Research Article

Vol.8, No 1, 2025
ISSN 2591–6769
eISSN 2953–2663

East African Journal of Applied Health Monitoring and Evaluation

Enhancing Healthcare Data Quality in Regional Referral Hospitals: Does Self-Regulation of Healthcare Workers Matter?

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Received: January 20, 2025 Accepted: December 18, 2025 Published: December 27, 2025

Abstract

Introduction

The global healthcare industry relies on high-quality data to support informed decision-making, inform policy, and improve health outcomes. Human error during data entry is a leading source of data quality issues. Thus, this study assessed the perceived healthcare data quality (accuracy, completeness, timeliness, consistency) and determined whether healthcare workers' self-regulation skills (emotional self-control, adaptability, trustworthiness) are associated with data quality.

Methods

A cross-sectional study was conducted across eight regional referral hospitals in Tanzania, employing simple random sampling. A total of 336 healthcare workers participated in the study. Data were collected through a structured questionnaire and analyzed using Excel and IBM SPSS version 27. Perceived healthcare data quality levels were categorized according to percentile-based thresholds. Multiple linear regression was used to examine the relationships between healthcare workers' three self-regulation skills and the four dimensions of data quality.

Results

Findings indicated that 65.2% of healthcare workers rated the quality of healthcare data as moderate, 31.5% rated it as high, and 3.3% rated it as low. Emotional self-control and trustworthiness were positively and statistically significantly associated with healthcare data quality, whereas adaptability was negatively associated. Emotional self-control predicted higher scores across all data-quality subdomains (β range = 0.260–0.674; all $p < 0.001$). Adaptability showed consistent negative associations (β range = −0.311 to −0.461, all $p < 0.001$). Trustworthiness was positively associated with healthcare data quality (β range = 0.145–0.725; $p \leq 0.001$). Models explained 40.4–55.9% of variance in subdomain scores (R^2 range = 0.404–0.559).

Conclusion

The study concludes that healthcare data quality is currently moderate, indicating satisfactory but improvable quality. It underscores the critical role of self-regulation, particularly emotional self-control and trustworthiness, among healthcare workers in improving data quality and advocates for the implementation of targeted training programs and mentorship programs to strengthen healthcare workers' self-regulation, ethical awareness, and decision-making in data management.

Keywords: *Self-regulation, healthcare data quality, healthcare workers, regional referral hospital, Tanzania*

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INTRODUCTION

The global demand for Healthcare Data Quality (HDQ) is imperative. Such data plays a crucial role in improving health outcomes, influencing public health policies, and enhancing the overall efficiency of healthcare systems (Ehsani-Moghaddam et al., 2021). The World Health Organization (WHO) considers HDQ to be a cornerstone for advancing health outcomes and ensuring effective governance in global health (WHO, 2021). It underscores the necessity of HDQ for informed decision-making. To facilitate this, WHO offers technical support and training to member states to enhance data collection, analysis, and reporting. It also established best practice guidelines and has created a framework to assess and improve data quality in health information systems, with a focus on completeness, consistency, accuracy, and timeliness (Snäll, 2022; WHO, 2023). Operationally, completeness is measured as the proportion of required fields completed; accuracy as the proportion of records that agree with verified sources; consistency as the proportion of records that are consistent across systems; and timeliness as the proportion of records reported within an acceptable time window.

Many developed nations have embraced healthcare Monitoring And Evaluation (M&E) systems, such as Electronic Health Records (EHR), which standardize data collection and enhance the accuracy and accessibility of patient information (Sikhondze & Erasmus, 2016). While some studies have raised concerns about the quality of data produced by these systems (Orfanidis et al., 2004), the systems have nonetheless significantly improved data quality compared to traditional paper-based methods (Reza et al., 2020).

Despite various challenges, numerous developing countries have made steps in developing or enhancing their healthcare M&E systems to more effectively collect, manage, and analyze health data (Sikhondze & Erasmus, 2016). Initiatives, often backed by international organizations, have resulted in the creation of more robust data infrastructures. For example, nearly all African nations have adopted District Health Information Software 2 (DHIS2) to improve the collection, processing, and dissemination of healthcare data (Muhoza, 2020). The maintenance of HDQ remains a widely recognized challenge, although it is critical for effective healthcare delivery (Ngugi, 2021).

In Tanzania, the government has made notable progress in enhancing the quality of healthcare data and stimulating its M&E systems through data quality assessment at national, regional and health facility level (MoHCDGEC, 2021). An integrated Health Management Information System (HMIS) has been established to gather and combine health data from different levels in the healthcare framework (Holl et al., 2024). Additionally, the government promotes Mobile Health Initiatives to facilitate data collection and reporting. In Tanzania, through assistance from international partners, there has been a determined effort to train healthcare workers in data collection and management, thereby improving local capabilities to effectively generate and utilize quality of healthcare data (Holl et al., 2024). Nevertheless, the literature indicates that challenges related to poor data quality in the healthcare sector persist in the country (Lwoga & Musheiguza, 2023).

Literature highlights several factors contributing to poor HDQ, with human error being a major concern (Clarke et al., 2016). Studies (Barchard & Pace, 2011; Begum et al., 2020) show that data entry errors, such as typos, missing information, and inconsistent abbreviations, can lead to misidentification, communication breakdowns, and incomplete patient records, affecting treatment decisions and care quality. Such input errors pose significant challenges, particularly in healthcare, where a single mistake can have severe consequences, including incorrect medication administration.

In Tanzania, for instance, a tragic incident occurred in 2007 when Emmanuel Didas underwent surgery on the wrong body part due to a mix-up in patient information. This mistake led to the death of Emmanuel Mgaya and resulted in significant financial losses for the hospital, as documented in Sisti Marishay vs The Board of Trustee Muhimbili Orthopaedic Institute (2017).The error occurred because both patients shared the same first name, Emmanuel. Hospital documents for Emmanuel Mgaya were mistakenly given to Emmanuel Didas, and vice versa. The error, attributed to nursing staff, was characterised as a human error with no intent to harm. As a result, Emmanuel Didas underwent surgery on his head instead of his leg, while Emmanuel Mgaya received surgery on his leg instead of his head. Despite being transferred to India for further treatment, Emmanuel Mgaya's condition was too severe, and he tragically died after the procedure. This incident is just one of many, both reported and unreported, that highlight the need for systemic improvements in patient data handling. To mitigate such errors, it is crucial to implement self-regulation skills for all healthcare workers involved in data management.

Self-regulation, the capability of individuals to monitor and control their emotions, behaviors, actions, or processes without external intervention, is a key component of emotional intelligence, as outlined by Goleman's theory (Goleman, 2006, 2011, 2020). Goleman identifies emotional self-control, adaptability, and trustworthiness as critical self-regulatory skills that enhance professional performance (Goleman, 2020). According to Goleman, Emotional self-control is the capacity to manage disruptive emotions, so behaviour and decisions remain steady. Adaptability is the capacity to flex behaviour in response to changing demands. Trustworthiness denotes honesty and integrity in actions and reporting. Together, these self-regulation skills support clinician performance and improve outcomes. For example, Vivian et al. (2019) found that nurses who practised mindfulness and emotional self-control experienced less stress and better performance. Similarly, Roczniewska and Bakker (2021) noted that nurses lacking self-regulation skills were more prone to burnout, negatively impacting job performance and healthcare data quality. Simon and Durand-Bush (2015) also found that physicians who manage their emotions effectively are more likely to maintain a work-life balance and excel in their roles. Research by Siddiqui et al. (2021) and Jahanzeb et al. (2023) further supports the importance of self-regulation in preventing burnout and improving job performance in healthcare settings.

Although previous studies have investigated self-regulation in relation to burnout and performance, they have not assessed its direct link to HDQ in low-resource settings. This study examines how self-regulation, as defined by Goleman's emotional intelligence theory, impacts the quality of healthcare data in Tanzania's regional referral hospitals.

Conceptual framework and hypothesis

To achieve the objective of the study of determining whether self-regulation matters in enhancing quality healthcare data, the conceptual framework was developed. This framework covers three aspects of self-regulation that are indicative of enhancing quality healthcare data, as illustrated in Figure 1.

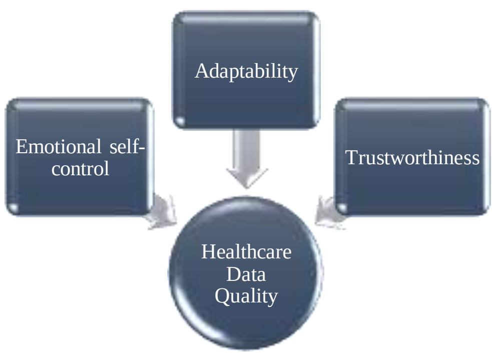

Figure 1. Conceptual framework

Thus, emotional self-control, adaptability, and trustworthiness were incorporated into the study. Researchers also formulated three hypotheses for achieving the study objective: -

- H1. The emotional self-control of healthcare workers has a positive and statistically significant influence on HDQ in Regional Referral Hospitals (RRHs).
- H2. The adaptability skills of healthcare workers have a positive and statistically significant influence on HDQ in RRHs.
- H3. The trustworthiness of healthcare workers has a positive and statistically significant influence on HDQ in RRHs.

METHODS

Study design and context

A cross-sectional study was conducted over three months, from August to October 2024, across eight (8) RRHs in Tanzania mainland. The country has a total of 28 RRHs, organized into eight administrative zones, with one RRH randomly selected from each zone. The RRHs chosen were Mount Meru (Northern zone), Mwalimu Nyerere Memorial (Lake zone), Maweni (Western zone), Singida (Central zone), Morogoro (Eastern zone), Mbeya (South-West highland zone), Sokoine (Southern zone), and Iringa RRH (Southern Highland zone).

Study population and sample size

The study population comprised 2,650 healthcare workers across these hospitals. This group comprised all healthcare workers who regularly use M&E systems to enter or process healthcare data, including physicians, nurses, medical technicians, laboratory technicians, information technology workers, pharmacy workers, administrative staff, and other support staff such as social workers and accountants. The sample size was calculated using (Cochran, 1977) formula as detailed below:-

$$n_0 = \frac{N \cdot Z^2 \cdot p \cdot (1-p)}{E^2(N-1) + Z^2 \cdot p(1-p)}$$

The sample size was determined using the following parameters: n_0 represents the sample size, Z denotes the Z-value of 1.96 corresponding to a 95% confidence level, P indicates the estimated population proportion of 0.5 to account for maximum variability, e signifies the margin of error set at 0.05 for ±5%, and N refers to the total population size.

$$n_0 = \frac{2650 \cdot 1.96^2 \cdot 0.5 \cdot (1-0.5)}{0.05^2(2650-1) + 1.96^2 \cdot 0.5(1-0.5)}$$

$$n_0 = \frac{2650 \cdot 0.9604}{6.6225 + 0.9604)}$$

$$n_0 = \frac{2544.66}{7.5829}$$

$$n_0 = 335.54$$

The total sample size of 336 was determined and allocated proportionately across 8 RRHs based on the number of healthcare workers at each location. Within each RRH we used simple random sampling to select participants. Randomization was performed in Microsoft Excel using the RAND () function. The procedure was: (1) we generated a complete sampling frame (unique ID and basic roster information) for the RRH, (2) added a column with the formula =RAND () and copy down for all entries, (3) sorted the roster by the RAND column in ascending order, and (4) selected the top n_i records. The random numbers and the sorted list were saved as a CSV and a screenshot of the sorted roster was retained for reproducibility. If a selected individual was unavailable or declined participation, the next person on the sorted list was invited as a replacement.

Data collection

A self-administered questionnaire was developed for data collection. The dependent variable, HDQ, and the self-regulation constructs—emotional self-control (ESC), adaptability (ADP), and trustworthiness (TRS)—were measured using multi-item scales with 5-point Likert responses ranging from 1 (strongly disagree) to 5 (strongly agree). For each construct, the mean item score was computed, and these scores (composite) were treated as continuous variables in subsequent multiple linear regression analyses.

For descriptive presentation, HDQ was also categorized into tertiles (percentile thirds) to produce three levels: Low (≤33rd percentile), Moderate (>33rd to ≤66th percentile), and High (>66th percentile). Tertile cut-points were chosen because no validated HDQ cutoffs exist and tertiles yield balanced groups for descriptive comparisons; this approach is comparable to categorization methods used where instrument cut-offs are not established (see, for example, studies done by Gazmararian et al. (2003) and Muhanga (2020). To avoid loss of information from categorization, the main inferential analyses used the continuous HDQ score and sensitivity analyses using the tertile categories were also performed.

Data management and analysis

Multiple linear regression analysis was employed due to its suitability for estimating the value of an outcome variable based on several explanatory variables (Hair et al., 2019). Prior to the analysis, a range of statistical tests was conducted to ensure that the assumptions of normality, linearity, multicollinearity, and homoscedasticity were met. Normality was evaluated using skewness and kurtosis statistics, while scatterplots were used to assess linearity. Furthermore, the Breusch–Pagan test was conducted to investigate homoscedasticity, and the Variance Inflation Factor (VIF) was computed to evaluate multicollinearity among the variables (Field, 2017; Hair et al., 2019).

Ethical considerations

The research study obtained ethical clearance from the Ministry of Health under reference number PA.104/262/01/336. This authorization was formally communicated to all eight hospitals involved in the study. Participation in the study was entirely voluntary, and each participant provided written informed consent after receiving an explanation of the study's purpose, procedures, and their rights as participants. The study posed no anticipated physical, emotional, or psychological risks. It was also clarified that participation would not yield direct personal benefits, thereby ensuring transparency and fostering trust among participants.

All participants were treated with fairness and respect, irrespective of their professional roles. With regard to data management, all collected information was handled with strict confidentiality. The data were securely stored on password-protected devices accessible only to the research team, ensuring the protection of sensitive information and preserving the integrity of the research during and after its completion.

RESULTS

Demographic characteristics of healthcare workers

Table 1 presents a summary of the demographic characteristics of healthcare workers. The study sample consisted of 336 participants, with a majority of male respondents (56.6%) compared to female respondents (43.4%). By age, most participants were between 20 and 39 years old (88.7%), whereas a smaller proportion were in the 40-59 age group (21.3%). The largest professional groups were physicians (28.1%) and nurses (23.9%). In terms of job experience, the majority (59.8%) had between 5 and 12 years of experience. Regarding marital status, most participants were single (58.1%).

Educationally, the most significant proportion held a bachelor's degree (53%), followed by those with certificates or diplomas (40.7%) and a smaller group with master's degrees (6.2%). When it comes to M&E systems, 84.7% used AfyaCare, while 15.3% used other systems such as DHIS2, Government of Tanzania Health Operations Management Information System (GoTHOMIS), and Human Resource for Health Information System (HRHIS). The majority (94.3%) used the M&E system daily, and 55.1% had received formal training on these systems. However, 92.7% of respondents reported a lack of sufficient computers to effectively use the systems. Regarding experience with the existing system, 57% had less than nine years of experience, while 43% had more than nine years.

Table 1. Demographic characteristics of healthcare workers

Characteristics	Frequency	Percentage
Sex		
Male	191	56.6
Female	145	43.4
Age		
20-39	298	88.7
40-59	38	11.3
Profession		
Physicians	94	28.1
Nurses	80	23.9
Laboratorians	14	4.2
Administrators	15	4.4
Pharmacists	53	15.8
Finance staff	11	3.4
HIMS staff	28	8.3
Supportive staff	40	11.9
Job experience (in years)		
0-4	66	19.6
5-12	201	59.8
13+	69	20.5
Marital status		

Single	195	58.1
Married	141	41.9
Education level		
Certificate and Diploma	137	40.7
Bachelor degree	178	53.0
Master degree	21	6.2
M&E system (s) currently in use		
DHIS2, GoTHOMIS, HRHIS, CTC database, Afya-EHMS	51	15.3
AfyaCare	285	84.7
Frequency of using the M&E system		
Daily	316	94.3
Weekly and monthly	19	10.7
Have you attended any training on M&E systems?		
0=NO,	151	44.9
1=YES	185	55.1
Does the hospital have enough computers to ease the use of M&E systems?		
0=NO,	315	92.7
1=YES	26	7.3
How experienced are you (years) in using the existing system?		
1. Less than 9 years	192	57
2. More than 9 years	142	43

Reliability testing, exploration of data, and correlation analysis

The reliability test presented in Table 2 used Cronbach's Alpha to evaluate the internal consistency among the items in the scale. The findings revealed that the Alpha values fell within the acceptable range of 0.89 to 0.94 (Osborne, 2014). In addition, Table 3 indicates that skewness and kurtosis fall within an acceptable range of -1 to 1. According to Hair et al. (2010) and Byrne (2010), data is deemed normal when skewness is between -2 and +2, and kurtosis is between -7 and +7. Also, Table 2 offers information on each variable's mean and standard deviation. The findings show that healthcare workers' mean was fairly uniform, with HDQ having the highest mean of 3.4.

Table 2: Reliability Testing, Exploration of data and correlation analysis

Variable	Items	Alpha (s)	Skewness	Kurtosis	Mean	SD
ESC	6	0.902	0.497	0.406	3.320	1.085
ADP	3	0.892	0.271	0.449	3.140	1.170
TRS	4	0.947	-0.366	-1.140	3.248	1.288
HDQ	26	0.933	0.142	0.372	3.473	0.690

Furthermore, Table 3 shows the correlation coefficients between the dependent variable (HDQ) and the other 3 independent variables of the study, and each variable is correlated with every other variable.

Table 3: Correlation coefficients

Variable	ESC	ADP	TRS	DQ
ESC	1.000			
ADP	.642**	1.000		
TRS	.831**	.710**	1.000	
DQ	.748**	.588**	.514**	1.000

Evaluation of healthcare data quality in the studied hospitals

Table 4 presents an overview of HDQ levels across specific hospitals. The HDQ scale was measured using percentiles (<33.33rd, between 33.33 and 66.66th and above 67.00th percentile), leading to the classification of data quality into three categories: Low, Moderate, and High. Among the eight hospitals assessed, H2 and H8 were identified as having high data quality, whereas the remaining six RRH were rated as having moderate data quality. Notably, no hospitals were classified as having low perceived HDQ. Overall, 65.2% of healthcare workers rated the quality of healthcare data as moderate, 31.5% rated it as high, and 3.3% rated it as low.

Table 4: Quality of Healthcare Data in Study Areas

		Healthcare Data Quality Levels			Total
		Low HDQ	Moderate HDQ	High HDQ	
RRH	H1	2 (4.5%)	28 (63.6%)	14 (31.8%)	44 (13.1%)
	H2	1 (2.5%)	18 (45%)	21 (52.5%)	40 (11.9%)
	H3	1 (2.3%)	31 (72.1%)	11 (25.5%)	43 (12.8%)
	H4	1 (2.4%)	29 (70.7%)	11 (26.8%)	41 (12.2%)
	H5	1 (2.5%)	30 (75%)	9 (22.5%)	40 (11.9%)
	H6	2 (4.5%)	32 (72.7%)	10 (22.7%)	44 (13.1%)
	H7	3 (6.6%)	32 (71.1%)	10 (22.2%)	45 (13.4%)
	H8	0 (0%)	19 (48.7%)	20 (51.3%)	39 (11.6%)
Total		11 (3.3%)	219 (65.2%)	106 (31.5%)	336 (100%)

Analysis of self-regulation skills and healthcare data quality

The regression analysis examined how ESC, ADP, and TRS influence four critical dimensions of data quality: Data Accuracy (Model 1), Data Completeness (Model 2), Data Timeliness (Model 3), and Data Consistency (Model 4). The results in Table 5 indicate that tolerance values exceeded 0.1 and VIF values remained below 10, suggesting that multicollinearity was not a problem in this dataset and that further analysis was warranted.

Table 5: Test of Collinearity

Independent Variable	Tolerance	VIF
ESC	0.487	2.052
ADP	0.303	3.298
TRS	0.256	3.903

Tables 6 shows that, the models explained a substantial portion of the variance in each aspect of HDQ, as demonstrated by high R-squared values (ranging from 0.538 to 0.559) and significant F-statistics (from 86.02 to 160.75, $p = 0.000$). Furthermore, the results in the same table indicated that Emotional self-control and trustworthiness were positively associated with HDQ subdomains, whereas adaptability was negatively associated. Specifically, a one-unit increase in emotional self-control was associated with higher data accuracy ($\beta = 0.260$, 95% CI [0.106, 0.414], $p < 0.001$), data completeness ($\beta = 0.667$, 95% CI [0.272, 1.062], $p < 0.001$), data timeliness ($\beta = 0.546$, 95% CI [0.222, 0.870], $p < 0.001$), and data consistency ($\beta = 0.674$, 95% CI [0.275, 1.073], $p < 0.001$). Adaptability was negatively associated with data accuracy ($\beta = -0.311$, 95% CI [−0.495, −0.127], $p < 0.001$), completeness ($\beta = -0.375$, 95% CI [−0.597, −0.153], $p < 0.001$), timeliness ($\beta = -0.326$, 95% CI [−0.519, −0.133], $p < 0.001$), and consistency ($\beta = -0.461$, 95% CI [−0.734, −0.188], $p < 0.001$). Trustworthiness showed positive associations with outcomes (e.g., data accuracy, $\beta = 0.725$, 95% CI [0.295, 1.155], $p < 0.001$; completeness, $\beta = 0.145$, 95% CI [0.059, 0.231], $p = 0.001$). Models explained 40.4–55.9% of the variance in subdomain scores (R^2 range = 0.404–0.559; all model Fs $p < 0.001$). Consequently, H1 and H3 were supported (ESC and TRS positive, $p<0.001$), while H2 (ADP) was negatively significant.

DISCUSSION

The study's findings indicate that Healthcare workers rated the quality of healthcare data as moderate. This finding suggests that respondents generally consider the quality of health data acceptable but not outstanding. While this reflects a satisfactory level of quality, it also highlights areas for improvement, indicating potential gaps or shortcomings in HDQ. These findings align with those of (Kaloyanova et al., 2021) and (Fraser et al., 2024), who similarly reported moderate HDQ and proposed strategies for improvement.

Furthermore, the study's results reveal that all explanatory variables illustrated in Figure 1 are significantly associated with the quality of healthcare data. Notably, emotional self-control emerged as a key factor in improving HDQ, as evidenced by strong beta coefficients and p-values across all four data quality models. This finding is consistent with the research of Jahanzeb et al. (2023), who argued that while burnout is a prevalent issue among medical professionals, ESC serves as a protective mechanism by enhancing mindfulness, thereby aiding the management of job-related stress and improving task performance. In the words of Siddiqui et al. (2021) Healthcare workers encounter intense emotional challenges daily, as they are often exposed to human suffering and mortality, necessitating a means of achieving balance. Jiménez-Picón et al. (2021) suggested that this balance can be attained through self-control training, they argue that these people need to be trained on ESC techniques, particularly mindfulness, to mitigate emotional exhaustion and improve performance in daily tasks. The present study aligns with this viewpoint by demonstrating that healthcare workers exhibited task mindfulness during data entry. This focused attention not only reduces stress associated with data entry tasks but also ensures data integrity.

The present study revealed a significant negative relationship between adaptability and HDQ, as all regression models produced negative coefficients. This finding contrasts with the view of Kewalramani et al. (2024), who argued that adaptability is a vital competency for coping with the rapid digital transformation in healthcare, including shifts from paper-based systems to electronic health records, and the integration of telemedicine and artificial intelligence. In theory, adaptable healthcare workers should adjust effectively to new technologies and processes, thereby enhancing performance. However, the negative association observed in this study may reflect the disruptive nature of frequent and poorly supported system changes in low-resource settings. Continuous transitions such as those reported by several RRHs shifting from the Afyacare M&E system to Afya-EHMS, or from GoTHOMIS to Afyacare, may create uncertainty, data entry inconsistencies, and temporary declines in data quality. When adaptability is stretched by repeated changes without adequate training or technical support, it can manifest as fatigue, confusion, or inconsistent reporting practices, ultimately lowering HDQ. This suggests that adaptability alone is insufficient to ensure high data quality unless accompanied by stable systems, clear guidelines, and ongoing capacity-building during digital transitions.

The study found that trustworthiness is a strong predictor of healthcare data quality. In Goleman's model of emotional intelligence, trustworthiness is a self-management competency that reflects honesty, integrity, and reliability in one's actions; trustworthy individuals are more likely to follow professional norms and resist unethical shortcuts. In healthcare settings, this disposition translates into behaviours such as accurate and complete record-keeping, timely reporting, correcting detected errors, and protecting patient confidentiality, all of which directly protect HDQ. Where staff feel accountable and act with integrity, under-reporting, fabrication, and careless entry are less likely, improving completeness and accuracy and sustaining organizational trust (Gray & Tejay, 2014; Savitz et al., 2020; Berkowitz, 2022). Thus, the link between trustworthiness and HDQ reflects not only individual moral commitment but also its amplification through workplace accountability mechanisms (supervision, audit trails, and peer checks) that make ethical behaviour observable and rewarded. Embedding EI training that emphasizes trustworthiness alongside institutional policies (codes of conduct, audit logs, and clear sanctions/rewards) should therefore be part of any strategy to strengthen ethical data management and overall HDQ.

Existing global frameworks for health information system quality emphasize that improving data quality requires both technical fixes and institutional strategies that shape worker behaviour and accountability. The WHO Data Quality Assurance / Data Quality Review (DQR) approach and allied guidance (WHO, 2023) recommend routine data quality assessments, capacity building, supervision and feedback loops, and system-level safeguards to identify and correct data problems and to institutionalize good practice.

Complementary frameworks such as MEASURE Evaluation or DQR toolkit explicitly highlight the behavioural and organizational determinants of Routine Health Information System (RHIS) performance such as training, supportive supervision, performance feedback, and clear governance as essential to sustaining improvements in data completeness, accuracy, consistency and timeliness. Together these strategies both reduce technical causes of poor data and create the organizational environment that enables self-regulated behaviors (honesty, careful record-keeping, timely reporting). Embedding emotional-intelligence–oriented training (to build self-regulation), structured on-the-job mentoring, regular audits with transparent feedback, and robust digital audit logs can therefore link individual competencies to organisational accountability and better HQD.

IMPLICATION OF THE STUDY

The findings of this study imply that improving healthcare data quality in Tanzanian regional referral hospitals requires a dual focus on technical and human factors. Since emotional self-control and trustworthiness positively influence data accuracy, completeness, and timeliness, integrating emotional-intelligence training, particularly in self-regulation, ethical conduct, and responsible decision-making, into Continuous Professional Development (CPD) can strengthen workers' capacity to manage stress, avoid documentation errors, and uphold integrity in reporting. The negative relationship between adaptability and data quality also suggests that frequent, poorly supported changes to digital systems may undermine performance; therefore, adaptability must be reinforced through stable transitions, adequate training, and consistent technical support. Overall, the study indicates that targeted, EI-oriented capacity building, combined with stronger accountability mechanisms and well-managed digital reforms, can significantly enhance healthcare data quality and improve health system performance.

CONCLUSION

This study examined the quality of healthcare data in regional referral hospitals in Tanzania, highlighting the critical importance of reliable data for effective service delivery and decision-making. The findings showed that healthcare data quality in most RRHs is generally moderate, indicating substantial room for improvement. Emotional self-control and trustworthiness were each found to support better healthcare data quality: emotional self-control helps reduce impulsive or stress-related documentation errors, thereby improving accuracy and timeliness, while trustworthiness encourages honest, complete, and careful record-keeping, thereby strengthening completeness and consistency and reinforcing accountability mechanisms. In contrast, adaptability demonstrated a negative association with HDQ in this context, likely because frequent, insufficiently supported system changes and limited training contribute to confusion, inconsistent practices, and change fatigue, which undermine data entry and reporting.

Based on these findings, hospital administrations and the Ministry of Health should develop targeted training and mentorship programmes to strengthen healthcare workers' self-regulation, ethical awareness, and data-related decision-making. Incorporating emotional intelligence components—particularly emotional self-control, adaptability, and trustworthiness—into continuous professional development can promote ethical conduct and accountability in data management. Enhancing self-regulation in this way not only improves data integrity but also contributes to stronger overall health system performance by supporting accuracy, timeliness, and responsible use of information in Tanzanian health facilities.

STUDY LIMITATIONS

This study has several limitations. The cross-sectional design precludes causal inference, indicating a need for longitudinal or experimental studies to more rigorously test causal relationships. The use of self-reported composite scores introduces the risk of common-method variance and social desirability bias; therefore, future research should consider combining survey data with facility audits or electronic health record–based quality indicators. The sample, drawn proportionately from eight Tanzanian regional referral hospitals, may not be generalizable to primary care settings, private hospitals, or health systems in other countries. In addition, concurrent health information system transitions (such as AfyaCare, GoTHOMIS, and Afya-EHMS) may have introduced heterogeneity or transient effects, that could partly account for the observed negative association between adaptability and HDQ.

ACKNOWLEDGEMENTS

We would like to express our sincere appreciation to the healthcare workers from the regional referral hospitals who participated in this study. Their willingness to share their time, expertise, and experiences was essential to the successful completion of this work. We are also grateful to the journal editors and anonymous reviewers for their constructive comments and thoughtful feedback, which substantially strengthened the clarity and rigor of the manuscript. Their insights significantly improved the overall quality of this article.

CONFLICT OF INTERESTS

The authors declare no conflict of interest.

AUTHORS' CONTRIBUTIONS

RP, JM, and MM collaboratively developed and designed the study. RP was responsible for data collection, conducting analyses, and writing the initial manuscript. JM and MM provided close supervision and contributed to editing and revising the manuscript. All authors reviewed and approved the final version.

DATA AVAILABILITY

The data underlying this study are not publicly available but may be obtained from the authors upon request.

LIST OF ABBREVIATIONS

ADP—Adaptability
Afya-EHMS—Afya Electronic Hospital Management System
DHIS2—District Health Information Software 2
EHR—Electronic Health Record
ESC—Emotional Self-Control
GoTHOMIS—Government of Tanzania Health Operations Management Information System
HDQ—Healthcare Data Quality
HF—Health Facility
HIS—Health Information System
HMIS—Health Management Information System
HRHIS—Human Resource for Health Information System
M&E—Monitoring and Evaluation
MoH—Ministry of Health
OECD/DAC—Organisation for Economic Co-operation and Development/Development Assistance Committee
RRH—Regional Referral Hospital
RRHs—Regional Referral Hospitals
TRS—Trustworthiness
WASH—Water, Sanitation and Hygiene
WHO—World Health Organization

Vol.8, No 1, 2025
ISSN 2591–6769
eISSN 2953–2663

East African Journal of Applied Health Monitoring and Evaluation

Table 6: Multiple regression results of Self-regulation and Healthcare Data Quality

Independent variable	Data Accuracy			Data Completeness			Data Timeliness			Data Consistency		
	β	SE	95% CI	β	SE	95% CI	β	SE	95% CI	β	SE	95% CI
Emotional self-control (ESC)	0.260	0.078	[0.106, 0.414]	0.667	0.201	[0.272, 1.062]	0.546	0.164	[0.222, 0.870]	0.674	0.203	[0.275, 1.073]
p-value	**$p < 0.001$**			**$p < 0.001$**			**$p < 0.001$**			**$p < 0.001$**		
Adaptability (ADP)	−0.311	0.094	[−0.495, −0.127]	−0.375	0.113	[−0.597, −0.153]	−0.326	0.098	[−0.519, −0.133]	−0.461	0.139	[−0.734, −0.188]
p-value	**$p < 0.001$**			**$p < 0.001$**			**$p < 0.001$**			**$p < 0.001$**		
Trustworthiness (TRS)	0.725	0.218	[0.295, 1.155]	0.145	0.044	[0.059, 0.231]	0.295	0.089	[0.120, 0.470]	0.243	0.073	[0.099, 0.387]
p-value	**$p < 0.001$**			**$p = 0.001$**			**$p < 0.001$**			**$p < 0.001$**		
Model fit	**$R^2 = 0.538$**	$F = 147.78$ $p < 0.001$		**$R^2 = 0.404$**	$F = 86.02$ $p < 0.001$		**$R^2 = 0.559$**	$F = 160.75$, $p < 0.001$		**$R^2 = 0.492$**	$F = 122.78$ $p < 0.001$	

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