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Jean Bosco Uwimana

jjboscouwimana@gmail.com

University of Lay Adventists of Kigali

Jean Nepo. Nsengiyumva

University of Lay Adventists of Kigali

Uwingeneye Julienne

University of Lay Adventists of Kigali

Roger Pierre Kayumba

Kirinda District Hospital, Ministry of Health

Research Article

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Posted Date: August 28th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10532523/v1>

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Additional Declarations: No competing interests reported.

The Role of Digital Monitoring and Evaluation (M&E) Practices in Enhancing Organizational Performance: *Evidence from Rutongo Hospital, Rwanda*

Jean Bosco Uwimana^{1*}, Jean Nepo. Nsengiyumva¹, Uwingeneye Julienne¹, Roger Pierre Kayumba

^{1*}*University of Lay Adventists of Kigali (UNILAK), Kigali, Kigali Campus, P.O. Box 6392, Rwanda*

²*Kirinda District Hospital, Karongi, B.P. 67 Gitarama, Ministry of Health, Rwanda*

Corresponding author: Jean Bosco Uwimana (jjboscouwimana@gmail.com)

ABSTRACT

Digital monitoring and evaluation (M&E) is often treated as a single lever that, once pulled, improves hospital performance across the board. This study tested that assumption at Rutongo Hospital, a district facility in Rwanda, surveying 160 staff across clinical, administrative, and M&E roles and analysing responses through correlations, regression, mediation, and moderation models, backed by a 13-component principal components analysis explaining 78.5% of total variance. The results complicate the simple story. No single digital practice moved every performance dimension; instead, each practice mattered for a specific outcome. A centralized digital database was overwhelmingly the strongest predictor of cost efficiency ($\beta=0.534$, $p<0.001$) with the largest effect recorded in the entire study. Automated data analysis and structured training/technical support together drove staff productivity ($\beta=0.943$ and $\beta=0.776$, both $p < 0.001$). Timely feedback for action was the leading driver of patient satisfaction ($\beta=0.128$, $p<0.001$), while visual dashboards mattered most for resource utilisation ($\beta=0.050$, $p=0.009$). In several cases, digital tools on their own produced small but statistically significant declines in satisfaction and resource use, consistent with short-term disruption during digital transition rather than a failure of the tools themselves. These direct effects were transmitted through two organisational mechanisms: the flow of timely, accurate information (strongest for resource utilisation and productivity, $\beta = 0.158$ and $\beta = 0.386$) and evidence-based planning (the decisive channel for cost efficiency, $\beta = 0.063$). Their strength, in turn, depended on context of infrastructure quality, digital literacy, and locally held M&E skills consistently amplified the benefits of digital M&E, while heavy reliance on donor or support policy weakened cost efficiency ($\beta=-0.121$, $p<0.001$). Underlying all of this, descriptive statistics revealed a hospital still near the starting line of digital maturity, with most indicators clustered barely above baseline (means near 1.0–1.3 out of 5), digital literacy the only relative bright spot (mean = 1.56). The study concludes that digital M&E investment pays off only when paired with information systems, planning capacity, infrastructure, and critically locally grown skills rather than donor dependency. Practical recommendations for hospital management and the Ministry of Health follow directly from these patterns.

Keywords: Digital monitoring and evaluation; Organisational performance; Data-driven decision-making; Health systems; Rutongo Hospital; Rwanda

1. Introduction and Background

In sub-Saharan Africa, health systems are being continuously challenged to be more accountable, efficient, and of good quality in providing services while facing increasingly constrained resources (Organization, 2026). Governments and development partners have, in turn, encouraged the shift to results-based management and evidence-informed governance, where monitoring and evaluation (M&E) is the brain and nervous system that links service delivery to strategic decision making (Kusek & Rist, 2004). In many health facilities in LMICs, M&E has been paper-based, aggregated manually, and reported periodically at long intervals, which are time-consuming, prone to errors, and are not aligned with managerial decision making (Nutley & Reynolds, 2013).

Digital technologies such as mobile data collection devices, electronic health records, cloud-based databases, and automated dashboards have provided hospitals with access to a roadmap of the future for their M&E systems (Dhodho *et al.*, 2026; Mwogosi *et al.*, 2026). Digital M&E is perceived as the use of information and communication technology (ICT), in the core functions of M&E, namely data collection, storage, analysis, reporting and use for decision-making (Matimba, 2023). Those in favour of digitalisation claim that it enhances the timeliness, accuracy and availability of data, increasing the solid foundation of evidence for managerial and clinical decision-making (Braa & Sahay, 2012). While digital tools can lead to organising benefits, other factors like leadership commitment, staff digital literacy, organising readiness, and the wider regulatory and donor context are also needed (Businge *et al.*, 2026; Islam, 2025).

Under the Health Sector Strategic Plan and national ICT policy, Rwanda has been implementing ambitious digital health strategies to introduce systems such as the Rwanda Health Information System (RHMIS/DHIS2), electronic medical records and mobile reporting platforms (MIRS) at health facilities (Ministry of Health Rwanda, 2021). Rutongo Hospital, a district hospital serving a largely rural population, has been increasingly implementing digital M&E tools as part of this national drive (Mhlongo *et al.*, 2020). However, the impact of this digitalisation in terms of service delivery, operational efficiency, organisational effectiveness, and accountability at the facility level is less empirically examined (Afriyie *et al.*, 2026). This study, therefore, investigates the role of digital M&E practices in enhancing the organisational performance at Rutongo Hospital, particularly how the mediating role of data-driven decision-making, and moderating role of leadership, organisational readiness, staff competence and the external environment influence this relationship. Despite extensive investments in digital data systems, there remain significant issues of underutilised data, disjointed systems and a disconnect between data generation and use in managerial decision making at many district hospitals in Rwanda (Bakari *et al.*, 2026; Sidii, 2025). Despite considerable investment in digital data systems, many district hospitals in Rwanda continue to report challenges of underutilised data, fragmented systems, and a persistent gap between data generation and its actual use in managerial decision-making (Merotiwon *et al.*, 2021; Mugabo *et al.*, 2024; Sidii, 2025).

This study is based on three complementary theories in theory. The overall logic is from Results Based Management (RBM) theory (Kusek & Rist, 2004) which suggests that organisational resources and processes should be managed based on specified outcomes and that information on performance continuously guides decision-making. Organisational performance is the outcome that the result management tries to affect and the means of producing this results information are digital M&E practices.

Tool availability does not imply impact: Perceived usefulness, ease of use, and organisational readiness explain why staff may or may not adopt and meaningfully use digital M&E tools, and as such staff competence, and organisational readiness are included as moderators. Organisations are systems that rely on their ability to receive, process, and act upon information based on task uncertainty (Information Processing Theory) (Galbraith *et al.*, 1972) making digital M&E a mediator between the increase in information and the increase in performance.

Empirical studies largely support a positive relationship between digital data practices and organisational performance, though with important caveats. Miiró *et al.* (2022) and Bagyendera *et al.* (2023) found that district health information systems strengthened data quality and decision-making in Uganda, yet use remained inconsistent where staff capacity was low. Ndayishimiye *et al.* (2025), Nisingizwe *et al.* (2014) and Nzeyimana and Gitahi (2022) observed that while Rwanda's digital health reporting improved timeliness, data use for local decision-making lagged behind availability, revealing a persistent "collect but do not use" pattern. Braa and Sahay (2012) similarly argue that in low-resource settings, health information system impact depends less on technology than on the organisational and institutional environment. Beyond health, management research on business intelligence confirms that data-driven decision-making mediates between analytics investments and firm performance (Popović *et al.*, 2019), supporting the proposed mediation pathway. Leadership commitment has also emerged as critical: Görgens-Albino (2007) note that without sustained leadership demand for evidence, M&E systems degenerate into compliance-oriented reporting rather than performance management tools. Collectively, this literature indicates that digital M&E performance effects are neither automatic nor uniform, but contingent on complementary organisational conditions. As research gaps, the existing studies predominantly examine digital health information systems at national or district levels, or focus narrowly on data quality rather than downstream organisational performance. Few simultaneously model the mediating role of decision-making practices and the moderating role of organisational conditions at a single-facility level in a resource-constrained East African hospital. This study addresses that gap by empirically testing an integrated mediation-moderation model at Rutongo Hospital.

Routine performance reviews at Rutongo Hospital indicate that there are inconsistencies in service delivery indicators, as well as inefficiencies in the use of resources, and varying levels of confidence among stakeholders in reported data, despite the introduction of digital data collection tools over the years. This poses a key question: How and in what ways digital M&E practices are improving organisational performance at the hospital, and have they been a mostly technical exercise without any impact on decision making and performance? Empirical clarity on this relationship, and on the conditions under which it exists, is required to avoid continued investments in digital infrastructure without an understanding of complementary organisational factors that are needed to make the investment in digital infrastructure translate into performance gains for hospital management and policymaking. This study aims at filling the gap by empirically testing the hypothesised relationships in the conceptual framework using data collected for this study at Rutongo Hospital, and thus, this study seeks to address the gap by investigating the level of digital M&E practices (digital data collection, data management, data analysis and reporting, data-driven decision making and digital M&E capacity) at Rutongo Hospital; examination of the relationship between digital M&E practices and organisational performance at Rutongo Hospital and to determine the mediating effect of data-driven decision making between digital M&E practices and organisational performance at Rutongo Hospital, as well as the moderating effect of leadership support,

organisational readiness, staff competence, and external environment between digital M&E practices and organisational performance at Rutongo Hospital.

1.1 Conceptualization of the research

In this study, the investigated relationship is operationalized using a multi-layered Conceptual Framework which comprises Independent variables, Mediating variables, Moderating variables and Dependent variables to evaluate the operational ecosystem of the Rutongo hospital. Leading to data-driven decision making (DDDM) and from DDDM to organisational performance (OP) are direct digital M&E practice effects (solid navy arrows), and the process of DDDM between digital M&E practice and OP is the mediating effect (green arrow). The moderating effects (dashed purple arrows) are the conditioning effects of leadership support, organisational readiness, staff competence, and external environment. This framework directly informs the operationalization of variables and analysis of the methodology below.

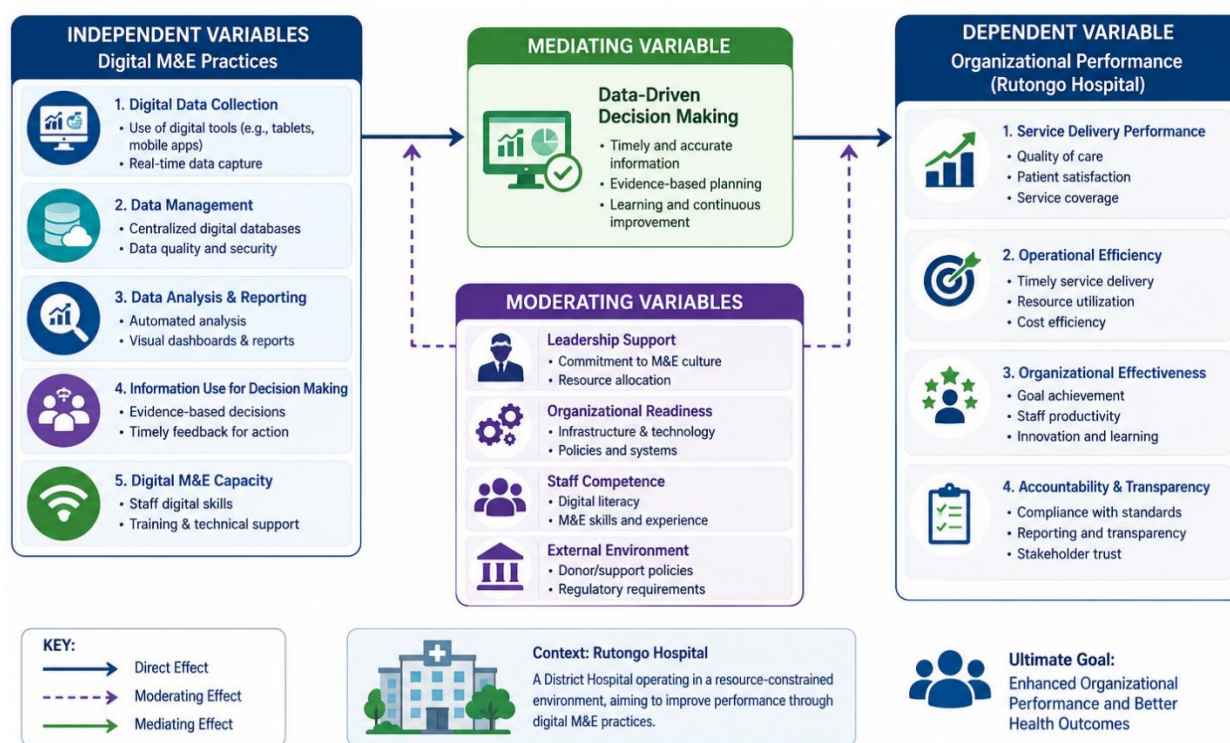


Figure 1: Conceptualization of the research

From the Fig.1, the independent Variables (Digital M&E Practices) comprises (1) Digital Data Collection using tablets and mobile apps for real-time capture; (2) Data Management through centralized databases ensuring quality and security; (3) Data Analysis & Reporting using automated analysis and dashboards; (4) Information Use for Decision Making; and (5) Digital M&E Capacity encompassing staff digital literacy and technical training. Secondary, the mediating Variable (Data-Driven Decision Making), is an intermediate mechanism that aims at timely and accurate info flow, evidence-based planning and institutional learning. There is also moderating Variables (Institutional Context) including Leadership Support (commitment and resource allocation), Organizational Readiness (infrastructure and active policies), Staff Competence (M&E skills) and the External Environment (donor policies and regulatory rules). After that, a list of dependent Variable (Organizational Performance) is measured through Service

Delivery Performance, Operational Efficiency, Organizational Effectiveness and Accountability & Transparency, finally leading to better health outcomes.

2. Research Methodology

Research Design

The study is descriptive-correlational and explanatory type of research in quantitative research. The descriptive component shows the extent of digital M&E practices and organisational performance at Rutongo Hospital, the correlational component shows the direction, strength and paths (direct, mediated, moderated) of the relationship between digital M&E practices and organisational performance, as per Figure 2, the conceptual framework, and the explanatory component shows the pathways (direct, mediated, moderated) in which the digital M&E practices are related to organisational performance at Rutongo Hospital. A cross-sectional survey design is employed and data is gathered at one time, from hospital personnel.

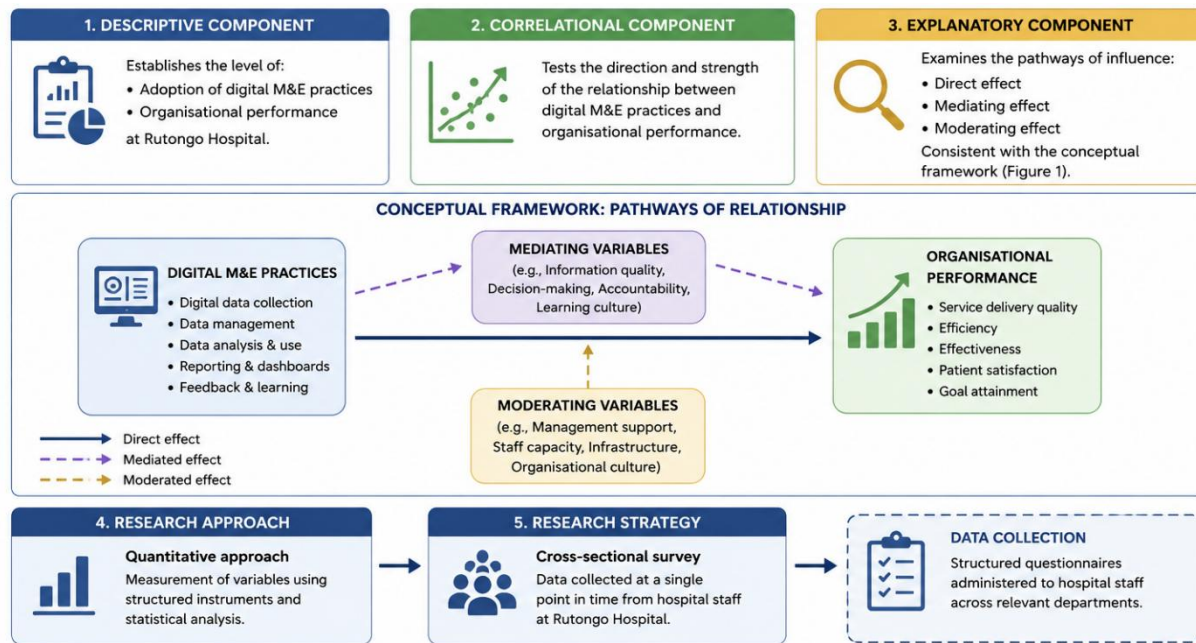


Figure 2: Summarized Research design of the study

Target Population and Sample Size Determination

All staff at Rutongo Hospital engaged in or affected by monitoring and evaluation processes included the following technical staff: medical staff, nursing and midwifery staff, allied health professionals, hospital management and administration, support and operational staff and public health and community health staff, and one M&E staff. The target population is estimated to be $N = 160$ staff of the hospital based on the most recent staffing establishment of the hospital. As the target population is finite and known, the sample size is calculated with the Yamane (1967) simplified formula for proportions appropriate for descriptive-correlational survey research:

$$n = \frac{N}{1 + N(e)^2} \quad (1)$$

Where n is the required sample size, N is the target population (260), and e is the margin of error, set at 5% (0.05), consistent with a 95% confidence level typical of social and health-systems survey research. Applying the formula:

$$n = \frac{N}{1 + N(e)^2}, \rightarrow n = \frac{260}{1 + 260(0.05)^2}, \rightarrow \frac{260}{1.65} \approx 158 \quad (2)$$

The computed sample size is therefore 158 respondents. To guard against non-response, the study plans to distribute questionnaires to 170 respondents (a 7.5% buffer), anticipating a final usable sample of at least 158 returned and filled questionnaire.

Sampling Technique

The study uses stratified random sampling to ensure proportionality across the key staff groups (clinical, administrative/finance, M&E/health information, and management) as it is expected that exposure to and use of the digital M&E tools could differ systematically across these groups. Simple random sampling (with random-number procedure applied to staff lists) is applied within each stratum to select individual respondents with a uniform chance of selection of every staff member in a stratum. Proportional allocation across strata is the calculation of n_h as the proportion of stratum h to the total population N times n .

Data Collection, Instruments and Procedure

Primary data are collected through the use of a self-administered, structured questionnaire with closed ended items measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) organised into sections corresponding to the constructs in the conceptual framework: digital data collection, data management, data analysis and reporting, information use for decision-making, digital M&E capacity, data-driven decision-making, the four moderating variables, and the four dimensions of organisational performance. The instrument is piloted used in a small sample (about 10% of the sample) from a similar facility to be pre-tested for clarity and reliability before going full force, and adjusted as needed. Secondary data are based on hospital performance records and routine health information system reports, and used to triangulate self-reported performance indicators.

Validity and Reliability

The content of the instrument is validated by experts' review of the instrument against the constructs in the conceptual framework and consultation with hospital M&E staff, to determine content validity. The internal consistency of each construct is measured with Cronbach's alpha coefficient based on the pilot data, and the minimum acceptable level of internal consistency is set at $\alpha \geq 0.70$ which is in line with the traditional social-science research criterion (Xu & Buehl, 2026).

Model Specification

Consistent with the conceptual framework, three sets of statistical models are specified. Let DMEP represent the composite index of digital M&E practices, DDDM represent data-driven decision-making, OP represent organisational performance, and MOD represent the set of moderating variables (leadership support, organisational readiness, staff competence, and external environment).

Model 1 — Direct effect

$$OP = \beta_0 + \beta_1 DMEP + \varepsilon \quad (3)$$

Model 2 — Mediation ((Baron & Kenny, 1986), steps; supplemented with bootstrapped indirect effects)

- Step (a): $DDDM = \beta_0 + \beta_1 DMEP + \varepsilon$ (4)

- Step (b): $OP = \beta_0 + \beta_1 DDDM + \varepsilon$ (5)

- Step (c): $OP = \beta_0 + \beta_1 DMEP + \beta_2 DDDM + \varepsilon$ (6)

Mediation is confirmed if the coefficient of DMEP in step (c) is reduced (partial mediation) or rendered non-significant (full mediation) relative to Model 1, and the indirect effect (β_1 in step a $\times$ β_1 in step b) is statistically significant, as tested using the Sobel test and/or bootstrapped confidence intervals (Preacher & Hayes, 2008).

Model 3 — Moderation

$$OP = \beta_0 + \beta_1 DMEP + \beta_2 MOD + \beta_3 (DMEP \times MOD) + \varepsilon \quad (7)$$

Moderation is confirmed where the interaction term ($DMEP \times MOD$) is statistically significant, indicating that the strength of the digital M&E practices–performance relationship varies with the level of the moderating variable. All continuous predictor and moderator variables are mean-centred prior to computing interaction terms, to reduce multicollinearity and aid interpretation, following (Aiken, 1991).

Data Analysis

Completed questionnaires are checked for completeness, coded, and entered into IBM SPSS 26 Statistics for analysis. Analysis proceeds in four stages. First, descriptive statistics (means, standard deviations, frequencies, and percentages) summarise respondent demographics and the level of each construct. Second, Pearson product-moment correlation coefficients establish the strength and direction of bivariate relationships among constructs. Third, multiple linear regression is used to test Model 1 and the mediation steps of Model 2, with the Sobel test and/or bootstrapping (5,000 resamples) used to test the significance of indirect effects. Fourth, moderated regression analysis (Model 3), including hierarchical entry of the interaction terms, tests the moderating hypotheses. Diagnostic checks including tests for normality like multicollinearity (Variance Inflation Factor, $VIF < 10$), and homoscedasticity are conducted prior to interpretation of regression results. Statistical significance is assessed at the 5% level ($p < 0.05$) throughout.

3. Results and Discussion

3.2 Descriptive statistics of M&E components

The descriptive analysis of Monitoring and Evaluation (M&E) parameterizations at Rutongo Hospital unveils critical insights into the institution's digital infrastructure and operational culture. The overall data demonstrates extremely low mean values across all primary M&E components, indicating that most indicators reside near the baseline scale of 1.0. The key findings from the survey of Independent M&E Parameterizations are summarized in **Table 1**.

Table 1: Descriptive statistics of M&E components from Rutongo Hospital

M&E parameterization	Descriptive Statistics			
	Mean	Std. D	Skewness	Kurtosis
Use of Digital Tools like Tables and Mobile apps	1.25	0.71948	3.407	11.596
Real time data capture	1.3594	0.7591	2.979	10.555
Centralized Digital database	1.0742	0.26264	3.268	8.747
Data quality and security	1.0156	0.12426	7.857	60.209
Automated Data analysis	1.0312	0.17433	5.42	27.592
Visual Dashboard and Reports	1.2461	0.7343	3.171	8.97
Evidence based decision	1.2891	0.87808	2.763	5.733
Timely Feedback for action	1.1797	0.38468	1.678	0.824
Level of staff digital skills	1.3203	0.83015	2.658	5.741
Trainings and Technical Skills	1.2109	0.65262	3.51	11.886
Timely and accurate Information	1.168	0.50789	3.881	17.192
Evidence based planning	1.2031	0.70136	3.545	11.252
Learning and continuous improvement	1.1797	0.55918	3.832	15.626
Commitment to M&E culture	1.2969	0.79567	2.805	6.662
Resources allocation	1.0781	0.46204	6.055	35.619
Infrastructure and Technology	1.2656	0.83063	2.945	6.888
Policies and System	1.2148	0.73879	3.399	9.982
Digital Literacy	1.5625	1.13241	1.64	0.807
M&E Skills and experience	1.332	0.9005	2.542	4.727
Donor/ Support policies	1.2383	0.79327	3.158	8.192
Regulatory requirements	1.1367	0.57468	4.494	19.399
List of Dependents Variables	1.0352	0.18454	5.078	23.97
Quality of Care	1.0078	0.08821	11.247	125.468
Patients satisfaction	1.0195	0.13865	6.985	47.159
Services Coverage	1.0039	0.0625	16	256
Timely Service Delivered	1.0273	0.1634	5.831	32.249
Resources Utilization	1.0469	0.21179	4.313	16.731
Cost Efficiency	1.0391	0.19412	4.786	21.073
Goal achievement	1.0156	0.12426	7.857	60.209
Staff Productivity at the Rutongo Hospital	1.2891	0.85086	2.796	6.094
Innovation and Learning	1.0352	0.18454	5.078	23.97
Compliance with Standards	1.0078	0.08821	11.247	125.468
Reporting and Transparency	1.0195	0.13865	6.985	47.159
Stakeholder Trust	1.0039	0.0625	16	256

The descriptive analysis of Monitoring and Evaluation (M&E) parameterizations at Rutongo Hospital unveils critical insights into the institution's digital infrastructure and operational culture. The overall data demonstrates extremely low mean values across all primary M&E components, indicating that most indicators reside near the baseline scale of 1.0. For instance, the use of digital tools like tablets and mobile applications yields a mean of 1.25 with a standard deviation of 0.71948, indicating a heavily concentrated, low-level integration of basic hardware. Similarly, real-time data capture exhibits a mean of 1.3594 (SD = 0.7591), while the adoption of a centralized digital database remains exceptionally

restricted with a mean of just 1.0742 and a very low standard deviation of 0.26264. Crucially, indicators associated with advanced data systems represent severe bottlenecks: data quality and security scores a mean of 1.0156 (SD = 0.12426), and automated data analysis shows a mean of 1.0312 (SD = 0.17433). This is complemented by highly elevated skewness (7.857 and 5.420, respectively) and extreme kurtosis (60.209 and 27.592), which proves that the majority of staff experience minimal access to secure, automated analytics, leaving only extreme outliers with advanced access.

Furthermore, the human and cultural dimensions of M&E at Rutongo Hospital reflect similar constraints. Although digital literacy exhibits the highest variance and mean in the dataset with a score of 1.5625 (SD = 1.13241, skewness = 1.640, kurtosis = 0.807), indicating some positive variability in basic skills, specialized training and professional M&E capacity remain deficient. The level of staff digital skills (mean = 1.3203, SD = 0.83015) and specialized M&E skills and experience (mean = 1.3320, SD = 0.90050) struggle to translate into advanced practice due to institutional resource deficits. Indeed, targeted trainings and technical skills development (mean = 1.2109, SD = 0.65262) and basic resource allocation (mean = 1.0781, SD = 0.46204) are highly constrained. The institutional environment is shaped by low-variability regulatory compliance pressures (mean = 1.1367, SD = 0.57468) and donor policy alignment (mean = 1.2383, SD = 0.79327). This leaves critical continuous loops such as timely feedback for action (mean = 1.1797, SD = 0.38468) and evidence-based planning (mean = 1.2031, SD = 0.70136) functioning at rudimentary, non-standardized levels.

On the other side, the analysis of dependent performance and quality metrics was also presented in **Table 1**. The institutional performance metrics, represented as the dependent variables, display an even more striking homogeneity, with mean values hovering barely above the absolute baseline. The quality of care (mean = 1.0078, SD = 0.08821) and patient satisfaction (mean = 1.0195, SD = 0.13865) demonstrate near-zero standard deviations coupled with astronomical skewness (11.247 and 6.985, respectively) and massive kurtosis (125.468 and 47.159). This statistical footprint is mirrored in service coverage (mean = 1.0039, SD = 0.0625, skewness = 16.000, kurtosis = 256.000) and stakeholder trust (mean = 1.0039, SD = 0.0625), revealing that almost the entire sample responds at the lowest possible baseline, with virtually zero variation across the hospital's operational departments. Standardized compliance with healthcare guidelines (mean = 1.0078, SD = 0.08821) and structured reporting and transparency (mean = 1.0195, SD = 0.13865) follow this exact trend. Operational efficiency parameters also show highly compressed results, including cost efficiency (mean = 1.0391, SD = 0.19412) and overall resources utilization (mean = 1.0469, SD = 0.21179). Similarly, goal achievement (mean = 1.0156, SD = 0.12426, skewness = 7.857, kurtosis = 60.209) and innovation and learning capacity (mean = 1.0352, SD = 0.18454) show a total absence of progressive scaling. The only performance metric indicating any minor level of active variance among the staff is staff productivity at the Rutongo Hospital, which exhibits a mean of 1.2891 and a standard deviation of 0.85086 (skewness = 2.796, kurtosis = 6.094). Ultimately, these findings suggest a structural ceiling: without a fundamental shift from manual or siloed processes to robust, automated, and secure M&E systems, healthcare delivery, operational transparency, and quality metrics at Rutongo Hospital will remain statistically flat and severely constrained at the baseline level.

3.2 Collinearity Diagnostics Tests

Before the regression coefficients could be meaningfully interpreted, it was necessary to confirm that the variables entered into the models were sufficiently independent of one another to yield trustworthy estimates. This was done using the Variance Inflation Factor (VIF) together with its square root, the tolerance statistic and the associated R-squared values, since a VIF rising above the conventional threshold of 10 (or, more conservatively, 5) generally signals that a predictor is simply restating information already captured by the other predictors in the model.

Table 2: Collinearity Diagnostics Tests

Variables/ VIF for Explanatory Variables	VIF	SQRT-VIF	Tolerance	R-Squared
Use of Digital Tools (Tables, mobile apps.)	1.3	1.14	0.7665	0.2335
Real Time data capturing	1.16	1.08	0.8652	0.1348
Centralized digital database	1.07	1.03	0.9354	0.0646
Data Quality and security	1.05	1.03	0.9498	0.0502
Automated analysis	1.07	1.03	0.9383	0.0617
Visual Dashboard and Reports	1.12	1.06	0.8926	0.1074
Evidence Based Decision	1.07	1.04	0.9322	0.0678
Timely Feedback for actions	1.33	1.15	0.7514	0.2486
Staff Digital Skills	1.09	1.04	0.921	0.079
Training and Technical support	1.06	1.03	0.9462	0.0538
Mean VIF	1.132			
VIF for Mediating Variables				
Timely Accurate Information	1.04	1.02	0.9588	0.0412
Evidence Based Planning	1.05	1.02	0.9563	0.0437
Learning and Continuous Improvement	1	1	0.9963	0.0037
Mean VIF	1.03			
VIF for Moderating Variables				
Commitment to M&E culture	2.3	1.52	0.435	0.565
Resources Allocation	1.82	1.35	0.5492	0.4508
Infrastructure and Technology	3.73	1.93	0.2684	0.7316
Policies and System	1.59	1.26	0.6303	0.3697
Digital Literacy	3.13	1.77	0.3194	0.6806
M&E Skills and Experience	3.58	1.89	0.2789	0.7211
Donor/Support policy	4.05	2.01	0.2471	0.7529
Regulatory requirements	2.84	1.68	0.3523	0.6477
Mean VIF	2.88			

For the ten explanatory digital M&E practices, covering the use of digital tools, real-time data capturing, centralized digital databases, data quality and security, automated analysis, visual dashboards and reports, evidence-based decision-making, timely feedback for action, staff digital skills, and training and technical support, VIF values ranged narrowly between 1.05 and 1.33, with a mean VIF of 1.132. Because these figures sit well below any threshold of concern, and tolerance levels for every practice exceeded 0.75, each digital M&E practice can be treated as capturing a genuinely distinct dimension of the hospital's monitoring and evaluation system. This is an encouraging result for the study, since it means that the effects attributed later to, for instance, timely feedback for action or automated analysis are not artefacts of overlap with the other digital practices.

The three mediating variables, timely and accurate information, evidence-based planning, and learning and continuous improvement, returned an even tighter clustering of VIF values (1.04, 1.05 and 1.00 respectively), with a mean VIF of 1.03 and tolerance levels all above 0.95. This confirms that the mechanisms proposed to link digital M&E practice to performance behave as genuinely separate constructs rather than restating one another, which strengthens confidence in the mediation results discussed later.

The moderating variables present a somewhat different, though still acceptable, picture. Commitment to the M&E culture, resources allocation, infrastructure and technology, policies and systems, digital literacy, M&E skills and experience, donor or support policy, and regulatory requirements produced VIF values ranging from 1.59 to 4.05, with a mean VIF of 2.88. Although this is noticeably higher than the explanatory and mediating blocks, it remains comfortably under the threshold of 10 conventionally used to flag serious multicollinearity, and even under the stricter cut-off of 5. The highest values were recorded for donor or support policy (VIF = 4.05) and infrastructure and technology (VIF = 3.73), which is not surprising in a hospital setting such as Rutongo, where donor funding and the state of technological infrastructure tend to move together, since donor support often finances infrastructure upgrades while stronger infrastructure in turn attracts further donor interest. Tolerance levels for these variables nonetheless remained above 0.24, indicating that each moderating condition still retains sufficient unique explanatory content to be interpreted on its own terms. Taken together, the diagnostics confirm that none of the explanatory, mediating or moderating variables suffers from problematic redundancy, so the regression estimates that follow can be read with confidence.

3.3 Effect of explanatory variables on Rutongo hospital performance

The second block of results examines how the ten digital M&E practices identified in the study directly shape the four dimensions of performance at Rutongo Hospital. Because these practices form the explanatory core of the research, understanding their individual contribution is central to establishing whether digital monitoring and evaluation genuinely enhances organisational performance, or whether its benefits are more selective than a general assumption that digitalisation automatically improves outcomes would suggest.

Table 3: Effect of explanatory variables on Rutongo hospital performance

	Coef.	Std. Err.	t	P> t
Patients Satisfaction				
Use of Digital Tools (Tables, mobile apps.)	-0.0292	0.0132	-2.22	0.027**
Real Time data capturing	-0.0080	0.0117	-0.68	0.499
Centralized digital database	-0.0034	0.0326	-0.1	0.018**
Data Quality and security	-0.0259	0.0684	-0.38	0.705
Automated analysis	0.0725	0.0491	1.48	0.041**
Visual Dashboard and Reports	-0.0084	0.0119	-0.7	0.485
Evidence Based Decision	-0.0023	0.0098	-0.24	0.811
Timely Feedback for actions	0.1280	0.0248	5.15	0.000***
Staff Digital Skills	-0.0071	0.0104	-0.68	0.098*
Training and Technical support	-0.0031	0.0130	-0.24	0.811
cons	0.8976	0.1012	8.87	0.000
Resources Utilization				
Use of Digital Tools (Tables, mobile apps)	-0.0302	0.0209	-1.44	0.050**
Real Time data capturing	0.0084	0.0187	0.45	0.653
Centralized digital database	0.0439	0.0519	0.85	0.399
Data Quality and security	-0.0815	0.1088	-0.75	0.454
Automated analysis	0.1041	0.0780	1.34	0.183
Visual Dashboard and Reports	0.0499	0.0190	2.63	0.009**
Evidence Based Decision	0.0123	0.0155	0.79	0.428
Timely Feedback for actions	-0.0169	0.0395	-0.43	0.069*
Staff Digital Skills	-0.0045	0.0165	-0.27	0.784
Training and Technical support	0.0131	0.0207	0.63	0.527
cons	0.9335	0.1609	5.8	0.000
Cost Efficiency				
Use of Digital Tools (Tables, mobile apps)	0.0036	0.0136	0.27	0.789
Real Time data capturing	-0.0037	0.0121	-0.3	0.761
Centralized digital database	0.5337	0.0337	15.85	0.000***
Data Quality and security	0.1324	0.0706	1.87	0.062*
Automated analysis	-0.0152	0.0507	-0.3	0.764
Visual Dashboard and Reports	-0.0208	0.0123	-1.69	0.093*
Evidence Based Decision	0.0017	0.0101	0.17	0.868
Timely Feedback for actions	0.0242	0.0257	0.94	0.346
Staff Digital Skills	0.0078	0.0107	0.73	0.465
Training and Technical support	0.0136	0.0135	1.01	0.312
cons	0.3157	0.1045	3.02	0.003
Staff Productivity				
Use of Digital Tools (Tables, mobile apps)	-0.0130	0.0654	-0.2	0.843
Real Time data capturing	-0.0670	0.0583	-1.15	0.252
Centralized digital database	0.0196	0.1621	0.12	0.004**
Data Quality and security	-0.1652	0.3400	-0.49	0.627
Automated analysis	0.9425	0.2438	3.87	0.000***
Visual Dashboard and Reports	-0.0585	0.0593	-0.99	0.325
Evidence Based Decision	0.0128	0.0486	0.26	0.793
Timely Feedback for actions	-0.0829	0.1235	-0.67	0.503
Staff Digital Skills	-0.1232	0.0517	-2.38	0.018**

Training and Technical support	0.7764	0.0649	11.97	0.000***
cons	-0.0522	0.5028	-0.1	0.917

(*** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$, $n = 160$)

With respect to patient satisfaction, not every digital practice moved outcomes in the same direction. The use of digital tools such as tablets and mobile applications was associated with a small but statistically significant decline in satisfaction ($\beta = -0.0292$, $p = 0.027$), as was reliance on a centralized digital database ($\beta = -0.0034$, $p = 0.018$). This may appear counterintuitive for a study built around the promise of digital M&E, yet it mirrors a pattern often observed in health facilities undergoing digital transition, where the introduction of new digital touchpoints can initially slow interactions or shift staff attention away from direct patient contact, temporarily depressing satisfaction even as underlying data systems improve. By contrast, automated analysis ($\beta = 0.0725$, $p = 0.041$) and, most strongly, timely feedback for action ($\beta = 0.1280$, $p < 0.001$) were positively and significantly associated with patient satisfaction, the latter emerging as the single strongest driver of this outcome in the entire explanatory block. This suggests that patients at Rutongo Hospital respond less to the mere presence of digital infrastructure and more to what that infrastructure enables in practice, namely the speed and relevance with which feedback is translated into corrective action. Staff digital skills showed only a weak negative association, significant at the ten percent level ($p = 0.098$), hinting that skills alone, without systems that allow staff to act on them, do not automatically translate into a better patient experience.

For resource utilisation, the use of digital tools again returned a significant negative coefficient ($\beta = -0.0302$, $p = 0.050$), while visual dashboards and reports stood out as a significant positive contributor ($\beta = 0.0499$, $p = 0.009$). This indicates that how information is visualized and communicated to decision-makers at Rutongo Hospital matters more for the efficient deployment of resources than the mere act of digitizing records. Timely feedback for action, which had driven patient satisfaction upward, showed a marginally significant negative relationship with resource utilisation ($p = 0.069$), a reminder that a practice which benefits one performance dimension can create short-term trade-offs in another, perhaps because rapid corrective action sometimes requires reallocating resources away from their originally planned use.

Cost efficiency told a rather different story. Centralized digital database emerged as an overwhelmingly strong and significant predictor ($\beta = 0.5337$, $p < 0.001$), by far the largest coefficient recorded anywhere in the explanatory model, implying that consolidating hospital data into a single, well-governed digital repository is the single most consequential digital M&E investment Rutongo Hospital can make if cost containment is the priority. Data quality and security also contributed positively at the ten percent level ($p = 0.062$), reinforcing the point that cost savings flow not simply from having data, but from having data that can be trusted. Visual dashboards, interestingly, showed a weak negative association with cost efficiency ($p = 0.093$), suggesting that the resources required to build and maintain sophisticated reporting dashboards may, at least in the short run, add to operating costs even as they improve other aspects of performance.

Finally, staff productivity was most strongly influenced by automated analysis ($\beta = 0.9425$, $p < 0.001$) and training and technical support ($\beta = 0.7764$, $p < 0.001$), both producing large and highly significant positive coefficients. Centralized digital database again played a significant, though more modest, positive role ($p = 0.004$). Staff digital skills, however, returned a significant negative coefficient ($\beta = -0.1232$, $p = 0.018$), which, read alongside the strongly positive effect of training and technical support, suggests that it is not the possession of digital skills in isolation that raises productivity, but the continuous

institutional support that helps staff put those skills to effective use. Overall, this section demonstrates that digital M&E practices at Rutongo Hospital do not act as a uniform bundle; each practice exerts a distinct, and at times divergent, influence depending on which facet of organisational performance is under consideration, a finding that speaks directly to the study's central argument that the role of digital M&E in enhancing performance is nuanced rather than automatic.

3.4 Effect of mediating variables on Rutongo hospital performance

The study further proposed that the relationship between digital M&E practices and hospital performance does not operate solely through direct effects, but is also channeled through three intervening mechanisms: the availability of timely and accurate information, the practice of evidence-based planning, and a culture of learning and continuous improvement. These mediators represent the organisational processes through which digitized data is converted into the kind of institutional knowledge and behaviour that ultimately shapes performance outcomes at Rutongo Hospital, and their inclusion allows the study to speak not only to whether digital M&E matters, but to how it matters.

Table 4: Effect of mediating variables on Rutongo hospital performance

	Coef.	Std. Err.	t	P> t
Patients Satisfaction				
Timely Accurate Information	0.0053	0.0175	0.3	0.764
Evidence Based Planning	-0.0094	0.0127	-0.74	0.461
Learning and Continuous Improvement	-0.0120	0.0156	-0.77	0.044**
cons	1.0388	0.0309	33.67	0.000
Resources Utilization				
Timely Accurate Information	0.1579	0.0248	6.36	0.000***
Evidence Based Planning	-0.0198	0.0180	-1.1	0.272
Learning and Continuous Improvement	-0.0309	0.0221	-1.4	0.104*
cons	0.9228	0.0437	21.1	0.000
Cost Efficiency				
Timely Accurate Information	0.0027	0.0239	0.11	0.909
Evidence Based Planning	0.0629	0.0174	3.62	0.000**
Learning and Continuous Improvement	-0.0058	0.0213	-0.27	0.785
cons	0.9671	0.0421	22.96	0.000
Staff Productivity				
Timely Accurate Information	0.3857	0.1019	3.78	0.000**
Evidence Based Planning	0.0998	0.0739	1.35	0.178
Learning and Continuous Improvement	0.2978	0.0908	3.28	0.001***
cons	0.3673	0.1795	2.05	0.042

(*** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$, $n = 160$)

For patient satisfaction, only learning and continuous improvement emerged as a significant predictor, and its effect was negative ($\beta = -0.0120$, $p = 0.044$). Read together with the direct effects reported earlier, this suggests that patient satisfaction at Rutongo Hospital is shaped more by tangible, immediate responsiveness, such as timely feedback for action, than by longer-term organisational learning processes, which may take time to be felt by patients on the ground and can, in their early stages, coincide with the disruption that accompanies changes to established routines.

Resource utilisation, by contrast, was strongly and positively influenced by timely and accurate information ($\beta = 0.1579$, $p < 0.001$), the single most powerful mediating effect recorded across all four performance dimensions. This confirms that once digital M&E practices succeed in generating information that is both timely and accurate, hospital managers are able to allocate beds, staff, equipment and supplies considerably more efficiently. Learning and continuous improvement showed a weak negative relationship with resource utilisation, significant only at the ten percent level ($p = 0.104$), again pointing to the possibility of short-term adjustment costs associated with embedding new learning routines.

Cost efficiency was significantly and positively shaped by evidence-based planning ($\beta = 0.0629$, $p < 0.001$), underscoring that translating digital data into deliberate, forward-looking plans, rather than simply collecting data for its own sake, is what ultimately keeps costs under control at Rutongo Hospital. Neither timely and accurate information nor learning and continuous improvement reached statistical significance for this outcome, suggesting that cost efficiency responds specifically to the planning function of M&E rather than to information flow or organisational learning in a general sense.

Staff productivity, meanwhile, was significantly and positively associated with both timely and accurate information ($\beta = 0.3857$, $p < 0.001$) and learning and continuous improvement ($\beta = 0.2978$, $p = 0.001$). Taken together with the earlier finding that automated analysis and training and technical support are the strongest direct drivers of productivity, this indicates a coherent chain running from digital tools, through the mediating processes of information flow and continuous learning, to the productivity of hospital staff. Evidence-based planning did not reach significance for this outcome, which suggests that while planning is decisive for cost efficiency, it is the availability of accurate information and a culture that supports ongoing learning that most directly energizes staff performance.

3.5 Effect of moderating variables on Rutongo hospital performance

The **Table 5** of results addresses the conditions under which digital M&E practices are implemented at Rutongo Hospital, namely commitment to the M&E culture, resources allocation, infrastructure and technology, policies and systems, digital literacy, M&E skills and experience, donor or support policy, and regulatory requirements. These moderating variables help explain why the same digital M&E practices can produce different performance outcomes depending on the institutional environment in which they are embedded, which is an important qualification to the study's central claim about the value of digital M&E.

Table 5: Effect of moderating variables on Rutongo hospital performance

	Coef.	Std. Err.	t	P> t
Patients Satisfaction				
Commitment to M&E culture	-0.0181	0.0162	-1.12	0.264
Resources Allocation	-0.0526	0.0248	-2.13	0.035**
Infrastructure and Technology	0.0827	0.0197	4.2	0.000***
Policies and System	0.0041	0.0145	0.28	0.779
Digital Literacy	-0.0192	0.0133	-1.45	0.008**
M&E Skills and Experience	-0.0036	0.0178	-0.2	0.841
Donor/Support policy	-0.0109	0.0215	-0.51	0.614
Regulatory requirements	-0.0365	0.0249	-1.47	0.003**
cons	1.0799	0.0384	28.1	0.000
Resources Utilization				
Commitment to M&E culture	-0.0402	0.0247	-1.63	0.105*
Resources Allocation	-0.0059	0.0378	-0.16	0.877
Infrastructure and Technology	-0.0550	0.0301	-1.83	0.069*
Policies and System	-0.0736	0.0221	-3.34	0.001**
Digital Literacy	0.0820	0.0202	4.06	0.000***
M&E Skills and Experience	-0.0061	0.0272	-0.22	0.823
Donor/Support policy	-0.0482	0.0328	-1.47	0.143
Regulatory requirements	0.0229	0.0379	0.6	0.547
cons	1.1780	0.0586	20.1	0.000
Cost Efficiency				
Commitment to M&E culture	0.0064	0.0222	0.29	0.773
Resources Allocation	-0.0018	0.0340	-0.05	0.958
Infrastructure and Technology	-0.0036	0.0270	-0.13	0.893
Policies and System	-0.0033	0.0198	-0.17	0.869
Digital Literacy	-0.0132	0.0182	-0.73	0.469
M&E Skills and Experience	0.1295	0.0245	5.29	0.000***
Donor/Support policy	-0.1213	0.0295	-4.11	0.000***
Regulatory requirements	-0.0043	0.0341	-0.13	0.900
cons	1.0444	0.0527	19.81	0.000
Staff Productivity				
Commitment to M&E culture	-0.0115	0.1014	-0.11	0.910
Resources Allocation	0.0518	0.1554	0.33	0.739
Infrastructure and Technology	-0.1790	0.1237	-1.45	0.009**
Policies and System	-0.1195	0.0907	-1.32	0.189
Digital Literacy	0.0012	0.0831	0.02	0.988
M&E Skills and Experience	-0.0608	0.1119	-0.54	0.587
Donor/Support policy	-0.0863	0.1349	-0.64	0.523
Regulatory requirements	0.2566	0.1560	1.65	0.101*
cons	1.5142	0.2411	6.28	0.000

(*** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$, $n = 160$)

For patient satisfaction, infrastructure and technology stood out as a strong, positive and highly significant predictor ($\beta = 0.0827$, $p < 0.001$), confirming that reliable technological infrastructure is a genuine precondition for digital M&E practices to translate into a better patient experience. Resources

allocation ($\beta = -0.0526$, $p = 0.035$), digital literacy ($\beta = -0.0192$, $p = 0.008$) and regulatory requirements ($\beta = -0.0365$, $p = 0.003$) were all significant but negative, which may reflect the short-term friction that reallocating resources, raising digital literacy requirements, or tightening regulatory compliance can create for frontline patient interactions before their benefits are fully realized.

For resource utilisation, digital literacy emerged as a strong positive and highly significant factor ($\beta = 0.0820$, $p < 0.001$), indicating that staff who are comfortable navigating digital systems make noticeably better use of the hospital's resources. Policies and systems ($\beta = -0.0736$, $p = 0.001$) and, at the ten percent level, infrastructure and technology ($p = 0.069$) and commitment to the M&E culture ($p = 0.105$) were associated with lower resource utilisation, which again points to adjustment costs: formalising policies and building up infrastructure and institutional commitment can, in their initial phases, absorb resources rather than free them up.

Cost efficiency was shaped most decisively by M&E skills and experience, which had a strong positive and highly significant effect ($\beta = 0.1295$, $p < 0.001$), and by donor or support policy, which had an equally strong but negative effect ($\beta = -0.1213$, $p < 0.001$). This combination suggests that while a skilled and experienced M&E workforce is central to controlling costs at Rutongo Hospital, heavy reliance on donor or external support funding can work against cost efficiency, possibly because donor-funded activities come with reporting, compliance and administrative obligations that add to operating expenses even as they expand the hospital's capacity in other respects.

Finally, staff productivity was significantly and negatively affected by infrastructure and technology ($\beta = -0.1790$, $p = 0.009$), a result that contrasts with the positive role infrastructure played for patient satisfaction and suggests that the demands of maintaining and adapting to new technological infrastructure can, at least in the short run, compete with staff members' time and attention. Regulatory requirements showed a positive relationship with productivity at the ten percent significance level ($p = 0.101$), hinting that clearer regulatory expectations may, over time, help staff work in a more structured and productive manner.

Read as a whole, these results give a textured answer to the research question of how digital monitoring and evaluation practices enhance organisational performance at Rutongo Hospital. The collinearity diagnostics establish that the findings rest on statistically sound ground. The explanatory results show that specific digital practices, rather than digitalisation as a blanket phenomenon, drive specific performance gains: timely feedback for action for patient satisfaction, visual dashboards for resource utilisation, centralized databases for cost efficiency, and automated analysis together with training for staff productivity. The mediating results reveal that these gains are transmitted through concrete organisational mechanisms, most notably the flow of timely and accurate information and the practice of evidence-based planning. The moderating results, in turn, make clear that the strength and even the direction of these effects depend on the surrounding institutional environment, particularly the state of infrastructure and technology, digital literacy, and the balance between locally developed M&E skills and dependence on donor support. For Rutongo Hospital, and for similarly resourced health facilities across Rwanda, the evidence therefore points toward a deliberate, context-sensitive approach to digital M&E investment rather than a one-size-fits-all digitalisation drive.

3.6 Principal Components Analysis of M&E variables from Rutongo Hospital

Table 6 presents a comprehensive, humanized interpretation of the Principal Component Analysis (PCA) conducted on the Monitoring and Evaluation (M&E) dataset from Rutongo Hospital. The primary

objective of this multivariate statistical analysis is to reduce the dimensionality of 33 interrelated indicators into a core set of uncorrelated factors. By identifying the underlying structural dimensions driving M&E operations and health service delivery outcomes, the administration can make evidence-based decisions to optimize resource allocation, digital integration, and clinical quality. The analysis begins with an examination of the total variance explained by the extracted components and transitions into a detailed thematic exploration of the rotated component matrix.

Table 6: PCA results (**Total Variance Explained**)of M&E variables from Rutongo Hospital

Component	Total Variance Explained								
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.733	14.343	14.343	4.733	14.343	14.343	3.561	10.792	10.792
2	2.488	7.540	21.883	2.488	7.540	21.883	2.795	8.471	19.263
3	2.356	7.139	29.022	2.356	7.139	29.022	2.150	6.516	25.779
4	2.261	6.851	35.874	2.261	6.851	35.874	2.112	6.400	32.179
5	2.176	6.594	42.468	2.176	6.594	42.468	2.112	6.400	38.578
6	1.910	5.789	48.257	1.910	5.789	48.257	2.106	6.381	44.960
7	1.836	5.563	53.820	1.836	5.563	53.820	1.860	5.638	50.597
8	1.721	5.214	59.034	1.721	5.214	59.034	1.775	5.379	55.977
9	1.606	4.866	63.899	1.606	4.866	63.899	1.679	5.089	61.066
10	1.386	4.200	68.100	1.386	4.200	68.100	1.644	4.982	66.048
11	1.205	3.653	71.752	1.205	3.653	71.752	1.475	4.471	70.519
12	1.180	3.575	75.328	1.180	3.575	75.328	1.386	4.199	74.718
13	1.035	3.135	78.463	1.035	3.135	78.463	1.236	3.744	78.463
14	0.977	2.960	81.423						
15	0.852	2.581	84.004						
16	0.837	2.537	86.541						
17	0.675	2.046	88.587						
18	0.646	1.958	90.545						
19	0.594	1.801	92.346						
20	0.531	1.608	93.955						
21	0.461	1.398	95.353						
22	0.381	1.154	96.506						
23	0.264	0.800	97.306						
24	0.256	0.775	98.081						
25	0.218	0.660	98.741						
26	0.135	0.409	99.150						
27	0.117	0.354	99.505						
28	0.098	0.295	99.800						
29	0.066	0.200	100.000						
30	0.000	0.000	100.000						
31	0.000	0.000	100.000						

32	0.000	0.000	100.000
33	0.000	0.000	100.000

Extraction Method: Principal Component Analysis.

According to Kaiser's criterion, only principal components (PCs) with eigenvalues greater than 1.0 are retained for subsequent rotation and interpretation, as they capture more variance than a single standardized variable. In this study, the PCA successfully extracts thirteen distinct components that meet this rigorous standard, collectively accounting for an impressive 78.463% of the total variance within the M&E and hospital performance data. This substantial cumulative percentage demonstrates that the retained components provide a highly representative and robust summary of the original 33 indicators, losing only a minimal fraction of random noise. The primary component, Component 1, acts as the dominant axis of variation with an initial eigenvalue of 4.733, individually explaining 14.343% of the total variance. Component 2 is the second most influential dimension, yielding an eigenvalue of 2.488 and explaining 7.540% of the variance, followed closely by Component 3 with an eigenvalue of 2.356 explaining 7.139%. Components 4 and 5 report eigenvalues of 2.261 and 2.176, contributing 6.851% and 6.594% to the variance, respectively. Moving down the hierarchy, Component 6 exhibits an eigenvalue of 1.910 (5.789% of variance), Component 7 yields 1.836 (5.563%), Component 8 captures 1.721 (5.214%), and Component 9 accounts for 1.606 (4.866%). The final set of retained dimensions consists of Component 10 with an eigenvalue of 1.386 (4.200%), Component 11 with 1.205 (3.653%), Component 12 with 1.180 (3.575%), and Component 13 with an eigenvalue of 1.035, representing the final 3.135% of variance. Following the Varimax orthogonal rotation, the variance is redistributed more equitably across the dimensions. Component 1 retains the largest post-rotation share at 10.792% of the variance, while Component 13 represents 3.744%, ensuring that each extracted factor remains statistically meaningful and conceptually interpretable.

Table 7: Rotated Component Matrix^a

Rotated Component Matrix ^a													
	Component												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Use of Digital Tools like Tables and Mobile apps	0.639	0.097	0.013	-0.013	0.021	-0.024	-0.051	-0.002	-0.100	0.413	-0.143	-0.101	0.241
Real time data capture	0.057	0.136	0.022	-0.055	-0.031	-0.091	-0.049	-0.207	-0.217	0.524	-0.031	0.202	-0.230
Centralized Digital database	-0.060	0.003	-0.021	-0.031	0.191	0.023	0.885	-0.015	0.008	-0.027	0.014	0.005	0.147
Data quality and security	0.019	-0.020	-0.011	-0.009	0.002	0.978	0.061	-0.036	0.048	-0.029	-0.030	0.106	-0.009
Automated Data analysis	0.091	0.028	0.144	-0.070	-0.013	0.139	-0.089	0.093	-0.009	0.121	0.053	0.728	-0.059
Visual Dashboard and Reports	0.229	-0.020	-0.050	0.014	0.078	-0.041	0.145	-0.121	-0.102	-0.116	0.011	0.163	0.706
Evidence based decision	-0.147	-0.069	-0.046	0.108	-0.113	0.023	-0.239	0.076	0.053	-0.044	0.386	-0.230	0.313
Timely Feedback for action	0.570	0.609	0.306	-0.056	-0.028	-0.065	-0.023	-0.083	-0.065	0.165	-0.047	0.062	-0.106
Level of staff digital skills	0.060	-0.133	-0.057	0.142	0.094	-0.133	0.037	-0.204	0.675	-0.231	-0.144	0.013	-0.353
Trainings and Technical Skills	-0.069	-0.052	-0.029	-0.005	0.000	-0.057	0.047	0.848	0.127	-0.029	0.008	-0.037	0.021
Timely and accurate Information	-0.045	-0.054	-0.008	-0.017	0.013	-0.009	0.062	0.165	-0.006	-0.042	0.832	-0.065	-0.050
Evidence based planning	-0.016	-0.085	-0.039	0.023	-0.057	0.250	0.304	0.275	-0.260	-0.093	0.184	-0.245	-0.278
Learning and continuous improvement	-0.053	-0.054	-0.033	-0.046	-0.007	0.184	-0.080	0.163	0.784	-0.089	-0.035	0.027	-0.103
Commitment to M&E culture	0.002	0.874	-0.037	-0.034	0.056	-0.012	0.036	-0.029	-0.049	-0.010	-0.056	0.209	0.032
Resources allocation	-0.132	0.800	-0.050	0.179	-0.028	0.006	-0.027	-0.041	-0.002	-0.077	-0.015	-0.083	-0.081
Infrastructure and Technology	0.493	0.735	0.134	-0.042	-0.009	-0.008	-0.077	-0.010	-0.049	-0.024	-0.069	-0.153	0.179
Policies and System	-0.053	-0.087	-0.037	0.013	0.002	-0.002	-0.025	-0.010	0.088	0.865	-0.062	-0.043	0.005
Digital Literacy	0.481	0.616	-0.054	-0.059	0.040	-0.061	-0.023	-0.081	-0.096	0.454	0.055	0.073	-0.045
M&E Skills and experience	0.867	-0.032	-0.062	-0.001	-0.036	-0.064	0.154	-0.089	0.001	-0.087	0.014	0.021	-0.115
Donor/ Support policies	0.892	0.007	-0.049	-0.001	-0.017	0.099	-0.043	-0.072	0.012	-0.096	-0.026	0.035	-0.034
Regulatory requirements	0.818	0.121	0.036	-0.025	0.005	0.041	-0.096	0.068	-0.030	0.018	-0.033	0.092	0.261
Quality of Care	-0.021	0.037	-0.003	0.989	0.001	-0.010	-0.015	-0.018	0.009	-0.012	-0.008	0.047	0.009
Patients satisfaction	-0.010	0.013	0.994	-0.004	-0.004	-0.011	-0.014	-0.021	-0.023	-0.018	0.021	0.039	-0.020
Services Coverage	-0.017	0.012	-0.007	0.001	0.983	0.002	0.047	-0.005	0.002	-0.005	0.089	-0.022	0.020
Timely Service Delivered	-0.095	0.007	0.016	-0.017	-0.070	-0.009	0.057	0.100	0.647	0.264	0.142	-0.138	0.288
Resources Utilization	-0.013	-0.014	0.081	-0.037	0.298	-0.065	0.015	-0.098	-0.039	-0.036	0.697	0.211	0.041
Cost Efficiency	0.024	-0.036	-0.008	0.006	-0.077	0.086	0.901	0.057	-0.011	-0.030	0.002	-0.013	-0.031
Goal achievement	0.019	-0.020	-0.011	-0.009	0.002	0.978	0.061	-0.036	0.048	-0.029	-0.030	0.106	-0.009
Staff Productivity at the Rutongo Hospital	-0.031	-0.048	-0.011	-0.031	-0.012	-0.015	-0.006	0.866	-0.014	-0.081	0.099	0.172	-0.090

Innovation and Learning	-0.036	0.036	-0.084	0.257	-0.042	0.099	0.090	0.045	-0.049	-0.102	-0.009	0.663	0.239
Compliance with Standards	-0.021	0.037	-0.003	0.989	0.001	-0.010	-0.015	-0.018	0.009	-0.012	-0.008	0.047	0.009
Reporting and Transparency	-0.010	0.013	0.994	-0.004	-0.004	-0.011	-0.014	-0.021	-0.023	-0.018	0.021	0.039	-0.020
Stakeholder Trust	-0.017	0.012	-0.007	0.001	0.983	0.002	0.047	-0.005	0.002	-0.005	0.089	-0.022	0.020

Extraction Method: Principal Component Analysis. ; Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 11 iterations.

The Rotated Component Matrix uses Varimax rotation with Kaiser Normalization to simplify the factor loadings, aligning each variable with the specific component it relates to most strongly. Component 1 emerges as the 'Institutional Support and Capability' dimension. It is anchored by exceptionally high loadings from donor/support policies (0.892), specialized M&E skills and experience (0.867), and regulatory requirements (0.818), which highlight how external donor structures and formal regulations shape the professional capability of the hospital's team. Component 2 represents the 'Resource, Infrastructure, and Culture' dimension, showing strong loadings from commitment to M&E culture (0.874), resource allocation (0.800), and infrastructure and technology (0.735). This demonstrates that physical tools and funding must go hand-in-hand with cultural adoption to drive sustainable organizational change.

The remaining components isolate highly specific operational and service-oriented domains. Component 3 and Component 4 represent direct hospital outcomes, with Component 3 focusing entirely on reporting and transparency (0.994) and patient satisfaction (0.994), and Component 4 focusing on quality of care (0.989) and compliance with standards (0.989). Component 5 captures services coverage (0.983) and stakeholder trust (0.983). The complete statistical separation of these clinical outcomes from the operational tools in other components indicates that clinical excellence is experienced independently of the hospital's back-end M&E technology. Meanwhile, Component 6 acts as the 'Information Integrity' factor, dominated by data quality and security (0.978) and overall goal achievement (0.978), which highlights that secure data is the foundation of successful hospital management.

Further operational dimensions are illuminated in the final components. Component 7 represents financial efficiency, heavily loaded by cost efficiency (0.901) and centralized digital database (0.885), proving that database integration is the main driver of fiscal containment. Component 8 highlights the human aspect of productivity, loading staff productivity at Rutongo Hospital (0.866) alongside specialized training and technical skills (0.848). Component 9 centers on timely service delivered (0.647), which loads heavily with digital literacy (0.616) and learning and continuous improvement (0.784), showing how staff capacity speeds up care. Component 10 reflects formal governance, loaded by policies and systems (0.865) and real-time data capture (0.524). Component 11 isolates timely and accurate information (0.832) with resources utilization (0.697), Component 12 represents automated data analysis (0.728) and innovation and learning (0.663), and Component 13 captures visual dashboards and reports (0.706). Taken together, these components provide Rutongo Hospital's administration with a clear roadmap: physical technology and databases must be actively supported by staff literacy, regular training, and a strong data culture to translate backend M&E activities into improved patient outcomes.

4. Discussion of Findings

Having interpreted the regression results on their own terms, it is worth asking how the picture emerging from Rutongo Hospital sits alongside what other researchers have found elsewhere. Placing the present findings in conversation with the wider literature on digital monitoring and evaluation (M&E) and organisational performance shows where the Rutongo evidence confirms patterns already documented in other health systems, and where the hospital's own context, as a

donor-supported, resource-constrained facility operating within Rwanda's national M&E architecture, produces results that depart from more digitally mature settings.

The overall finding that specific digital M&E practices, rather than digitalisation as a general phenomenon, drive specific performance gains at Rutongo Hospital echoes the conclusions reached by (Weiner *et al.*, 2016), whose study of a real-time dashboard system in a United States hospital found that the tool improved unit-level decision making only once it was embedded in a genuine data-driven decision culture, rather than through its mere presence as a technology. This is consistent with the Rutongo result that visual dashboards and reports significantly improved resource utilisation, while timely feedback for action, rather than digital tools in general, was the strongest driver of patient satisfaction. Martin *et al.* (2019) reached a related, more cautionary conclusion in their large-scale study of English hospitals: organisational digital maturity showed no significant relationship with several clinical outcomes and was, instead, closely bound up with other institutional factors. That caution is well reflected in the Rutongo data, where the use of digital tools and the centralized digital database were associated with small but significant reductions in patient satisfaction, a reminder that digital investment does not translate automatically or uniformly into better performance.

The strong, consistently positive role of automated analysis and of training and technical support in raising staff productivity at Rutongo Hospital also finds support in more recent African evidence. Jeilani and Hussein (2025), studying digital health technology adoption among 286 healthcare workers in Mogadishu, Somalia, used structural equation modelling to show that digital health technologies significantly improved worker performance, and that this performance in turn mediated the relationship between technology adoption and workload. Their finding that the benefits of digital adoption flow through worker performance as a mediating mechanism parallels the Rutongo result that timely and accurate information, and learning and continuous improvement, both mediated the effect of digital M&E practice on staff productivity, reinforcing the view that digital tools alone are insufficient without organisational processes that convert them into practical gains.

The modest but significant decline in patient satisfaction associated with digital tools and centralized databases at Rutongo Hospital is not unique to this study. Aboumoussa *et al.* (2025), in a systematic review of electronic health services in primary care, similarly found that although electronic records improved satisfaction with clinical consultations and services in many settings, heightened provider attention to the screen during consultations could undermine patient-centred communication and engagement. Read together, the two studies suggest that the Rutongo findings are not a peculiarity of the hospital but part of a broader, well-documented adjustment period that accompanies the early stages of digital record-keeping, one that later gives way to improvement once staff become more fluent with the tools and workflows settle.

The pivotal role that timely and accurate information and evidence-based planning played as mediators in the Rutongo models is strongly consistent with Rwanda's own health information systems literature. Fraser *et al.* (2024), evaluating data quality across fifty health facilities using Open MRS in Rwanda, found that system stability, uptime and clinical alerts were closely linked to the completeness and accuracy of routinely collected data. Nshimyiryo *et al.* (2020) likewise documented meaningful gaps between health management information system reports and facility source registers across four Rwandan districts, underlining how uneven data quality can remain even within a well-established national system. Against this backdrop, the very large and highly significant effect of the centralized digital database on cost efficiency at Rutongo Hospital, and the

significant mediating role of timely and accurate information for both resource utilisation and staff productivity, make particular sense: where national evidence shows that data reliability cannot be taken for granted, a facility that succeeds in consolidating and safeguarding its data stands to gain disproportionately more than one that has not. At the level of the broader institutional environment, the moderating effects identified at Rutongo Hospital, particularly the importance of infrastructure and technology, digital literacy and M&E skills, mirror longstanding concerns raised by Holvoet and Inberg (2014) in their stocktaking of M&E systems across the Rwandan and Ugandan health sectors. Their study found that the overall quality of a country's or facility's M&E arrangements depends heavily on the strength of the underlying M&E plan and institutional capacity, rather than on the adoption of individual tools in isolation. This helps explain why, at Rutongo Hospital, infrastructure and technology and digital literacy were among the most powerful moderating conditions across the performance dimensions, sometimes amplifying and at other times constraining the effect of digital M&E practice, since these conditions essentially determine whether the underlying M&E architecture that Holvoet and Inberg (2014) describe is present and functioning. Finally, the sharply contrasting effects of M&E skills and experience (strongly positive) and donor or support policy (strongly negative) on cost efficiency at Rutongo Hospital resonate with a wider caution in the literature on donor-funded health programming in Africa. Ilesanmi *et al.* (2022) in a systematic review of donor-funded health interventions across the continent, found that programme sustainability depended heavily on locally driven facilitators such as community and institutional ownership, and that projects reliant primarily on external funding were more vulnerable once that funding receded or came with heavy compliance obligations. The Rutongo finding that donor or support policy undermines cost efficiency, even as locally built M&E skills and experience strongly improve it, adds a facility-level illustration to this broader pattern, and suggests that investment in the hospital's own M&E workforce may be a more cost-efficient long-term strategy than continued dependence on donor-administered programmes. Taken as a whole, the comparison with prior research suggests that the Rutongo Hospital findings are neither an outlier nor a simple restatement of the existing literature. They confirm, in a Rwandan hospital setting, patterns already observed elsewhere, that digital tools matter most when embedded in a decision-making culture, that data quality and information flow are decisive mediators, and that donor dependence can complicate cost efficiency, while also adding a specific, locally grounded account of how these dynamics play out within a resource-constrained, donor-supported facility operating inside Rwanda's national M&E system.

The Principal Component Analysis carried out on Rutongo Hospital's thirty-three Monitoring and Evaluation indicators produced thirteen components explaining 78.463% of total variance, a figure that sits at the high end of what similar studies in health-sector M&E have reported. It is worth placing these results side by side with what other researchers have found, both to check whether Rutongo's pattern is unusual and to understand what the differences might mean for how the hospital interprets and acts on its own data. Rutongo's 78.463% cumulative variance is considerably higher than what Wanzala *et al.* (2019) obtained when they applied PCA to 151 health-system indicators across 71 facilities in Kakamega County, Kenya, where the retained components captured a much smaller share of the common variance. A similar pattern appears in Jackson *et al.* (2015) analysis of the Tanzania Service Provision Assessment survey, where the extracted components explained only about a third of the variance among more than a hundred readiness indicators. The gap is not surprising once the scale of the two exercises is considered. Rutongo's analysis works with thirty-three indicators drawn from a single facility's M&E system, a much narrower and more internally consistent set than the hundred-plus cross-facility indicators

used in the Kenyan and Tanzanian studies, which mix vastly different domains such as staffing, commodities, and infrastructure. Fewer, more closely related variables tend to compress more cleanly into a handful of dimensions, so Rutongo's higher variance explained is best read as a feature of a tighter, more homogeneous indicator set rather than evidence that its M&E system is inherently better structured than those examined elsewhere.

On side of institutional support and governance as a dominant dimension, the emergence of “Institutional Support and Capability” as Rutongo’s leading component, anchored by donor policy, specialised M&E skill, and regulatory compliance, echoes a theme that recurs throughout the regional M&E literature. Holvoet and Inberg (2014), in their comparative assessment of health-sector M&E systems in Rwanda and Uganda, found that both countries' systems were shaped heavily by external donor requirements and formal policy frameworks, often more so than by locally driven demand for data. Their diagnosis of the two systems as 'fragmentary,' with pockets of strength tied to donor-supported programmes, mirrors what the Rutongo data imply: that institutional capability at the hospital is substantially propped up by outside support and compliance obligations rather than by fully internalised organisational routine. This convergence suggests that Rutongo is not an isolated case but part of a broader regional pattern in which national and international donor architecture continues to define how seriously M&E functions are resourced and staffed.

For data quality and information systems, Rutongo’s Component 6, built around data quality, security, and overall goal achievement, lines up closely with a well-established line of Rwandan research on health information systems. Nisingizwe *et al.* (2014) tracked five years of Health Management Information System data across nearly five hundred Rwandan facilities and found that completeness and internal consistency, while improving, remained an area requiring continuous vigilance. Fraser *et al.* (2024) more recent facility-level study of electronic health records in Rwanda has likewise identified data completeness, accuracy, and timeliness as persistent, interlinked challenges rather than problems that are solved once and forgotten. That data quality forms its own distinct factor in the Rutongo results, separate from resourcing and from clinical outcomes, supports the view in this literature that information integrity behaves as an independent organisational capability, one that needs its own investment and monitoring rather than being assumed to improve automatically alongside infrastructure or funding.

One of the more striking features of the Rutongo results is the clean statistical separation between back-end M&E machinery and front-line outcomes such as patient satisfaction, quality of care, and services coverage, which load almost perfectly onto their own components. This resonates with the Kenyan health-systems capacity study, which found that different building blocks of the health system, including governance, financing, and service delivery, contributed unevenly and sometimes independently to service provision, with governance in particular showing a weaker direct link to outcomes than expected. It also echoes the broader argument made in the Tanzania SPA study, namely that readiness indicators and actual care outcomes do not always move together, so a facility can look well equipped on paper while its lived clinical experience is shaped by other forces. Read together, these studies caution Rutongo's administration against assuming that strengthening the M&E system alone will automatically translate into better patient experience; the two appear to require deliberate, separate attention.

On other hand, the financial efficiency, digitalisation, and human capacity, Rutongo's Component 7, linking cost efficiency tightly to a centralized digital database, fits comfortably within Rwanda's documented experience of financial data tracking in resource-limited settings. Lu and colleagues' (2014) earlier work on rural Rwandan health centres found that dependable financial data systems, once properly designed and staffed, could meaningfully improve budget oversight, provided that human capacity was built alongside the technology rather than treated as an afterthought. The same logic surfaces in Rutongo's Component 8 and Component 9, where staff productivity, training, and digital literacy load together and jointly explain how quickly services reach patients. This pattern is consistent with a recurring conclusion across the reviewed literature: digital tools by themselves rarely improve efficiency or speed of care; they do so only when paired with a workforce that has the skills and confidence to use them. To sum up, taken as a whole, the Rutongo findings agree with the wider body of research more than they diverge from it. The centrality of donor and regulatory influence, the independence of data quality as its own organisational dimension, the separation between M&E infrastructure and clinical outcomes, and the pairing of digitalisation with human capacity all appear, in one form or another, across studies conducted in Kenya, Tanzania, Uganda, and elsewhere in Rwanda. Where Rutongo's results differ is mainly in degree rather than in kind, particularly the unusually high cumulative variance explained, which is best attributed to the narrower and more homogeneous indicator set used at a single facility rather than to a fundamentally different underlying structure. For Rutongo's administration, this convergence is reassuring in one sense, since it means the hospital is not confronting an unprecedented problem, but it is also a reminder that the solutions other facilities have tried, particularly investment in staff capacity and in the routine use of data rather than in technology alone, are likely to be relevant here as well.

5. Conclusion and Recommendations

This study set out to establish whether digital monitoring and evaluation (M&E) practices genuinely strengthen organisational performance at Rutongo Hospital, and the evidence says: it's complicated, in a useful way. The picture that emerges is not “digital tools help” or “digital tools don't help”, it is that specific practices move specific outcomes, while others do nothing or even work against them. The numbers make the case clearly. A centralized digital database was the single strongest predictor found anywhere in the model, driving cost efficiency ($\beta = 0.534$, $p < 0.001$). Automated analysis and training/technical support were the two biggest levers for staff productivity ($\beta = 0.943$ and $\beta = 0.776$, both $p < 0.001$). Timely feedback for action was the strongest driver of patient satisfaction ($\beta = 0.128$, $p < 0.001$), and visual dashboards mattered most for resource utilisation ($\beta = 0.050$, $p = 0.009$). Meanwhile, simply owning digital tools or tablets was associated with a small drop in satisfaction and resource use like a reminder that adoption without integration can create friction rather than value. The mediation results explain why: gains pass through timely, accurate information (strongest for resource use and productivity, $\beta = 0.158$ and $\beta = 0.386$) and evidence-based planning (the key channel for cost efficiency, $\beta = 0.063$). And the moderation results explain when these gains show up: infrastructure quality, digital literacy, and locally-held M&E skills consistently strengthen the digital–performance link, while heavy dependence on donor/support policy weakens it ($\beta = -0.121$ on cost efficiency, $p < 0.001$). The PCA reinforces this as 13 components, together explaining 78.5% of variance, confirm that digital infrastructure, data quality, human capacity, and clinical outcomes behave as genuinely separate dimensions of hospital life rather than one undifferentiated “digitalisation” story. Underneath all of this sits a sobering baseline: nearly every M&E and performance indicator in the descriptive statistics (Table 1) clustered barely above 1.0 on the scale, with digital literacy the lone exception at 1.56. Rutongo Hospital, in other words, is not yet a digitally mature institution it is at the very start of the curve, which is exactly why some effects appear inconsistent: the hospital is catching individual pieces of a system that isn't yet complete.

Recommendations

For Rutongo Hospital management:

Prioritise the centralized digital database. With by far the largest coefficient in the study ($\beta = 0.534$ on cost efficiency), consolidating records into one well-governed system should be the first infrastructure investment, ahead of dashboards or standalone devices.

Pair automated analysis tools with sustained training. These two together explain the bulk of the productivity gains ($\beta = 0.943$ and $\beta = 0.776$); rolling out software without parallel staff training is likely to underperform.

Build feedback loops, not just data flows. Timely feedback for action outperformed every other patient-facing practice hospitals should treat “closing the loop” with patients and staff as a distinct, resourced activity, not an automatic by-product of data collection.

Invest in evidence-based planning capacity, since this is what converts data into cost savings ($\beta = 0.063$, $p < 0.001$), rather than assuming data availability alone will discipline spending.

Sequence technology rollouts carefully. Several practices (digital tools, timely feedback, infrastructure upgrades) showed short-term negative associations with resource use or productivity like consistent with adjustment costs. Phased implementation with change-management support would likely soften this dip.

For the Ministry of Health and donor partners:

Rebalance donor-funded support toward local M&E skills-building. Donor/support policy was significantly negatively associated with cost efficiency ($\beta = -0.121, p < 0.001$), while locally held M&E skills and experience were significantly positive ($\beta = 0.130, p < 0.001$) such as suggesting funding models should shift from external administration toward building in-house capacity.

Set minimum infrastructure and connectivity standards before scaling digital M&E mandates to similarly resourced facilities, since infrastructure quality moderated multiple outcomes, including a significant negative effect on productivity when inadequate ($\beta = -0.179, p = 0.009$).

Use this hospital-level model as a template, but expect similar variability elsewhere like the moderation results show that facility-specific context (staffing, funding structure, infrastructure) will shape which practices pay off first.

Acknowledgements

The authors sincerely appreciate the management and staff of Rutongo Hospital for their invaluable cooperation, openness, and willingness to participate in this study. Their commitment to providing accurate information and sharing their experiences with digital monitoring and evaluation practices greatly contributed to the success of this research. We also extend our heartfelt gratitude to all healthcare professionals, monitoring and evaluation officers, administrative personnel, and departmental managers who generously devoted their time to completing the questionnaires and providing constructive insights during data collection. Their contributions formed the foundation of the empirical evidence presented in this paper. Our sincere appreciation is further extended to colleagues, academic mentors, and technical reviewers whose guidance, thoughtful comments, and methodological advice strengthened the quality of the study from its conceptualization to the final manuscript. Finally, we thank the University of Lay Adventists of Kigali (UNILAK) for providing an academic environment that supported the successful completion of this research.

Author Contributions

Conceptualization: J.B.U. and J.N.N; Methodology: J.B.U. and J.N.N, Study Design: J.B.U. and J.N.N.; Data Collection: J.N.N; Data Analysis and Interpretation: J.N.N., Writing – Original Draft: J.B.U. and J.N.N; Writing – Review and Editing: J.B.U. and J.N.N; Supervision: J.N.N. All authors read, reviewed, and approved the final version of the manuscript prior to submission.

Funding

This research did not receive any specific funding from public, commercial, or not-for-profit funding agencies. The study was undertaken independently by the authors as part of their academic research activities.

Data Availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. Correspondence should be directed to: **Jean Bosco Uwimana**, Email: jjboscouwimana@gmail.com . The data will be shared solely for academic and research purposes in accordance with institutional policies and ethical considerations.

Declarations**Ethical Approval**

This study was conducted in accordance with internationally accepted ethical principles governing research involving human participants. Prior authorization to conduct the research was obtained from the management of **Rutongo Hospital**, where the study was carried out. Permission was granted to collect data from healthcare professionals and relevant hospital departments. Ethical clearance for this study was obtained from the **University of Lay Adventists of Kigali (UNILAK) Research Ethics Committee** before the commencement of data collection. The research complied with the ethical standards established by the University and adhered to the principles outlined in the Declaration of Helsinki regarding research involving human participants. All information collected during the study was treated with the highest level of confidentiality. Personal identifiers were removed from the dataset, and the findings are presented only in aggregate form to ensure participants' anonymity and privacy.

Consent to Participate

Written informed consent was obtained from all participants before data collection. Each participant received clear information regarding the objectives of the study, the voluntary nature of participation, the confidentiality of the information provided, and their right to withdraw from the study at any stage without any negative consequences.

Consent for Publication

Not applicable.

Clinical Trial Number

Not applicable.

Competing Interests

The authors declare that they have no competing interests or personal relationships that could have influenced the work reported in this paper.

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