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Factors influencing data quality in routine health information systems in Maridi county, South Sudan

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Background: Health system planning and monitoring rely on routine data collection, analysis and utilisation. However, underdeveloped countries need more data for decision-making. South Sudan's data management framework only partially functions, with delayed data collection and inaccurate data. The study examined the factors affecting data quality in Maridi County, South Sudan, aiming to improve resource forecasting and equitable health service delivery.

Objective: The study sought to identify the obstacles and opportunities for improving data quality in health information systems (HIS) in Maridi County, Western Equatoria State, South Sudan.

Methods: A cross-sectional study involving 106 respondents was conducted on 12 healthcare facilities in Maridi County. Statistical Package for the Social Sciences (SPSS) version 25 was used for descriptive, factor and thematic analysis to understand data quality, focussing on behavioural, organisational and technical aspects.

Result: The study revealed that insufficient motivation, negative staff attitudes, excessive workloads, a lack of cooperation, personnel insufficiency, inadequate supervision, feedback and training influenced data quality. These factors were interrelated, with over 50% of variables showing weak to strong correlations. Set of standard indicators correlated with the presence of standard data collection tools ($r = 0.51$). Regular feedback from the County Health Department linked with completeness ($r = 0.63$) and the training of personnel on health management information systems (HMIS) and completeness resulted in moderate association ($r = 0.488$).

Conclusion: Staff motivation, optimal staffing, training, regular feedback, and continuous supervision are crucial for maintaining the appropriate skill set for data quality.

Contribution: Data quality can be achieved when standard tools and human resources are maintained and are evenly distributed.

Keywords: data quality; routine health information system; health facilities; behavioral factors; technical factors; organizational factors.

Introduction

This study explored the interrelated factors that influence data quality in Maridi County, Western Equatoria State, South Sudan. It is conceived on the background that, as a young country, struggling with multiple health system challenges, effective management of health data will improve resource forecasting and equitable health service delivery. The question of data remains a sticking point for donors, the Ministry of Health and implementing partners. In most cases, critical shortages of drugs in many health facilities have been blamed on the absence of consumption reports; hence, the national Ministry of Health of South Sudan was compelled to employ the push method for drug distribution because of inaccurate and delayed reports of morbidity data. Unfortunately, such a system is so problematic that many health facilities struggle to meet set targets.

An effective health system must have the ability to provide health information. Global pledges to enhance health outcomes and systems have resulted in enhanced health management information systems (HMIS), which are used in programme planning and decision-making at all levels of the health system; HMIS generates data on the availability of health services and the general health of the population. All other aspects of the health system's decision-making processes should be guided by timely and high-quality data from an information system (Li, Brodsky & Geers 2018).

The challenges affecting data quality in routine health information systems (HIS) globally are related. In Lumbini province, Nepal, data quality was assessed through completeness and timelines, and the results revealed that overall completeness was found within 98% to 100% while timeliness ranged from 94% to 96% (Sanjel et al. 2024). Similarly, in Myanmar, 30.4% of routine health information system data are of good quality, with data completeness of 30.4% and reporting timeliness of 31.9% (Hlaing & Zaw 2022). In Oyo State, Nigeria, data completeness was 77.3% and data timeliness was 14% (Adejumo 2017). The results further showed that workers, infrastructure, and data collection and management procedures are the primary elements affecting data quality meanwhile in the neighbouring nation of Kenya, an evaluation of human immunodeficiency virus (HIV) data reporting performance reveals that in 2017, timeliness was 83% and completeness was 97%; however in 2018, there was a substantial reduction in timeliness by 11% and completeness by 13% (Ngugi et al. 2020).

According to the data from the District Health Information System version two (DHIS2) in South Sudan for 2021 revealed that completeness was 52.1% and timeliness 46.5%. In the Western Equatoria State of South Sudan, the completeness of data was 52.9%, while timeliness was 51.6%. In Maridi County, completeness of data was 76.1%, with timeliness was 72.8% (SSD DHIS2 2021). The South Sudan Data Quality performance targets are 90.0% for completeness and 85.0% for timeliness (Mathewos 2015).

An assessment conducted in Maridi County from September 12 to September 16, 2022, revealed discrepancies in the reported data for some selected data elements, such as penta3, outpatient consultation, antenatal care (ANC) first and fourth visits, and skilled deliveries. The analysis revealed that there was a prevalence of over-reporting or under-reporting in all health facilities. Because of these patterns, the accuracy, completeness, and timeliness of data in Maridi County have been compromised, leading to a performance that falls short of the national targets.

Although structurally well-developed, the implementation of HMIS in South Sudan remains weak. Limitations to poor quality data at the facility level are driven by multiple factors such as excessive and complex reporting systems, a lack of digital technology, low motivation among healthcare workers, a lack of feedback, low pay, unfavourable working conditions, a lack of training, and a lack of data management skills (Shamba et al. 2021). Poor health data quality results may misdirect decision-making regarding allocating resources and reliable regular healthcare data are necessary for the whole health information system to succeed (Kuyo, Muiruri & Njuguna 2018). Thus, the study aimed to identify the factors affecting data quality in health facilities in Maridi County of South Sudan.

Research questions

1. What are the technical factors affecting the data quality in the routine health information system at all health facilities in Maridi County?
2. What organisational factors influence data quality in the routine health information system at all health facilities in Maridi County?
3. What behavioural factors influence data quality in the routine health information system at all health facilities in Maridi County?

Objectives

General objective

The purpose of this study was to identify factors associated with data quality in the routine health information system in Maridi County, Western Equatoria State, South Sudan.

Specific objectives

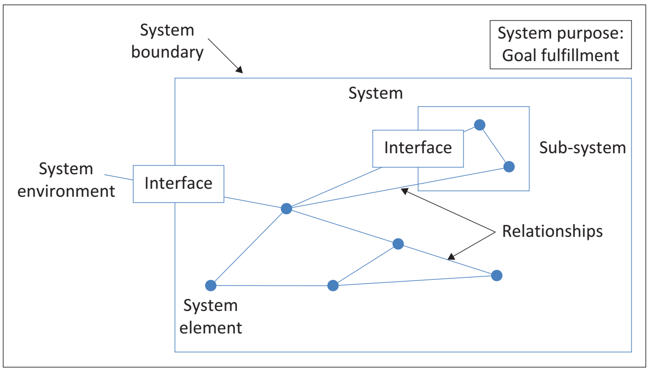
1. To determine the technical factors that affect data quality at all health facilities in Maridi County.
2. To examine the organisational factors that influence data quality at all health facilities in Maridi County.
3. To assess the behavioural factors associated with data quality at all health facilities in Maridi County.

Literature review

Theoretical framework

The systems theory

This study is grounded on the systems theory (Figure 1), which was developed by Ludwig Von Bertalanffy, an Australian biologist, in the 1940s. According to Hooker (2011), this theory posits a framework for examining any collection of components working together to achieve a goal. Systems designers of the HMIS seek to understand the internal and external factors of data quality and the feedback mechanisms involved in communicating results. These feedback loops occur when a system eventually feeds back into itself in a circular fashion because its outputs influence its inputs (Social Work Theories 2023). This theory aligns



Source: Matook, S. & Brown, S.A., 2008, 'Conceptualizing the IT Artifact for MIS Research'. *ICIS 2008 Proceedings* 102. https://aisel.aisnet.org/icis2008/102

FIGURE 1: The systems theory.

effectively with the goals of this study, which aims to investigate the related elements that impact the regular health information system. The study comprises three distinct components: technological, organisational, and behavioural aspects, the interplay of which determines the quality of medical data.

Review of related and empirical literature

Definition and evolution of the health management information systems

The practise of collecting, storing, and utilising health data is not new. In the 1960s, medical and HIS were introduced to facilitate administrative and medical responsibilities. These technologies had very limited scope to optimise financial returns and streamline the process of admitting patients.

The modern-day HMIS evolved from HIS. A concept popularised by Lippeveld as a comprehensive endeavour to gather, analyse, present, and utilise knowledge and data on health to impact policymaking, programme implementation, and research (Epizitone, Moyane & Agbehadji 2023).

The World Health Organization (WHO) refers to the HMIS as the production of information to enable healthcare system decision-makers to identify obstacles and needs, decide on health policies, and allocate limited resources efficiently (WHO 2008).

Performance of the routine health management information systems

A proficient HMIS acquires precise, uniform and pertinent data promptly to facilitate enhanced planning and monitoring of health activities (Meghani et al. 2022). However, despite clear universal guidelines, many countries have performed below country targets. The WHO's global assessment of the HMIS shows that approximately 40% of countries exhibit problematic practices in data quality assurance, and a significant number of countries lack the technological capacity to verify the accuracy of health data. The report also acknowledges that many lower- and middle-class countries depend on outside assistance for technical support and the infrastructure needed to build a strong HMIS.

Relatively low performance (accuracy and completeness 37% and 29%, respectively) was found in evaluating the HMIS in the Indian state of Kerela. The accuracy, comprehensiveness, and punctuality of the procedures in the facilities were 79%, 79%, and 88%, respectively. The level of proficiency in data analysis was 35%. The general degree of assurance in HMIS-related responsibilities was 69.4%, while the level of proficiency was 58%. According to Harikumar (2012), the percentages regarding the management duties of planning, monitoring, training, governance, and quality control at the facility level were 13.2%, 43.4%, 5.3%, 28.4%, and 44.7%, respectively.

The HMIS in most African nations exhibits a significant performance deficiency across various measures. Consequently, the data quality in these countries is persistently inadequate to the extent that Musa et al. (2023) described it as patchwork. This is because of insufficient data availability and frequently poor quality.

The data completeness percentage in Oyo State, Nigeria, was significantly higher at 77.3%. However, this did not align with its accuracy rate, which was a mere 14% (Adejumo 2017). The prevalence of such inconsistencies indicates the presence of systemic problems in their regular HMIS.

In Sudan, the HMIS's performance had increased but then stagnated. The reporting rates through the DHIS2 system increased from 30% in 2016 to 64% in 2020 but have since remained stable at 61.5% recorded in 2018 (WHO 2022). Similar to South Sudan, Sudan has plunged into a civil war that is reversing the advancements made in bolstering its healthcare system.

Rumisha et al. (2020) found that tally sheets were used in just 77.8% of basic health facilities in Tanzania. The instruments in the dispensary, health centre and hospital had availability rates of 91.1%, 82.2%, and 77.8%, respectively. Nevertheless, the metropolitan districts demonstrated a very low tool availability rate of 65%. Occurrences of inaccurately filled out paperwork and insufficient adherence to coding guidelines were observed.

According to Teklegiorgis et al. (2016), the overall data quality in Eastern Ethiopia's departments and/or units was 75.3. The data quality was assessed to be lower compared to the national standard. Health units demonstrated low-quality data compared to hospitals and health centres. Ethiopia is a vast country with decentralised governance structures, which means resources and efforts are not equally distributed.

According to Rumunu et al. (2022), the nationwide implementation of electronic reporting for Early Warning Alert and Response (EWARS) in South Sudan complemented the DHIS2. Compared to a baseline of 54% on both timeliness and completeness of reporting in 2019, the weekly reporting improved to 78% and 90% by week 39 of 2020. Unfortunately, most of these achievements are driven by donor funding, and the lack of government commitment to sustain these improvements means these efforts are not sustainable.

Factors associated with the performance of routine health information system

Looking back at the structure of the routine health information system (RHMIS), three main domains are derived and are popularly used to characterise the factors associated with its performance. These factors, documented in several studies, include technical, behavioural, and organisational factors (Sako et al. 2022). However, if these influencers are unpacked, they yield determinants such as data collection tools, standard indicators, and trained data team; feedback and supervision; motivation, level of knowledge, and attitudes of staff (Nguefack-Tsague et al. 2020).

Technical factors

The technical factors influencing data quality include systems, forms, procedures, techniques for gathering data, data collection tools, standard indicators, and trained staff (Dagnew, Woreta & Shiferaw 2018; Kirimi 2017). According to Wude et al. (2020), data quality is strongly influenced by the availability of trained staff and a standard set of indicators. This was a qualitative study, and it is challenging because of the absence of measurable evidence to gauge the extent to which these factors influence data quality.

A study in Myanmar discovered that multiple reporting, inexperienced personnel and a deficiency of reporting tools are among the technical issues influencing data quality (Hlaing & Zaw 2022).

Another qualitative study in Uganda involving 16 interviews with key informants and a workshop with several stakeholders established a link between the quality of the data and the availability and complexity of reporting tools (Wandera et al. 2019). However, because of the exclusive utilisation of qualitative approaches, it was impossible to assess statistical significance.

Similar technical gaps were found in Kenya; the insufficient competence of staff, the presence of multiple Health Information System tools, and the lack of computers affected data quality in Tharaka Nithi County, Kenya (Mucee et al. 2016).

Organisational factors

According to Glette & Wiig (2021), training personnel involved in health data management, feedback on data quality, supportive supervision, and working conditions for health personnel are examples of organisational factors. Lemma et al. (2020) suggest that capacity-building measures, such as training, data quality assessment and feedback provision to healthcare facilities, aid in raising the standard of the data. Their research attempts to offer a more comprehensive grasp of the utilisation and accuracy of routine health data in middle-class and underdeveloped nations.

A study performed by Moloko and Ramukumba (2022) in Tshwane, South Africa, revealed that training, supportive supervision, and enough human resources influence the quality of data. These findings corroborated the research conducted in North-west Ethiopia by Chekol et al. (2023), which indicated deficient feedback systems, insufficient human resources, and inadequate training as barriers to data quality.

In a cross-sectional study conducted in Kenya, Cheburet & Odhiambo-Otieno (2016) found that support supervision positively impacted data quality. They recommended addressing these organisational aspects to ameliorate the data's quality.

The results of a related study by Shiferaw et al. (2017) in Gojjamzone, North-east Ethiopia, showed that supportive supervision, HMIS training, and providing feedback to the health facilities were significantly associated with data quality. These results align with those of Tulu, Demie and Tessema (2021) in Ethiopia, which found that supportive supervision and HMIS training were significantly associated with data quality.

Behavioural factors

Behavioural factors are elements such as employee competence, skills for assessing the data's quality, solving issues related to tasks involving HIS, competence in HIS activities motivation, and the attitude of staff towards HIS (Chanyalew et al. 2021; Kleiman, Meijer & Janssen 2020).

Glèlè Ahanhanzo et al. (2014) identified worker demotivation and low capability as factors contributing to poor data quality in everyday operations related to HIS. Hlaing & Zaw (2022) suggested that work burdens affect healthcare data quality because human resource shortages can result in work overload. This study supports their theory that the competency of healthcare workers, as measured by their education and involvement at work, is related to the quality of the data.

According to Moses, Kaunda and Ezeron (2019), the efficiency of data collection, processing, and interpretation in South Sudan is impacted by the shortage of competent personnel at healthcare facilities. Inadequately trained people may fail to gather specific or erroneous data, compromising the overall quality of routine health information. Conversely, Haftu et al. (2021) identified the absence of a skilled HMIS focal person and a lack of motivation for HMIS responsibilities as obstacles to ensuring data accuracy in Ethiopia.

Identification of knowledge gap

The knowledge gap was determined by thoroughly examining the existing literature and desk research. In terms of literature, the search for routine health information in South Sudan yielded significant outcomes on Google and Semantic Scholar search engines. However, the majority of these studies were deemed irrelevant or lacked the necessary specificity to be included. Nevertheless, a thorough examination conducted in collaboration with development partners and the County Health Department determined the specific areas of inquiry for acquiring fresh insights. Only one study in Maridi County was relevant to the research issue and specifically focussed on data on family planning contained in the HMIS.

Conceptual framework

A conceptual framework is utilised in research to delineate potential alternatives for illustrating the favoured methodology (Suman 2014). They serve as the framework for constructing the research questions and analysis. The researcher explored and established the definitions of the topics and elucidated the connections between them. The study categorised the variables affecting data quality in RHMIS into two sets of variables: independent variables and dependent variables with an intervening variable (Figure 2).

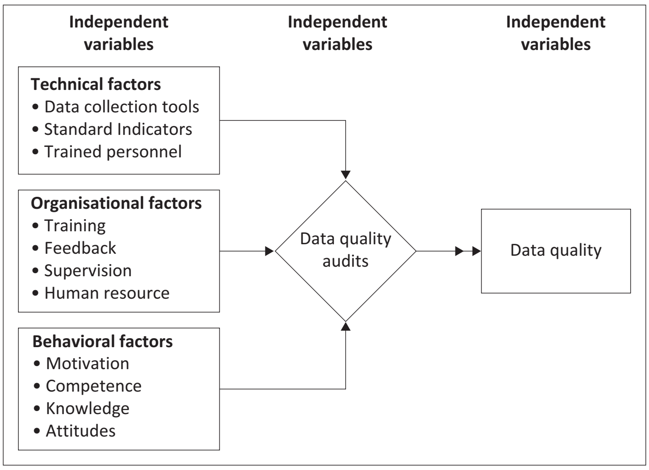


FIGURE 2: Conceptual framework.

The independent variables

An independent variable in a study may be changed to investigate its effects. It stands alone from any other variables (Bhandari 2023). Hence, the fundamental variables constituting this investigation's essence were technological, organisational, and behavioural elements. The variables were derived from the performance of routine information system management (PRISM) paradigm.

The dependent variable

The variable under investigation being measured or evaluated is known as the dependent variable and is influenced by modifying the independent variables, as stated by Cherry (2022). The study assessed data quality as the dependent variable, evaluated based on the timeliness and completeness of the data obtained from health facilities and reported to the County health department. Data quality management is an essential part of the data management process. It involves efforts to enhance data quality, commonly connected to data governance initiatives, which aim to preserve uniform data layout and use within an organisation (Stedman & Vaughan 2022).

Intervening variable

An intervening variable is a scientific concept that describes relationships between independent and dependent variables, adjusting for changes in the dependent variable because of the independent variable (Adeel 2023; Shaw 2018). The researcher posited that a data quality audit was a crucial intervention in this study, aiming to enhance data quality by identifying and rectifying errors and eliminating duplicate records (Figure 2)

Methodology

Research design

A descriptive cross-sectional quantitative and qualitative research approach was used in this study. The quantitative approach gathered information through scheduled interviews using the structured questionnaire, while key informant interviews helped to gather views about factors influencing data quality from the key informants. This approach allows one to get information from many people at once. The researcher preferred the cross-sectional approach because it is fast and cheaper (Kesmodel 2018).

Study area

The research was conducted in health facilities in Maridi County (Figure 3), located in Western Equatoria State. It is surrounded to the west by Ibba County, to the east by Mundri West County and the north by Mvolo County. It also borders the Democratic Republic of the Congo to the south-west, Lakes State (Wulu County) to the north-west and Yei County in Central Equatoria State to the south-east. The population of Maridi County was 82 461 in 2008. In 2020, according to South Sudan Bureau of Statistics 2022, the population of Maridi County had increased to 92 205.

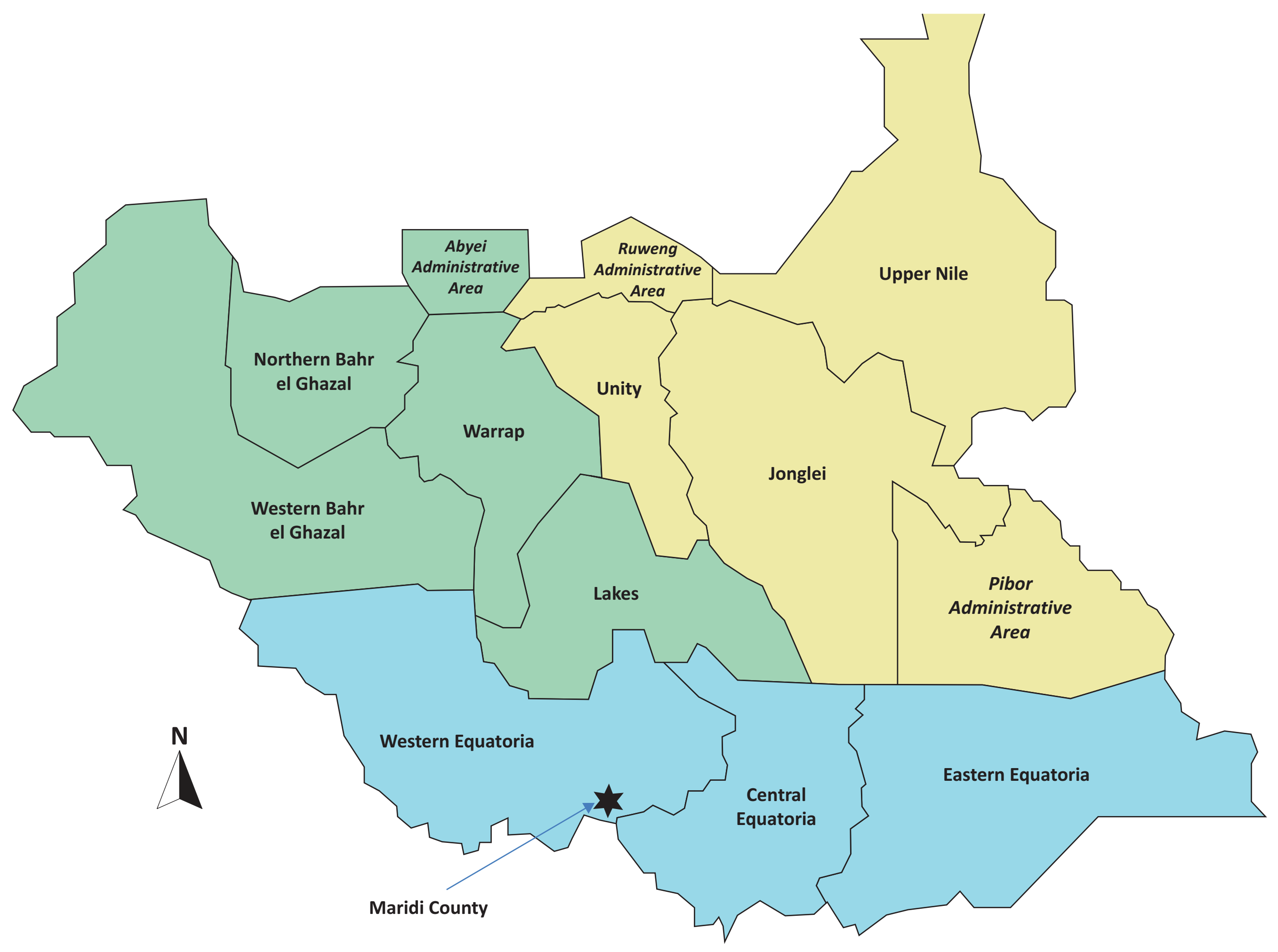
Target population

Broadly, the study focussed on the population of Maridi County, with its diverse characteristics and a total population of 82 461. Specifically, the participants were drawn from 12 healthcare facilities with a total population of 146 health workers. Out of these health workers, the researcher selected participants from the staff with an assigned role in data management, including clinical officers, nurses, midwives, and community health workers. These staff are involved in data collection, including outpatient and inpatient registration (data clerks) and preparation or reviewing of the monthly reports (facility in-charge).

Sampling procedure

Maridi County was selected through convenient sampling because it was easily accessible to the researcher, and because the 12 functional health facilities were manageable, all were considered for the study. Using probability proportional to size, health workers were chosen using simple random sampling for the quantitative study. A piece of paper with the options yes and no was cut into small pieces and folded. Each health professional was asked to choose one at random. Those who chose yes were then eligible for the interview and became research participants; the reason for using this was because of the small sample size in the health facilities, which can be easily managed using this method.

For the qualitative study, 12 key informants who are deemed experienced with the collection of health data and familiarity with the behavioural, organisational, and technical aspects that affect data quality at various levels were selected purposively for in-depth interviews, and the interviewees were identified from multiple healthcare facilities, which consist of one staff per facility and those who took part in the interview were all head of departments and the inclusion criteria were health workers who work with routine health data or those directly involved in the compilation of health facility reports.



Source: Lukaw, Y.S., Evuk, D.O., Abdelrahman, M.M., Mohammed, Y.O., Ochi, E.B., Elraya, I.E. et al., 2016, 'County South Sudan', *International Journal* 4(6), 1087–1092

FIGURE 3: Maridi county.

Sample size

The study includes each of the 12 healthcare facilities, and the Fisher's exact test, a precise formula was utilised to determine the sample size of health workers. This method helps in determining the optimum sample size (see Equation 1):

$$N = \frac{Z^2PQ}{e^2} \quad \text{[Eqn 1]}$$

where:

n is the sample size

Z is the normal standard deviation

p is the target population estimated at 0.5%, and

e is the degree of precision and applying the formulae

Thus, n = (1.96) ^2*(0.5) *(0.5)/0.05^2 = *384*

As there are fewer than 10,000 people, the population correction factor (*nf*) was utilised.

$N = n/(1+n/N)$

$nf = 384/(1+384/146) = 106$

Health workers were selected through probability proportional to the size of each health facility, which was calculated by $nx = x/No*n$. Where nx denotes a sample for a particular facility, the number of healthcare professionals in each facility is x, there are no overall health workers available in the health facility, and the sample size is n (see Table 1).

Data collection tool

With minor modifications, the PRISM version 3.1 was used. The tool was sorted so that questions not relevant to the study were removed and excluded to develop a pertinent tool for the study. It serves as the foundation for the questions, and the remaining questions added value to the tool's validity. It was divided into the following four sections:

The first section contained inquiries into the socio-demographics of the healthcare professionals, such as their age, education, job history, and others. Sections two and three of the questionnaires were to identify behavioural, organisational, and technical elements connected to data quality. The fourth section consists of interviews with the key informants guided by a Key Informant Interview guide to collect qualitative, in-depth information and/or data on the departments' data quality.

Validity

A validity test was conducted using Spearman's rank correlation between the questions to determine the data collection tool's accuracy in measuring the patterns of interest. If Sig. < 0.05, the question and/or instrument is valid, and if Sig. > 0.05, the question and/or instrument is not valid. However, questions were valid and few which failed the test were eliminated or excluded from the analysis.

Reliability

Using Cronbach's alpha statistic, the instrument's reliability was determined whereby if Cronbach's alpha > 0.6, the instrument is reliable; otherwise, it is not if it is < 0.6. According to the data presented in the Table 2, Cronbach's alpha was higher than 0.6, indicating that the tool was reliable.

Data collection procedures

Quantitative data were gathered through face-to-face scheduled interviews with a facility in-charge (data clerks, health departments), which took place at the respective health facilities, printed questionnaires consisting of open and close-ended questions given to respondents after thoroughly explaining and consenting to participate, the respondent filed the questionnaires and submitted to the research assistants. The allocated time for the interview was 45 min, although most of the time spent on each interview varied from 25 min to 35 min.

For qualitative data, face-to-face interviews were performed by the researcher and the interviewee. The participants identified as eligible and agreed to participate were invited for the interview, and primarily, the facility in-charge and heads of department were the critical participants for key informant interviews. The interviewer has a face-to-face discussion with the interviewee using the interview guide, and although each in-depth interview was given a minimum of 30 min, the actual time spent on each interview varied from 20 min to 25 min. All interviews were performed in Local Arabic and English to ensure clarity and to reduce the likelihood that the meaning of the data would be changed through translation. All information or answers for the interviews were written in a notebook by the research assistants for further analysis.

TABLE 1: Population sample distribution.

Serial number	Health facility type	Sample size (*nx*)	Total population (*Nx*)
1	Maridi hospital	43	59
2	Bethsaida PHCC	9	13
3	Don bosco PHCC	12	16
4	Woko PHCC	7	10
5	Olo PHCC	9	12
6	Dukudu olo PHCC	6	8
7	Kozi PHCU	7	9
8	Chochoro PHCU	5	7
9	Mabirindi PHCU	3	4
10	Longhua PHCU	3	4
11	Amaki PHCU	1	2
12	Make 2 PHCU	1	2
-	**Total**	**106**	**146**

PHCC, primary health care centre; PHCU, Primary health care unit.

TABLE 2: Reliability test score.

Cronbach's alpha	Score	Number of items
Reliability statistics	0.694	73

Data analysis

The quantitative data were analysed using the statistical software IBM (Armonk, NY, US). Data on the demographic characteristics of the respondents were compiled using descriptive statistics. Tables and graphs were created using the 'Analyse' field in the SPSS window, and appropriate frequency distribution tables were made. The researcher used the principal component analysis (PCA) to uncover salient correlations between the independent and dependent variables.

Principal component analysis

Principal component analysis is a statistical technique that organises and groups data based on inter-correlations within variables. Originating from Cauchy, it was first developed by Karl Pearson and later by Hotelling (Abdi & Williams 2010; Greenacre et al. 2022; Kovács et al. 2022) (Figure 4).

Correlations between the independent and dependent variables

To examine whether these variables are associated, the independent variables in their groups were correlated with the two data quality variables.

Thematic content analysis

Thematic content analysis (TCA) is a descriptive method for analysing qualitative data, including interview transcripts and other textual materials, focussing on the topic of study (Vaismoradi, Turunen & Bondas 2013). The qualitative data were manually examined by themes, reviewed twice for

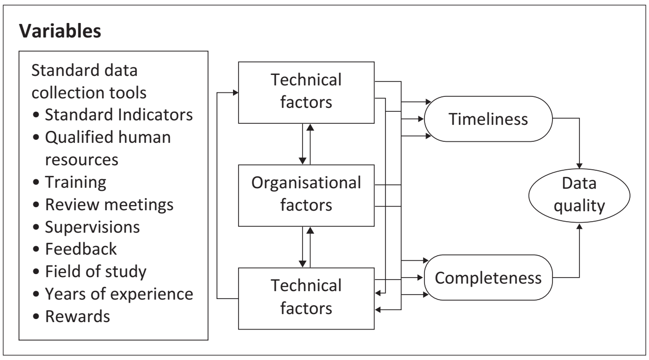


FIGURE 4: Principal component analysis working model.

accuracy and consistency, and then analysed using a thematic framework (Table 3). The data collected were categorised into four subthemes. Data quality was one of the major themes in addition to organisational, technical, and behavioural factors. The detailed notes of the key points were then aligned with the research objectives and coded.

Ethical considerations

The Amref International University approval letter was presented to South Sudan's Ministry of Health, Research, and Ethics Review Board, followed by the County Health Director-Maridi for further approval. Ethical clearance for the research was received with reference number: MOH/RERB/16/22/02/2023. Participants were given consent forms before administering a questionnaire, which was kept anonymous to protect their identities. No names were written on the data collection tools.

Results

Socio-demographic characteristics

The study involved 106 health workers in data management, mostly male (74.5%), possessing certificates and diplomas, and ranging in age from 26 years to 40 years old, predominantly from hospitals and Primary Health Care Centres (PHCCs) (see Table 4).

TABLE 3: Factors influencing data quality in routine health information system.

Behavioural factors	Organisational factors	Technical factors	Data quality practices
• A lack of motivation • Negative attitude towards work • Work overload • A lack of cooperation among staff • Recruiting more staff to the facilities	• Inadequate human resource • Poor supportive supervision • No training of staff on HMIS • A lack of performance feedback to facilities	• A lack of data collection and reporting tools • A lack of trained staff on HMIS	• Data were collected from facility registers and entered into monthly reports • Yes, such as data verification by the person in charge • Crosschecking the reports before submission • Preparing reports jointly with the team to avoid errors • Documenting all information about the patients

HMIS, health management information systems.

TABLE 4: Key socio-demographic characteristics.

Variable	Frequency	%
Age (years)		
less than 25	8	7.5
26–40	63	59.4
41–56	31	29.2
Above 56	4	4.0
Total	106	100.0
Gender		
Female	27	25.5
Male	79	74.5
Total	106	100.0
Level of education attained		
None	7	7.0
Certificate	72	68.0
Diploma	25	24.0
Bachelor's degree	2	2.0
Total	106	100.0

Data quality

Data quality was assessed through the completeness and timeliness of the data submitted to the County Health Department.

Timeliness

South Sudan's standard practice requires monthly reports to be submitted by the fifth of the following month, but only eight health facilities meet this deadline, resulting in 67% performance.

Completeness

The County Health Department is required to receive all health facility reports, but the overall performance fell below the requirements. Nine out of 12 facilities submitted all reports, achieving 75% performance.

Principal Component (PC) analysis results and qualitative analysis findings

Correlation between technical factors and data quality

All correlations between the technical factors and the data quality variables are insignificantly weak. The correlation of the set of standard indicators and timeliness is insignificantly higher among the lower values (r = -0.213, p = 0.253 > 0.05), followed by how often supplied with data collection tools and completeness (r = -0.204, p = 0.262 > 0.05) show weak, insignificant correlations. The correlation between a set of standard indicators and completeness was slightly higher (r = -0.174, p = 0.294 > 0.05) than the correlation between the frequency of supply of data collection tools and timeliness (r = -0.125, p = 0.349 > 0.05). Availability of qualified human resources showed no correlation with timeliness (r = 0.00, p = 0.500 > 0.05) and a much weaker insignificant correlation with completeness (r = 0.11, p = 0.366 > 0.05), respectively (Table 5).

Despite the fact that there are no significant correlation between technical factors and data quality in the quantitative results, the qualitative analysis shows that the technical factors influencing data quality commonly reported by the key informants include a lack of data collection and

TABLE 5: Correlations between technical factors and data quality.

Data quality	How often supplied with data collection tools	A set of standard indicators	Qualified human resources
Correlation matrix			
All the monthly RHIS submitted to the CHD (completeness)	-0.204	-0.174	0.111
p-values	0.262	0.294	0.366
Are monthly RHIS reports submitted on time (timeliness)	-0.125	-0.213	0.000
p-values	0.349	0.253	0.500

*, Correlation is significant at the 0.05 level (2-tailed).
RHIS, routine health information system; CHD, County Health Department.

TABLE 6: Correlation between organisational factors and data quality.

Data quality	Regular feedback from the CHD	Supportive supervisions on data quality	Training on HMIS	Review meetings conducted to discuss data quality
Correlation matrix				
All the monthly RHIS submitted to the CHD (Completeness)	0.683	0.258	0.488	0.522
P-values	0.007	0.209	0.054	0.041
Are monthly RHIS reports submitted on time (Timeliness)	0.120	0.158	0.239	0.426
P-values	0.356	0.312	0.227	0.083

*, Correlation is significant at the 0.05 level (2-tailed).

HMIS, health management information systems; RHIS, routine health information system; CHD, county health department.

TABLE 7: Correlation between behavioural factors and data quality.

Data quality	Respondent education's field of study	Years of work experience	Rewards or motivations
Correlation matrix			
All the monthly RHIS submitted to the CHD (completeness)	-0.113	-0.555	-0.098
p-values	0.363	0.031	0.381
Are monthly RHIS reports submitted on time (timeliness)	-0.277	0.062	0.478
p-values	0.191	0.424	0.058

RHIS, routine health information system; CHD, county health department.

reporting tools in the health facility and a lack of trained persons in the HMIS:

> 'Sometimes, if data collection tools like registers and reporting forms are not supplied regularly, our report is affected because the patients seen during that period are not going to be registered or their information will not be documented.' (Key informant 4, Male, Facility In-charge)

The results show strong significant correlations with regular feedback from the CHD and completeness of reporting (r = 0.683, p = 0.007 < 0.05) and review meetings (r = 0.522, p = 0.041 < 0.05). Moderate insignificant correlations resulted from the training of staff on HMIS and completeness (r = 0.488, p = 0.054 > 0.05), review meetings, and timeliness (r = 0.426, p = 0.083 > 0.05). The associations between training of staff on HMIS and timeliness, data quality supervision and timeliness and completeness, and regular feedback with timeliness were insignificantly weak (r = 0.239, p = 0.227 > 0.05), (r = 0.158, p = 0.312 > 0.05), (r = 0.258, p = 0.209 > 0.05) and (r = 0.120, p = 0.356 > 0.05) (see Table 6).

The findings revealed that regular feedback from the County Health Department to the health facilities staff and review meetings conducted to discuss data quality has a strong significant correlation with data quality.

The qualitative results corroborated the quantitative findings, as most participants reported that organisational factors influencing data quality includes a lack of performance feedback, review meetings conducted on data quality and other factors reported mostly by the key informants are inadequate human resources to perform the HMIS work, poor supportive supervision by the supervisor and inadequate training of staff on health management information system tools:

> 'Only the in charge and data clerk were trained in this facility for the new HMIS tools, but the rest of the department's heads were not trained yet they are required to use these tools.' (Key informant 1, Male, Facility in-charge)

> 'I am the only clinical officer clerking patients in this facility. If the nurse is not present, I occasionally have to do ward rounds and even dispense drugs, which can get tiresome.' (Key informant 5, Male, Facility in-charge)

Behavioural factors and data quality variables correlated to some extent. Years of experience have significant solid correlations with completeness (r = -0.555, p = 0.031 < 0.05), while motivations showed an insignificant moderate relationship with timeliness (r = 0.478, p = 0.058). The rest of the variables showed a weaker insignificant correlation with completeness and timeliness (r = -0.277, p = 0.191 > 0.05) (r = 0.061, p = 0.424 > 0.05) (r = -0.111, p = 0.363 > 0.05), (= -0.09759, p = 0.381 > 0.05) respectively (see Table 7).

Years of work experience have a significant correlation with data quality; however, the rest of the factors have insignificant correlations.

The qualitative analysis shows that the behavioural factors influencing data quality reported during the key informant interviews include; a lack of motivation to staff performing health management information tasks such as incentives, appreciation among others, negative attitude towards work by some of the staff, work overload and lack of cooperation among the staff:

> 'Facility staff sometimes have negative attitudes toward their jobs, and this is largely a result of the low pay some staff members give as an excuse for cultivating before coming to work so that they can support their families.' (Key informant 3, Male, Facility in-charge)

> 'I have a lot of work to do here. We have a lot of registers to fill out, and when it comes to reports, I have to gather all the reports from the wards.' (Key informant 7, Male, Head of Data Clerk)

> 'Lack of cooperation among us sometimes affects the quality of data because some staff disappear in the facility during a period of reporting.' (Key informant 2, Female, Data Clerk)

Discussion

Data quality in Maridi county

The data quality in Maridi County fell short of national requirements for completeness and timeliness, indicating chronic challenges. The digitisation of the RHMIS necessitates Internet connectivity for data transmission, but all health facilities use manual methods, limiting real-time data transmission. This issue is common in African countries, including those investing in health system strengthening, where meeting timeliness and completeness targets is challenging. In Uganda, the national average reporting timeliness and completeness from 2020 to 2021 staggered between 44% and 70%, below the national targets of 90% (Nansikombi et al. 2023). A study in Ethiopia found that health centres in the West Gojjam Zone have a data quality of

74%, below national targets, because of complex HIS and inadequate problem-solving skills (Chekol et al. 2023).

Technical factors and data quality

The results revealed a remarkable depiction of the technical components necessary to operate a regular health information framework effectively. The presence of standardised data-collecting instruments in 62.3% of health facilities and standard indicators in 81.1% indicates a significant disparity reinforced by the small link between the technical aspects and the data quality. Including one technical indication over others does not enhance the system's performance. The qualitative findings further supported the necessity of ensuring consistent dissemination of all tools and technical protocols throughout all healthcare institutions, encompassing competent personnel, standardised data collection instruments, and user-friendly reports and registration forms that are easily comprehensible. The crucial aspect of this element is the necessity for a consistent and sufficient provision of the technical prerequisites to enhance the effectiveness of the regular health management information framework. This study aligns with previous research conducted by Wude et al. (2020) and Wandera et al. (2019), which found that the presence of trained personnel and a standardised set of indicators strongly influence data quality. It is also consistent with the findings of Mucee et al. (2016) in Tharaka Nithi County, which demonstrated that the competence of staff and the use of standardised data collection tools have an impact on data quality. Hlaing & Zaw (2022) also identified multiple reporting, inexperienced personnel, and a need for reporting tools as key factors affecting data quality. The competence of staff play key roles in the use of the HMIS tools because with the availability of a standard set of indicators and reporting tools, if the staff using this tools does not have competence in using the tools then we will not be in position to get quality data from the health facilities and a set of standard indicators availability will also make it easier for the staff to collect the correct data.

Organisational factors and data quality

On a related point, the organisational factors revealed indicators, such as review meetings on data quality and regular feedback to be positively impacting data quality during quantitative analysis and this could be because of the fact that during the review meetings issues related to data quality are addressed and staff are provided with feedback on the type of data they are providing, hence the review meetings and regular feedback play key role in influencing data quality in health facilities. The qualitative findings revealed that more human resources and supportive supervision positively affect data quality. The results align with prior research conducted by Glette & Wiig (2021), which demonstrated that organisational elements such as people training, ongoing feedback on data quality, supportive supervision, and favourable working circumstances for healthcare staff are influential. According to Lemma et al. (2020), implementing capacity-building strategies, such as training, data quality evaluation, and feedback supply to healthcare facilities, can enhance data quality. Moloko and Ramukumba (2022) conducted prior investigations in Tshwane, South Africa, revealing that training, supportive supervision, and adequate human resources impact the data's quality. These findings support the research conducted in Northwest Ethiopia by Chekol et al. (2023) which identified deficient feedback systems, insufficient human resources, and inadequate training as barriers to data quality; aligning with a study conducted in Kenya by Cheburet & Odhiambo-Otieno (2016), which found that support supervision positively impacted the quality of the data. Similarly, a study conducted by Shiferaw et al. (2017) in Gojjamzone, Northeast Ethiopia, demonstrated that supportive supervision, HMIS training, and providing feedback to health facilities were significantly associated with data quality. These results align with the findings of Tulu et al. (2021) in Ethiopia, which revealed that supportive supervision and HMIS training were significantly associated with data quality. Thus, the findings of prior studies align with the current findings of this study, indicating that it is crucial to address these organisational issues to enhance data quality.

Behavioural factors and data quality

The study found that education level and years of experience significantly impact data quality. The qualitative findings revealed that factors such as lack of motivation among staff responsible for health management information tasks, negative attitude towards work, work overload, and lack of cooperation among staff also influence data quality. These findings align with the research conducted by Kleiman et al. (2020) and Chanyalew et al. (2021), which indicate that employee competence, motivation, and attitude towards HIS are behavioural factors that impact data quality. These findings are also consistent with the study by Glèlè Ahanhanzo et al. (2014), which identified worker demotivation and low capability as factors contributing to inadequate data quality. According to Laing et al. (2022), work burdens affect healthcare data quality because of a lack of available personnel, which can lead to excessive workloads. This study corroborates the hypothesis that the proficiency of healthcare professionals, as assessed by their level of education and engagement in their work, is connected to the accuracy of the data. Furthermore, all of these findings align with this study.

In a separate study conducted by Moses et al. (2019) in South Sudan, the effectiveness of gathering, analysing, and understanding data is hindered by a lack of skilled workers in healthcare facilities. More trained individuals may be able to collect precise data or may collect inaccurate data, thus lowering the overall quality of routine health information. In contrast, Haftu et al. (2021) found that the need for a competent HMIS focal person who is motivated to take on HMIS responsibilities hinders data accuracy in Ethiopia. These findings align with this study's findings, suggesting that addressing all behavioural factors will guarantee data quality.

Limitations

1. This study was conducted at rural public healthcare facilities in Maridi County, with a small geographic coverage. It only covered 12 of the 23 health facilities, representing 52% coverage. Readers should know that these results may not directly apply to urban and private healthcare facilities.
2. Because of the generality of the information, a limitation on context-specific literature emerged as a constraint. The researcher expanded the literature search to neighbouring countries to make inferences based on the assumption that these countries share some related characteristics. However, the complex context emerging from different health systems structures means that some readers may question some associations with practices of other countries.

Recommendations

1. The County Health Department will conduct refresher training on HMIS for all staff working in the health facilities; this will enable them to use the data collection and reporting tools efficiently and effectively.
2. The County Health Department should ensure the availability of data collection and reporting tools by ensuring an adequate supply of the tools in all health facilities to avoid issues of stockouts.
3. Addressing the human resource gap by recruiting enough staff in the health facilities, the County Health Department can close the gap and address the challenge of work overload because there will be enough staff to perform their duties in the health facilities.
4. Supportive supervision should be provided by the County Health Department, state ministry of health, and implementing partners. These visits should be frequent to the health facilities and mentorship should be conducted during those visits.
5. Providing regular feedback on data quality to the health facilities by the County Health Department will help them understand their performance status, encouraging them to work hard.
6. It is recommended that the County Health Department should motivate staff in the health facilities, especially those performing HMIS data, through appreciation or incentives.
7. Health facility staff should be encouraged to have a positive attitude towards their work, and cooperation among staff should be encouraged because good attitudes and cooperation among staff contribute significantly to data quality in the health facility. Addressing this can be a huge success as data quality is a concern in the health facility.

Conclusions

The study reveals challenges in data quality in routine HIS in Maridi County, such as inadequate training and lack of reporting tools as technical factors. In contrast, organisational factors include inadequate resources, poor supervision and regular feedback, whereas lack of motivation, work overload, and attitude towards work are behavioural factors. It suggests that several strategies can be used by the County Health Department to achieve high-quality data, which include staff motivation, hiring more health workers to fill human resource gaps, frequent facility supervision, feedback provision, staff training on HMIS, and provision of data collection and reporting tools.

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Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Authors' contributions

L.D.J., conducted the entire research. M.W.N., (PhD) supported the researcher by reviewing, guiding, and providing technical support during the research process. T.D.S.M., (PhD) supported the researcher by reviewing, guiding, and providing technical support during the research process.

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Data availability

Despite the availability of data for this research, there will be some restriction to access based on the data protections laws.

Disclaimer

The views and opinions expressed in this article are those of the authors and are the product of professional research. They do not necessarily reflect the official policy or position of any affiliated institution, funder, agency, or that of the publisher. The authors are responsible for this article's results, findings, and content.

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