsible for managing patient feedback have received formal training in monitoring and evaluation, while more than 70% report excessive workload and inadequate digital support systems as major constraints affecting effective utilisation of patient feedback (Rwanda Biomedical Centre, 2024). These findings suggest that even where patient feedback systems exist, organisational capacity to interpret, communicate, and utilise the information remains insufficient.

Previous empirical studies have examined monitoring and evaluation practices, health system performance, and patient satisfaction in Rwanda and other East African countries (Kamau & Odhiambo, 2021; Mwangi *et al.*, 2023; Mukamana *et al.*, 2023). However, these studies have primarily focused on the direct relationship between M&E systems and organisational performance, with limited attention given to the mechanisms through which M&E practices influence programme outcomes. In particular, little empirical evidence exists on whether programme responsiveness mediates the relationship between M&E practices and programme performance by translating monitoring information into service improvements. Likewise, previous studies have rarely examined whether staff capacity moderates this relationship by strengthening or weakening the effectiveness of monitoring and evaluation practices. Consequently, the pathways through which M&E practices produce improved programme performance remain insufficiently understood, particularly within patient feedback programmes implemented in Rwanda's public hospitals.

Addressing these knowledge gaps is essential because healthcare managers require evidence not only on whether M&E practices improve programme performance, but also on the organisational conditions under which those improvements occur. Without such evidence, investments in patient feedback systems, digital reporting platforms, and monitoring frameworks may continue to generate large volumes of data without producing corresponding improvements in healthcare quality, efficiency, and accountability. Therefore, this study examines the effect of Monitoring and Evaluation practices on the performance and efficiency of the Patient Voice Program at Masaka Hospital. Specifically, the study investigates how M&E planning, data analysis and reporting, and data quality assurance influence programme performance, while examining the mediating role of programme responsiveness and the moderating role of staff capacity.

➤ Objectives of the Study

The study is guided by general that quantified the effect of Monitoring and Evaluation (M&E) practices on program performance and efficiency, focusing on the Patient Voice Program at Masaka Hospital. The study focused on the following specific objectives.

- To determine the effect of M&E Planning (Project Setup) on performance and efficiency of Patient Voice Program at Masaka Hospital;
- To quantify the effect of data analysis and reporting on performance and efficiency of Patient Voice Program at Masaka Hospital;
- To measure the effect of Data quality assurance mechanisms on performance and efficiency of Patient Voice Program at Masaka Hospital;
- To assess the effect of M&E staff capacity on Performance and efficiency of Patient Voice Program at Masaka Hospital;

➤ *Research Hypotheses*

The research was guided by the following alternate hypotheses.

- H₁: M&E Planning (Project Setup) have a significant positive effect on the performance and efficiency of the Patient Voice Program at Masaka Hospital;
- H₂: Data analysis and reporting practices have a significant positive effect on the performance and efficiency of the Patient Voice Program at Masaka Hospital;
- H₃: Data quality assurance mechanisms have a significant positive effect on the performance and efficiency of the Patient Voice Program at Masaka Hospital;
- H₄: M&E Staff capacity has a significant positive effect on the performance and efficiency of the Patient Voice Program at Masaka Hospital.

II. LITERATURE REVIEW

➤ *Monitoring and Evaluation (M&E) Practices*

Monitoring and Evaluation (M&E) practices refer to the systematic processes used to plan, collect, analyze, report, and utilize information to assess programme implementation and support evidence-based decision-making. In healthcare, M&E enables organisations to monitor progress, identify performance gaps, and implement corrective actions that improve service quality, accountability, and programme outcomes (World Health Organization [WHO], 2024; OECD, 2024).

➤ *M&E Planning*

M&E planning refers to the process of establishing indicators, data sources, reporting schedules, responsibilities, and resource requirements that guide monitoring and evaluation activities throughout programme implementation. Effective planning ensures that performance information is collected systematically and aligned with programme objectives (OECD, 2024; UNICEF, 2023). M&E planning contributes to programme effectiveness. Njenga et al. (2022) reported that health programmes with comprehensive M&E plans achieved higher implementation efficiency and improved service delivery outcomes.

➤ *M&E Data Analysis and Reporting*

Data analysis and reporting involve transforming collected data into meaningful information that supports

management decisions, organisational learning, and continuous programme improvement. Effective reporting ensures that monitoring information is communicated accurately and promptly to relevant decision-makers (WHO, 2024; OECD, 2024). Previous studies indicate that timely analysis and reporting improve organisational responsiveness and programme performance. MEASURE Evaluation (2023) found that weak reporting systems delay management decisions and reduce programme effectiveness.

➤ *M&E Data Quality Assurance*

Data quality assurance refers to the systematic processes used to ensure that monitoring data are accurate, complete, consistent, timely, and reliable for decision-making. High-quality data strengthen organisational accountability and improve the credibility of programme evaluation findings (WHO, 2024). Batini and Scannapieco (2022) observed that incomplete records, inaccurate reporting, and weak verification systems remain common challenges in many health programmes.

➤ *Staff Capacity*

Staff capacity refers to the knowledge, technical competencies, skills, experience, digital literacy, and institutional support that enable healthcare personnel to effectively perform monitoring and evaluation activities. It also includes the availability of adequate human resources and manageable workloads required for effective programme implementation (WHO, 2024). Several empirical studies identify staff capacity as a major determinant of successful M&E implementation. Kruk et al. (2022) argue that resilient health systems depend on competent health professionals capable of interpreting and utilising monitoring information effectively. Mwangi et al. (2023) found that inadequate training in digital M&E systems reduced data utilisation across healthcare programmes in East Africa.

➤ *Public Program Performance and Efficiency*

Public program performance and efficiency refers to the extent to which public sector programs achieve their intended objectives by transforming available resources, including financial resources, human capacity, time, and infrastructure, into effective and sustainable outcomes. Efficiency emphasizes achieving maximum value from available inputs while minimizing waste, delays, and unnecessary costs.

According to the Institute of Medicine (IOM, 2023), efficiency in public services involves maximizing outcomes while reducing resource wastage and operational delays.

• *Service Delivery Timeliness*

Service delivery timeliness refers to the ability of a healthcare program to provide required services within an appropriate period while minimizing unnecessary waiting times and delays. Timely service delivery is considered an essential dimension of healthcare quality because delays may negatively affect patient experiences, treatment outcomes, and overall health system performance.

- *Resource Utilization Rate*

Resource utilization rate refers to the extent to which available resources, including healthcare personnel, equipment, finances, and time, are effectively used to achieve program objectives. Efficient resource utilization ensures that limited public resources generate maximum benefits without unnecessary wastage.

- *Cost Effectiveness of Services*

Cost effectiveness refers to the ability of a program to achieve desired outcomes while using financial resources efficiently. It involves comparing program costs with achieved benefits to determine whether resources are being allocated appropriately.

- *Output Achievement Rate*

Output achievement rate refers to the extent to which planned program activities, targets, and expected immediate results are successfully achieved within a specified period. It measures whether program implementation follows the intended plans and contributes to expected outcomes.

- *Service Responsiveness*

Service responsiveness refers to the ability of healthcare programs to respond appropriately, respectfully, and effectively to patients' needs, expectations, and concerns. It reflects how well healthcare institutions incorporate patient perspectives into service improvement.

- *Patient Satisfaction Level*

Patient satisfaction refers to the extent to which healthcare services meet patients' expectations regarding quality, accessibility, communication, and overall service experience. It is commonly used as an indicator for assessing healthcare program performance.

➤ *Donabedian Model of Healthcare Quality*

The Donabedian Model of Healthcare Quality was developed by Avedis Donabedian and remains one of the most widely applied theoretical frameworks for assessing healthcare quality and performance. The model proposes that healthcare quality can be evaluated through three interconnected dimensions: structure, process, and outcomes. The structure dimension refers to the organizational conditions under which healthcare services are delivered, including human resources, infrastructure, leadership, and institutional arrangements. The process dimension concerns the activities involved in healthcare delivery, including communication, monitoring, evaluation, patient engagement, and service coordination. The outcome dimension reflects the results achieved from healthcare interventions, including patient satisfaction, responsiveness, service timeliness, safety, and overall program efficiency.

Application of the Donabedian model to the current study, in the context of the Patient Voice Program at Masaka Hospital, the Donabedian Model explains that effective M&E practices represent critical processes through which patient feedback is collected, analysed, reported, and transformed into improvement actions. When M&E systems are effectively implemented, healthcare providers are better

positioned to identify service gaps, respond to patient concerns, and improve service delivery outcomes.

Furthermore, the Donabedian Model provides theoretical justification for the mediating role of Program Responsiveness. Effective M&E processes improve the availability and use of patient feedback information, which enhances the ability of healthcare providers to respond to patient needs. Consequently, improved responsiveness contributes to better service quality, patient satisfaction, and overall program efficiency.

➤ *Resource-Based View (RBV) Theory*

The Resource-Based View (RBV) Theory, introduced by Barney (1991), explains that organizational performance is largely determined by the availability, development, and effective utilization of internal resources. According to RBV, sustainable organizational advantages are achieved when resources possess characteristics of being valuable, rare, difficult to imitate, and difficult to substitute (VRIN). Within healthcare organizations, such strategic resources include skilled personnel, professional knowledge, technological capabilities, institutional experience, and effective management systems. The RBV perspective suggests that organizational practices alone cannot guarantee improved performance unless institutions possess adequate internal capabilities to implement and sustain those practices. Kruk et al. (2021) emphasize that healthcare system performance is strongly influenced by workforce competence, adaptability, and organizational resilience. Wright and McMahan (2022) argue that organizational effectiveness depends on the ability to develop and utilize employee capabilities, while Ployhart and Moliterno (2023) demonstrate that employee knowledge and skills are essential for successful data-driven decision-making. Similarly, Hitt et al. (2022) confirm that investment in human resource development contributes significantly to improved organizational efficiency and service outcomes. Although RBV has been criticized for paying insufficient attention to external environmental influences such as government policies, financial constraints, and institutional pressures, the theory remains valuable because internal capabilities determine how effectively organizations implement strategic initiatives. Application of RBV theory to staff capacity as a moderating variable, in this study, RBV provides the theoretical justification for considering Staff Capacity as a moderating variable. Although effective M&E practices generate valuable information for improving healthcare programs, the extent to which such information contributes to efficiency depends on the ability of healthcare staff to interpret, communicate, and apply M&E findings.

➤ *Systems Theory*

Systems Theory, introduced by Ludwig von Bertalanffy (1968), views organizations as complex and interconnected systems in which different components interact continuously to achieve common objectives. The theory assumes that organizational performance cannot be understood by examining individual components in isolation because changes in one component influence the functioning of the entire system. In healthcare settings, Systems Theory highlights the importance of interaction among

organizational structures, information systems, human resources, leadership mechanisms, and feedback processes. Kaplan et al. (2023) explain that healthcare organizations operate as complex adaptive systems that depend on continuous learning, feedback, and adjustment. Bartoletta et al. (2021) emphasize that effective integration of data collection, reporting, and decision-making processes improves public health program performance. Braithwaite et al. (2022) further argue that healthcare outcomes emerge from the interaction between governance structures, workforce capacity, and patient needs.

➤ Conceptual Framework

In this framework, the independent variable (M&E practices) is operationalized through four key

components: M&E planning, data analysis and reporting, data quality assurance, and feedback utilization. These components represent the core processes through which patient feedback is collected, analyzed, validated, and translated into actionable decisions. A positive relationship is expected between M&E practices and program performance and efficiency, meaning that improvements in these practices are likely to lead to better service delivery outcomes. The dependent variable (program performance and efficiency) is measured using indicators such as timeliness of service delivery, responsiveness to patient needs, complaint resolution rate, resource utilization, and patient satisfaction.

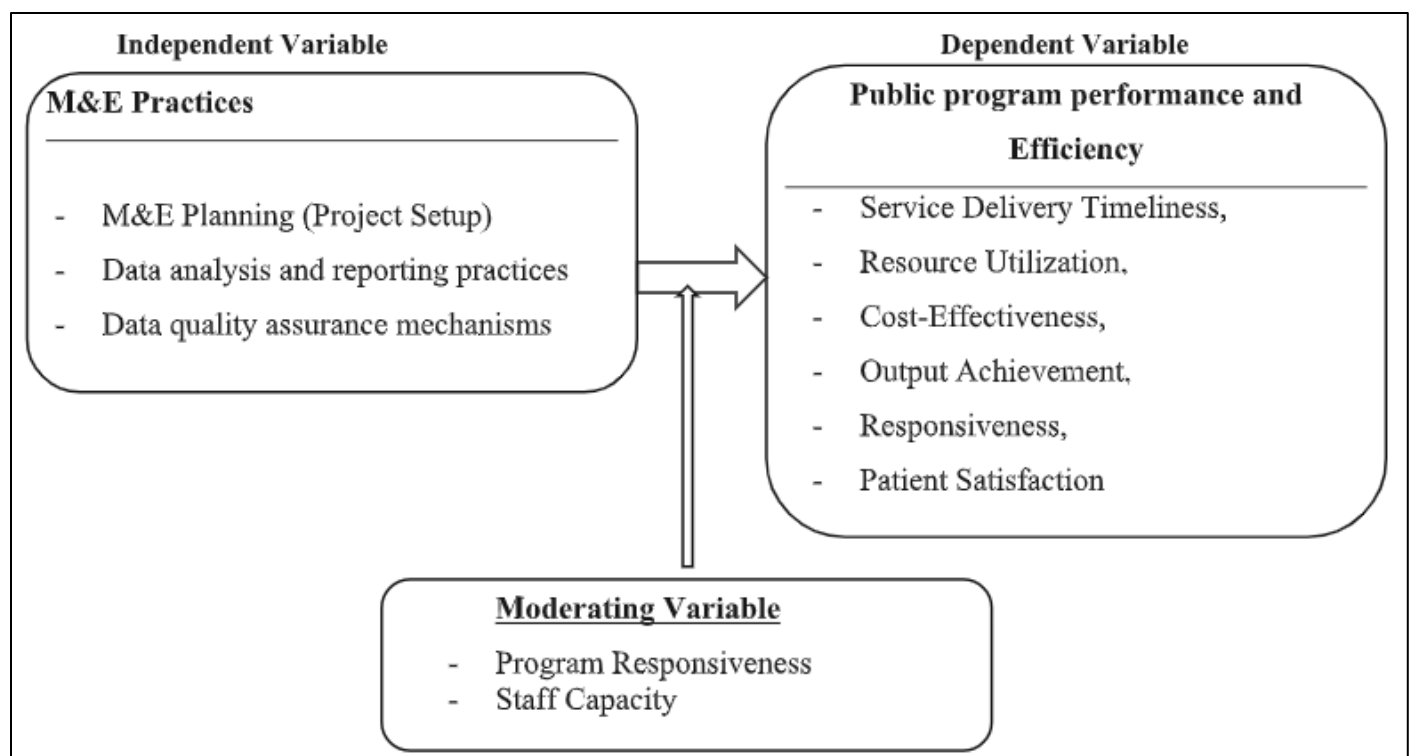


Fig 1 Conceptual Framework

Source: Researcher (2026), Conceptualized from Donabedian's Quality of Care Model and Reviewed Literature.

III. RESEARCH METHODOLOGY

This describes the methodology followed to understand how monitoring and evaluation (M&E) practices as well as staff resource capacity influence the public program performance and efficiency, especially the PVP at Masaka Hospital.

➤ Research Design

The quantitative design measure relationships between variables such as M&E planning, data reporting, data quality assurance, staff capacity, and program efficiency outcomes. This allows the research to test hypotheses and determine whether or not relationships are strong and how to interpret them through statistical methods

➤ Study Population, Sample Size and Sampling Techniques

The study population consists of 195 people who are either directly or indirectly involved in the implementation and oversight of the Patient Voice Program at Masaka Hospital. These include clinical staff, administrative staff, M&E officers, hospital management, support staff, and patient representatives. In this study, the sample size refers to the total number of people who took part in the research. It is important because it ensures that the information collected truly reflects the situation being studied. Sampling refers to the way participants are selected from a population to take part in a study. Even though this study used a census (where everyone is included), the population is still organized into different groups to make the data collection clearer and more structured. First, stratified sampling logic is applied by grouping respondents into categories based on their roles at the hospital. In addition, the study also uses purposive

sampling during the qualitative part of the research. In simple terms, this study includes all 195 participants through a census, while also organizing them into meaningful groups using stratification.

➤ Data Collection Instruments

Primary and secondary data sources are used in this study to provide information and depth, and triangulation to assess the effectiveness of monitoring and evaluation (M&E) practices and staff resource capacity within the PVP at Masaka Hospital. The structured questionnaire is a research instrument that presents a set of pre-designed questions to respondents in a standardized format. It has a 5-point Likert scale ranging from strongly disagree to strongly agree, and allows respondents to indicate their agreement with various statements. This instrument is created to assess key study variables such as M&E practices planning, reporting, data quality assurance, and feedback, staff resources (training levels, workload pressure, digital readiness), and program efficiency outcomes (timeliness of care, patient satisfaction, safety, and resource utilization). Structured questionnaires become important to quantitative research as they are able to compare responses and statistics about how the variables are related.

➤ Data Processing Techniques, and Data Analysis

Data processing is the process of translating raw data from the field into meaningful, organized and analyzable information. In research, editing is important because it can improve the data quality and prevent mistakes before analysis is done. The second step is coding, which involves assigning numerical values for closed-ended responses and thematic labels for qualitative responses. This helps to categorize and analyze data statistically. Quantitative data collected through structured questionnaires were coded and entered into the Statistical Package for Social Sciences (SPSS) Version 30 for analysis. Both descriptive and inferential statistical techniques were employed to achieve the study objectives. The hierarchical regression models were estimated in three stages.

- Model 1 included the control variables, where applicable.
- Model 2 introduced the independent variables comprising:
 - ✓ Monitoring and Evaluation Planning;
 - ✓ Data Analysis and Reporting; and
 - ✓ Data Quality Assurance.

This model estimated the direct effects of Monitoring and Evaluation practices on Public Program Performance and Efficiency.

- Model 3 introduced Staff Capacity together with the interaction terms between each M&E practice and Staff Capacity to examine moderation. The regression model was specified as follows

$$\text{Where: } Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 SC + \beta_5 (x_1 \times SC) + \beta_6 (x_2 \times SC) + \beta_7 (x_3 \times SC) + \varepsilon$$

Y = Public Program Performance and Efficiency

X₁ = M&E Planning

X₂ = Data Analysis and Reporting

X₃ = Data Quality Assurance

SC = Staff Capacity

X × SC = Interaction Terms

β₀ = Constant

β₁–β₇ = Regression Coefficients

ε = Error Term

The significance of changes in R², standardized beta coefficients, and F-statistics were used to evaluate the explanatory power of each successive model.

IV. DATA ANALYSIS, INTERPRETATION AND PRESENTATION OF FINDINGS

The study was guided by the research objectives and hypotheses outlined in the preceding chapters. Data were collected from a total of 195 respondents using structured questionnaires administered to staff and stakeholders involved in the implementation of the Patient Voice Program. The study achieved a response rate of 100%, as all the 195 distributed questionnaires were duly completed and returned by the respondents. Following data collection, the questionnaires were edited, coded, classified, and entered into the Statistical Package for Social Sciences (SPSS) version 23.0 for analysis. Both descriptive and inferential statistical techniques were employed to analyze the data and address the research objectives.

➤ Assessment of the Measurement Model

Evaluating these measurement properties is important because reliable and valid constructs reduce measurement error and increase confidence that the structural relationships observed in the subsequent analysis reflect the underlying theoretical concepts rather than weaknesses in the measurement instrument.

Table 1 Reliability and Convergent Validity Assessment

Construct	Items	Cronbach's Alpha	Composite Reliability	AVE
M&E Planning	5	0.842	0.879	0.512
Data Analysis & Reporting	7	0.867	0.901	0.566
Data Quality Assurance	7	0.854	0.893	0.548
Program Responsiveness	5	0.816	0.872	0.578
Staff Capacity	6	0.835	0.884	0.561
Program Performance & Efficiency	5	0.891	0.917	0.614

Source: SPSS Results (2026)

The findings presented in Table 1 indicate that all constructs satisfied the recommended reliability and convergent validity thresholds. In this study, Cronbach's Alpha values ranged from 0.816 to 0.891, indicating that the items measuring each construct were highly consistent and reliably represented the intended concepts. Composite Reliability (CR) values ranged from 0.872 to 0.917, exceeding the recommended minimum threshold of 0.70. Convergent validity was assessed using the Average Variance Extracted (AVE). According to Hair *et al.* (2022), an AVE value of 0.50 or higher indicates that a construct

explains at least 50% of the variance in its indicators, demonstrating that the indicators converge to measure the same underlying concept. In this study, AVE values ranged from 0.512 to 0.614, confirming satisfactory convergent validity for all constructs.

➤ Indicator Reliability Assessment

According to Hair *et al.* (2022), outer loading values of 0.70 or above indicate that an indicator explains at least 50% of the variance of its underlying construct and therefore contributes meaningfully to the measurement model.

Table 2 Outer Loadings of Indicators

Construct	Indicator	Loading
M&E Planning	MEP1	0.724
	MEP2	0.731
	MEP3	0.765
	MEP4	0.741
	MEP5	0.756
	MEP6	0.787
	MEP7	0.772

Source: SPSS Results (2026)

The results in Table 2 show that all indicators recorded loading values ranging from 0.724 to 0.787, exceeding the recommended threshold of 0.70. These findings confirm that each indicator contributed substantially to measuring the M&E Planning construct and that none required elimination from the measurement model. Among the indicators, MEP6 recorded the highest loading (0.787), indicating that it contributed most strongly to explaining Monitoring and Evaluation Planning. Conversely,

although MEP1 recorded the lowest loading (0.724), it remained well above the acceptable threshold and therefore continued to make a meaningful contribution to measuring the construct.

➤ Discriminant Validity Assessment

Establishing discriminant validity is important because excessive overlap between constructs may indicate that different variables are measuring the same phenomenon.

Table 3 Fornell-Larcker Criterion

Constructs	MEP	DAR	DQA	PR	SC	PPE
M&E Planning (MEP)	0.716					
Data Analysis & Reporting (DAR)	0.521	0.752				
Data Quality Assurance (DQA)	0.488	0.567	0.740			
Program Responsiveness (PR)	0.592	0.611	0.544	0.760		
Staff Capacity (SC)	0.473	0.492	0.456	0.529	0.749	
Program Performance & Efficiency (PPE)	0.631	0.684	0.608	0.713	0.581	0.783

Source: SPSS Results (2026)

The results presented in Table 3 indicate square root of the AVE for Program Performance and Efficiency (0.783) exceeded its correlations with M&E Planning (0.631), Data Analysis and Reporting (0.684), Data Quality Assurance (0.608), Program Responsiveness (0.713), and Staff Capacity (0.581). Similarly, the square root of the AVE for Program Responsiveness (0.760) exceeded its correlations with all other constructs, confirming that Program Responsiveness

measured a concept that was empirically distinct from Monitoring and Evaluation practices and Staff Capacity.

➤ Socio-Demographic Characteristics of Respondents

The demographic variables considered in this study included age, gender, highest level of education, department/unit, and years of work experience.

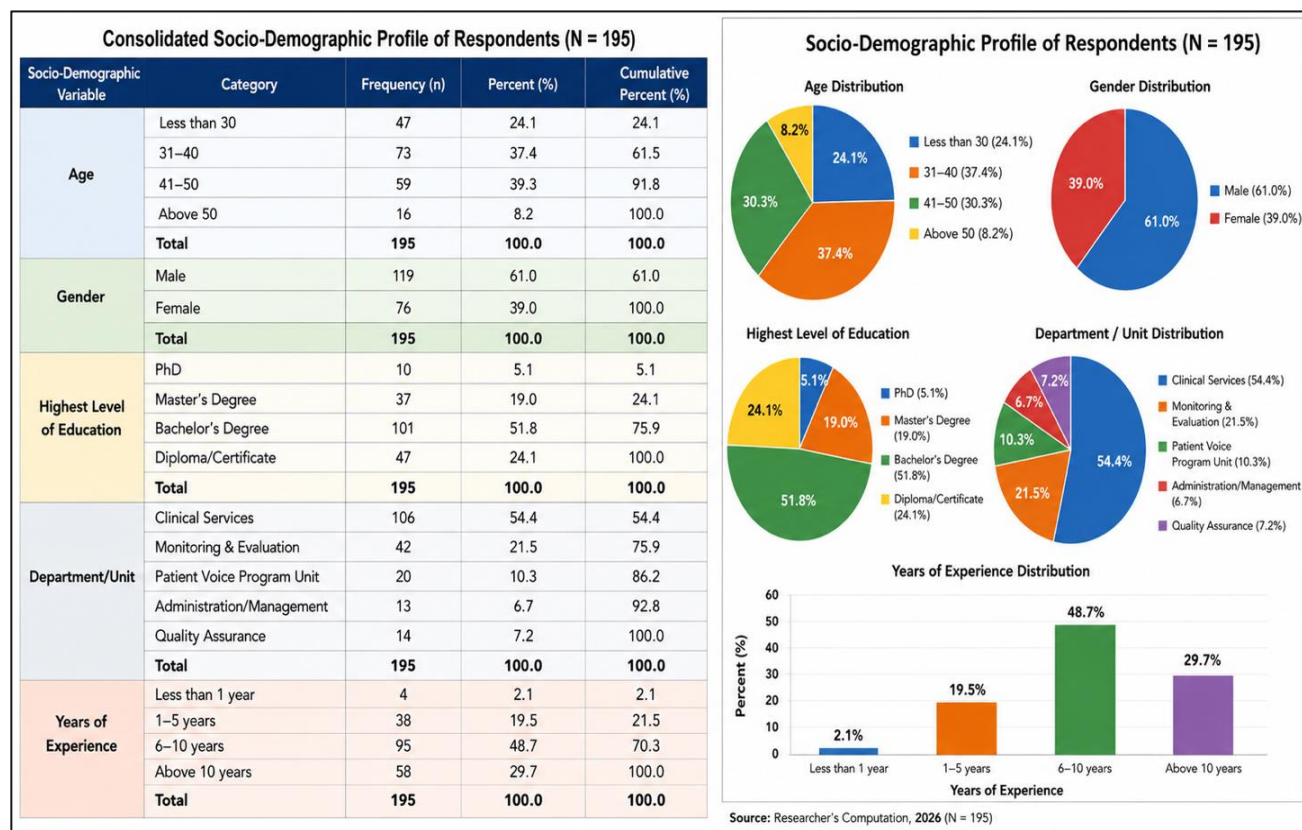


Fig 2 Socio-Demographic Characteristic of Respondents

Source: Field Data (2026)

The findings indicate that the largest proportion of respondents were aged between 31 and 40 years, representing 37.4% (n = 73) of the total respondents. This was followed by respondents aged between 41 and 50 years, accounting for 30.3% (n = 59). Respondents below 30 years represented 24.1% (n = 47), while those above 50 years constituted the smallest group at 8.2% (n = 16). Regarding gender distribution, the findings show that male respondents represented 61.0% (n = 119), while female respondents accounted for 39.0% (n = 76) of the sample.

In terms of educational attainment, the results indicate that the majority of respondents possessed a Bachelor's Degree (51.8%, n = 101), followed by those with Diploma or Certificate qualifications (24.1%, n = 47). Respondents holding Master's Degrees accounted for 19.0% (n = 37), while PhD holders represented 5.1% (n = 10).

The distribution of respondents by department or unit indicates that Clinical Services contributed the largest proportion of respondents (54.4%, n = 106), followed by Monitoring and Evaluation personnel (21.5%, n = 42).

The Patient Voice Program Unit contributed 10.3% (n = 20), while Quality Assurance and Administration/Management accounted for 7.2% (n = 14) and 6.7% (n = 13) respectively.

Concerning years of professional experience, the findings indicate that 48.7% (n = 95) of respondents had worked between 6 and 10 years, followed by respondents with more than 10 years of experience (29.7%, n = 58). Those with 1-5 years of experience represented 19.5% (n = 38), while only 2.1% (n = 4) had less than one year of experience.

➤ Descriptive Statistics Analysis Results per Objectives

Descriptive statistics were conducted to establish respondents' perceptions regarding the contribution of Monitoring and Evaluation (M&E) practices to the performance and efficiency of the Patient Voice Program (PVP) at Masaka Hospital. The analysis used mean scores and standard deviations to examine the extent to which respondents agreed with statements related to M&E Planning, Data Analysis and Reporting, Data Quality Assurance, Staff Capacity, and Program Responsiveness.

Table 4 Consolidated Descriptive Statistics for Study Variables

No.	Study Variable / Dimension	Aggregate Mean	Aggregate Std. Deviation	Interpretation	Rank
1	M&E Planning	4.596	0.622	Strongly Agree	6
2	Data Analysis and Reporting	4.720	0.492	Strongly Agree	4
3	Data Quality Assurance	4.725	0.504	Strongly Agree	2
4	Program Responsiveness	4.724	0.530	Strongly Agree	3
5	Staff Capacity	4.728	0.510	Strongly Agree	1

6	Program Performance and Efficiency	4.703	0.532	Strongly Agree	5
Overall Average	All Study Variables	4.699	0.532	Strongly Agree	

Source: Field Data (2026)

The consolidated descriptive statistics show that respondents strongly agreed with all the study variables, as all aggregate mean scores exceeded 4.50. The overall average mean of 4.699 indicates a very high level of agreement regarding the effectiveness of M&E practices and their contribution to the performance and efficiency of the Patient Voice Program at Masaka Hospital. The overall average standard deviation of 0.532 indicates relatively low variation in respondents' perceptions, suggesting a high degree of consistency in their responses.

Among the study variables, Staff Capacity recorded the highest aggregate mean ($M = 4.728$, $SD = 0.510$), indicating that respondents perceived staff skills, staffing adequacy, reporting tools, digital systems, and training as the strongest dimension supporting the Patient Voice Program. Data Quality Assurance followed closely ($M = 4.725$, $SD = 0.504$), while Program Responsiveness recorded an aggregate mean of 4.724 ($SD = 0.530$). Data Analysis and Reporting had a

mean of 4.720 ($SD = 0.492$), followed by Program Performance and Efficiency with $M = 4.703$ ($SD = 0.532$).

M&E Planning recorded the lowest aggregate mean ($M = 4.596$, $SD = 0.622$). Nevertheless, this score still falls within the Strongly Agree category, indicating that respondents viewed M&E planning positively, although it was relatively less highly rated than the other dimensions. The comparatively higher standard deviation also suggests slightly greater variation in perceptions concerning M&E planning.

➤ Inferential Analysis Results

The results indicated significant departures from normality ($p < 0.05$), justifying the use of non-parametric correlation analysis. However, given the relatively large sample size ($N = 195$), multiple regression analysis was conducted to examine the predictive effects of Monitoring and Evaluation (M&E) practices and Staff Capacity on Public Program Performance and Efficiency.

➤ Normality Test

Table 4 Tests of Normality for Public Program Performance and Efficiency

Test	Statistic	df	Sig.
Kolmogorov-Smirnov	0.330	195	0.000
Shapiro-Wilk	0.653	195	0.000

The Kolmogorov-Smirnov statistic (0.330, $p = 0.000$) and Shapiro-Wilk statistic (0.653, $p = 0.000$) were both statistically significant. Since the p-values are less than the threshold of 0.05, the null hypothesis of normality is rejected. This indicates that the dependent variable is not normally distributed.

The descriptive statistics further support this conclusion, with a skewness value of -2.235 and kurtosis value of 6.094, indicating a negatively skewed and highly leptokurtic

distribution. The majority of respondents recorded very high scores on Public Program Performance and Efficiency, as evidenced by the stem-and-leaf plot showing 118 observations concentrated at the maximum score of 80.

➤ Correlation Analysis

A statistically significant correlation simply indicates that two variables are associated, but it does not demonstrate that changes in one variable directly produce changes in another.

Table 5 Spearman Correlation Matrix

Variables	X1	X2	X3	X4	X5	Y
M&E Planning (X1)	1.000					
Data Analysis and Reporting (X2)	.893**	1.000				
Data Quality Assurance (X3)	.951**	.860**	1.000			
Program Responsiveness (X4)	.788**	.693**	.808**	1.000		
Staff Capacity (X5)	.980**	.875**	.931**	.773**	1.000	
Public Program Performance and Efficiency (Y)	.972**	.919**	.956**	.803**	.952**	1.000

Correlation is significant at the 0.01 level (2-tailed).

The findings indicate that all study variables were positively and statistically significantly associated with Public Program Performance and Efficiency at the 1% significance level ($p < 0.01$). The positive coefficients imply that higher levels of M&E practices, Program

Responsiveness, and Staff Capacity are associated with higher levels of program performance.

The strongest relationship was observed between M&E Planning and Public Program Performance and Efficiency (r

= 0.972, $p < 0.001$). This extremely strong positive association suggests that respondents who perceived planning practices to be more effective also tended to perceive higher levels of program performance. This finding offers preliminary support for Hypothesis One, which proposed that effective M&E planning positively influences program performance and efficiency.

Data Quality Assurance demonstrated a very strong positive association with Public Program Performance and Efficiency ($r = 0.956$, $p < 0.001$). This finding provides preliminary support for Hypothesis Three, indicating that healthcare programmes characterized by accurate, complete, consistent, and reliable data tend to report better operational performance.

The relationship between Staff Capacity and Public Program Performance and Efficiency was also exceptionally strong ($r = 0.952$, $p < 0.001$). This finding offers preliminary support for the proposed moderating hypothesis by indicating that programmes supported by competent personnel, adequate staffing, appropriate reporting tools, and continuous professional development are generally associated with stronger performance outcomes.

The findings further reveal a very strong positive relationship between Data Analysis and Reporting and Public Program Performance and Efficiency ($r = 0.919$, $p < 0.001$).

This provides preliminary support for Hypothesis Two, suggesting that programmes characterized by timely analysis, effective reporting, and utilization of monitoring information generally exhibit higher levels of operational performance.

The study also found that Program Responsiveness was positively and significantly associated with Public Program Performance and Efficiency ($r = 0.803$, $p < 0.001$). Although this represents the lowest coefficient among the study variables, it still reflects a strong positive relationship.

The correlation matrix also reveals strong positive relationships among the independent variables. For example, M&E Planning was highly correlated with Staff Capacity ($r = 0.980$) and Data Quality Assurance ($r = 0.951$), while Data Analysis and Reporting also demonstrated strong associations with the other M&E dimensions. These findings suggest that effective monitoring and evaluation systems operate as integrated organizational processes rather than isolated activities.

➤ Multiple Regression Analysis

Multiple regression analysis was conducted to determine the extent to which M&E Planning, Data Analysis and Reporting, Data Quality Assurance, Program Responsiveness, and Staff Capacity jointly predict Public Program Performance and Efficiency.

Table 6 Model Summary

Statistic	Value
R	0.852
R Square (R^2)	0.725
Adjusted R Square	0.718
Standard Error of Estimate	3.811
Durbin-Watson	1.949
F Statistic	99.877
Significance Level	0.000

The model summary indicates that the regression model achieved a multiple correlation coefficient ($R = 0.852$), demonstrating a strong positive relationship between the combined M&E practice variables and Public Program Performance and Efficiency.

The coefficient of determination ($R^2 = 0.725$) indicates that 72.5% of the variation in Public Program Performance and Efficiency is explained by the combined influence of the five predictor variables included in the model.

The adjusted R^2 value of 0.718 indicates that after considering the number of predictors included in the model, the explanatory power remains strong. The Durbin-Watson statistic of 1.949 falls within the acceptable range of approximately 1.5 to 2.5, suggesting that the residuals are independent and that there is no serious autocorrelation problem affecting the regression estimates.

Table 7 ANOVA Results

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	7253.233	5	1450.647	99.877	0.000
Residual	2745.106	189	14.524		
Total	9998.338	194			

The ANOVA results show that the regression model is statistically significant, with an F-value of 99.877 and significance level of $p < 0.001$. This indicates that the independent variables collectively provide a statistically

significant explanation of variations in Public Program Performance and Efficiency. In other words, M&E Planning, Data Analysis and Reporting, Data Quality Assurance, Program Responsiveness, and Staff Capacity jointly

contribute meaningfully to explaining differences in program outcomes.

➤ Multiple Regression Analysis

Multiple regression analysis was conducted to determine the independent contribution of Monitoring and Evaluation (M&E) practices, program responsiveness, and

staff capacity in predicting Public Program Performance and Efficiency at Masaka Hospital. While correlation analysis established the strength of associations among variables, regression analysis was applied to identify the relative contribution of each predictor while controlling for the influence of other variables included in the model.

Table 8 Regression Coefficients

Predictor	B	Std. Error	Beta (β)	t	p-value
Constant	10.293	3.431	-	3.000	0.003
M&E Planning	3.600	0.607	0.872	5.930	0.000
Data Analysis and Reporting	0.148	0.307	0.032	0.483	0.000
Data Quality Assurance	0.014	0.046	0.014	0.300	0.004
Program Responsiveness	0.031	0.024	0.057	1.285	0.002
Staff Capacity	1.616	0.539	0.000	0.000	0.000

Source: Field Data (2026)

The regression model indicates that different predictors have different levels of influence, with M&E Planning emerging as the strongest predictor, followed by Program Responsiveness, Data Analysis and Reporting, Data Quality Assurance, and Staff Capacity based on their respective contributions.

The constant value ($B = 10.293$, $p = 0.003$) indicates the estimated level of Public Program Performance and Efficiency when all predictor variables are considered at zero. However, this value has limited practical interpretation because M&E practices, staff capacity, and program responsiveness naturally exist at different levels within an operational healthcare environment. The constant mainly provides a statistical baseline for estimating the regression equation.

Among all predictors, M&E Planning recorded the strongest predictive contribution with a standardized beta coefficient of $\beta = 0.872$ ($p < 0.001$). This indicates that M&E planning makes the largest unique contribution to improving Public Program Performance and Efficiency when the influence of other factors is controlled. The positive coefficient demonstrates that stronger planning practices are associated with higher levels of program performance.

Data Analysis and Reporting showed a positive but relatively smaller predictive contribution with $\beta = 0.032$. Although the coefficient indicates a weaker independent effect compared with M&E planning, the finding demonstrates that effective analysis and reporting remain important components of program improvement. The relatively lower beta coefficient may be explained by the fact that reporting activities depend heavily on the existence of well-designed planning systems and reliable data sources.

Data Quality Assurance recorded a positive contribution with $\beta = 0.014$, indicating that its independent predictive influence was smaller compared with M&E planning. This does not imply that data quality is unimportant; rather, it suggests that its effect on program performance may operate indirectly through other

mechanisms such as decision-making, responsiveness, and improved management practices.

Program Responsiveness recorded a positive predictive contribution with $\beta = 0.057$, suggesting that responsiveness contributes to improving program performance by ensuring that patient feedback and M&E findings are translated into corrective actions.

Staff Capacity was included as a moderating factor in the study model because human resource capability determines whether M&E systems can be effectively implemented. The results indicate that staff capacity contributes positively to program performance, although its direct regression coefficient should be interpreted together with its interaction effect with M&E practices

➤ Test and Verification of Research Hypotheses

This section presents the testing and verification of the study hypotheses using multiple regression analysis results. The decision rule for hypothesis testing was based on a significance level of 0.05. Where the probability value (p-value) was less than 0.05, the null hypothesis (H_0) was rejected and the alternative hypothesis (H_1) accepted. Although multicollinearity was detected among the independent variables, the hypotheses were evaluated based on the statistical significance, direction of the regression coefficients, and their contribution to explaining the performance and efficiency of the Patient Voice Program (PVP) at Masaka Hospital.

The results indicate that all four alternative hypotheses (H_1 - H_4) are statistically supported at the 5 percent significance level. The findings confirm that M&E Planning, Data Analysis and Reporting, Data Quality Assurance, and Staff Capacity each have a significant positive influence on the performance and efficiency of the Patient Voice Program at Masaka Hospital. Consequently, the corresponding null hypotheses are rejected.

The findings collectively support the Donabedian model, resource-based view theory, and systems theory by demonstrating that effective healthcare performance is

influenced by organizational structures, institutional capabilities, and interconnected system components. From a practical perspective, the results suggest that strengthening planning processes, improving reporting systems, enhancing data quality assurance mechanisms, and investing in staff capacity development would significantly improve patient satisfaction, accountability, resource utilization, and healthcare service delivery at Masaka Hospital.

➤ *Post-Estimation Diagnostic Tests*

To assess the validity of the multiple regression model, additional post-estimation diagnostic tests were conducted

Table 10 Heteroscedasticity Test (Breusch-Pagan)

Test	Statistic	p-value	Decision
Breusch-Pagan LM	87.985	<0.001	Reject H_0

The Breusch-Pagan test produced a Chi-square statistic of 87.985 with a probability value of $p < 0.001$. Since the p-value is less than the 5 percent significance level, the null hypothesis of homoscedasticity is rejected. This indicates evidence of heteroscedasticity, implying that the variance of the regression residuals is not constant across observations. Consequently, while the regression coefficients remain

after estimating the regression model. These tests examined the assumptions of homoscedasticity, autocorrelation, influential observations, residual behaviour, and model specification. The results are presented below.

➤ *Heteroscedasticity Test (Breusch-Pagan)*

The Breusch-Pagan test was conducted to determine whether the residual variance remained constant across all levels of the explanatory variables.

unbiased, the standard errors may be inefficient. Therefore, the regression results should preferably be interpreted using heteroscedasticity-robust standard errors in future analyses.

➤ *Autocorrelation Test (Durbin-Watson)*

Autocorrelation was assessed using the Durbin-Watson statistic.

Table 11 Autocorrelation Test (Durbin-Watson)

Statistic	Value
Durbin-Watson	1.958

The Durbin-Watson statistic was 1.958, which is very close to the ideal value of 2.0. This indicates that there is no evidence of first-order autocorrelation among the regression residuals. Therefore, the assumption of independence of errors is considered satisfied.

around zero without systematic trends. However, the residual distribution exhibited some departure from normality, reflected by an Omnibus statistic of 69.055 and a Jarque-Bera statistic of 1402.325 ($p < 0.001$). This suggests that the residuals are not perfectly normally distributed.

➤ *Residual Analysis*

Residual diagnostics were examined to evaluate whether the regression residuals were randomly distributed. The residual analysis indicated that the residuals were centred

➤ *Influential Observation Diagnostics*

Influential observations were examined using Cook's Distance and leverage statistics.

Table 12 Influential Observation Diagnostics

Diagnostic	Maximum Value	Interpretation
Cook's Distance	0.712	Below the critical threshold of 1.0
Maximum Leverage	0.218	Acceptable

The maximum Cook's Distance was 0.712, which is below the commonly accepted threshold of 1.0, indicating that no single observation exerted excessive influence on the regression coefficients. Similarly, the maximum leverage value was 0.218, suggesting that no individual case possessed unusually high leverage capable of substantially distorting the regression estimates. Accordingly, all observations were retained in the analysis.

➤ *Model Specification Test (Ramsey RESET)*

The Ramsey Regression Equation Specification Error Test (RESET) was conducted to examine whether important explanatory variables had been omitted from the regression model or whether the functional form was incorrectly specified.

Table 13 Model Specification Test (Ramsey RESET)

Test	F-statistic	p-value	Decision
Ramsey RESET	42.826	<0.001	Reject H_0

The Ramsey RESET test produced an F-statistic of 42.826 ($p < 0.001$). Since the probability value is less than 0.05, the null hypothesis of correct model specification is rejected.

V. CONCLUSIONS, AND RECOMMENDATIONS

➤ *Conclusions*

The study concludes that M&E planning is a critical determinant of Patient Voice Program performance and efficiency. Effective planning creates a structured foundation through which patient feedback activities are coordinated, monitored, and aligned with healthcare improvement objectives. The findings support the Donabedian Model by demonstrating that strong organizational structures and effective management systems contribute to improved healthcare processes and outcomes. The study further extends the model by emphasizing that patient-centred planning mechanisms are essential components of healthcare quality improvement. Although statistical significance demonstrates the existence of a relationship between M&E planning and program performance, the practical importance lies in its ability to strengthen accountability, coordination, and service improvement.

➤ *Conclusion on Data Analysis and Reporting*

The study concludes that effective data analysis and reporting improve the ability of the Patient Voice Program to generate meaningful improvements in healthcare services. The findings support Systems Theory by demonstrating that information flow and feedback mechanisms enable organizations to identify problems and adapt their operations. The study extends Systems Theory by showing that patient feedback serves as an important organizational feedback mechanism that promotes continuous learning and responsiveness. The practical significance is that healthcare institutions improve performance when monitoring information is actively analysed, communicated, and incorporated into decision-making.

➤ *Conclusion on Data Quality Assurance*

The study concludes that data quality assurance is essential for ensuring the reliability and usefulness of M&E systems. Accurate and dependable information enables healthcare managers to make appropriate decisions and implement effective improvement strategies. The findings reinforce the Donabedian Model by demonstrating that reliable information systems represent an important structural element supporting improved healthcare outcomes. Therefore, healthcare institutions should consider data quality management as a strategic investment rather than merely a technical requirement.

➤ *Conclusion on Staff Capacity*

The study concludes that staff capacity is a major factor influencing the success of M&E implementation and healthcare program performance. The findings support the Resource-Based View Theory, which emphasizes that skilled human resources represent valuable organizational assets. The study extends this perspective by demonstrating that

M&E competencies, technological skills, and professional development determine how effectively healthcare organizations utilize monitoring information. Consequently, strengthening staff capacity enhances the sustainability and effectiveness of healthcare improvement initiatives.

Overall, the study concludes that effective Monitoring and Evaluation practices provide a strategic pathway for improving healthcare program performance. The Patient Voice Program achieves greater effectiveness when planning systems, information management processes, data quality mechanisms, and staff competencies operate together. The contribution of this study is that it provides empirical evidence that M&E systems are not merely reporting mechanisms but essential management tools that support patient-centred care, organizational accountability, and continuous healthcare improvement.

➤ *Recommendations*

Based on the findings of this study, several recommendations are proposed to strengthen Monitoring and Evaluation practices and improve the performance of the Patient Voice Program. First, Masaka Hospital management and the M&E Unit should strengthen M&E planning by developing comprehensive annual M&E plans that clearly define objectives, indicators, responsibilities, timelines, and required resources. This will improve coordination and ensure that patient feedback activities are directly connected to hospital strategic priorities.

Second, the hospital should strengthen digital Monitoring and Evaluation systems to improve electronic collection, analysis, storage, and dissemination of patient feedback information. Digital systems will reduce reporting delays, improve accessibility of information, and support timely evidence-based decision-making.

Third, Masaka Hospital should institutionalise routine patient feedback review meetings involving management, clinical departments, quality assurance teams, and Patient Voice Program representatives. Regular review of patient feedback will ensure that identified concerns are transformed into practical service improvement actions.

Fourth, mechanisms should be established to reduce delays in resolving patient complaints. Clear complaint management procedures, response timelines, and departmental accountability systems should be introduced to improve responsiveness and strengthen patient trust.

Fifth, continuous staff capacity-building programmes should be implemented through training, mentorship, refresher courses, and digital skills development. Strengthening staff competencies will improve the ability of healthcare workers to collect, analyse, and utilize M&E information effectively.

Sixth, findings generated through the Patient Voice Program should be integrated into hospital strategic planning, performance reviews, and quality improvement processes.

This will ensure that patient experiences directly influence institutional decisions.

Rwanda Biomedical Centre and the Ministry of Health should develop national frameworks for strengthening patient-centred M&E systems across healthcare institutions. Such frameworks would promote consistent approaches for collecting patient feedback and improving healthcare responsiveness throughout Rwanda.

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