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**HEALTH WORKER FACTORS INFLUENCING HEALTH INFORMATION  
UTILIZATION IN JUBA COUNTY, SOUTH SUDAN**

**James Lual Garang Diing and Dr. Lily Masinde, PhD**



## Health Worker Factors Influencing Health Information Utilization in Juba County, South Sudan

**James Lual Garang Diing**

*Corresponding Author, Kenya Methodist University*

**Dr. Lily Masinde, PhD**

*Lecturer, Department of Public Health, Human Nutrition and Dietetics School of Health Sciences, Kenya Methodist University*

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### Abstract:

**Purpose of Study:** This study aimed to examine health worker factors influencing health information utilization in Juba County, South Sudan. It focused on determining how professional training, information management competence, technology skills, access to routine data, and perceived data quality influence the use of health information for decision-making within public health facilities.

**Methodology:** A quantitative descriptive cross-sectional research design was used among 220 health workers from 12 public health facilities in Juba County. Data were collected using structured self-administered questionnaires and analyzed using SPSS version 27. Descriptive statistics, chi-square

tests, and Fisher's exact tests were applied to determine associations between health worker factors and information utilization.

**Findings:** The study achieved a 100% response rate. Training in data utilization ( $p=0.013$ ) and HMIS software ( $p=0.028$ ) significantly influenced health information use. Competence in information management tasks and ease of accessing routine data were strongly associated with utilization ( $p=0.0001$ ). All assessed data quality dimensions, including timeliness, accuracy, reliability, completeness, relevancy, and credibility, significantly predicted information use. Major barriers included lack of motivation and feedback (63.6%), multiple reporting levels (60.9%), excessive data demands, and inadequate training. Findings demonstrate that both individual capacity and organizational support are critical for effective health information utilization.

**Conclusion:** Health information utilization in Juba County depends on skilled health workers, reliable data systems, and supportive organizational practices. Strengthening targeted HMIS training, improving access to routine data, enhancing digital capacity, and establishing regular feedback mechanisms are essential strategies for promoting evidence-based decision-making and improving health system performance.

**Keywords:** *health worker factors, health information utilization, HMIS, data quality, Juba County, South Sudan*

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## 1.0 INTRODUCTION

Effective use of health information is central to well-functioning health systems. When health workers consistently generate, manage, and act on reliable data, health services become more responsive, resources are allocated more effectively, and disease surveillance improves. Conversely, when health information is collected merely as a formality rather than as a tool for decision-making, it fails to serve its core purpose. Across low- and middle-income countries, this failure is widespread, and South Sudan is no exception (Qian et al., 2023). Juba County, the administrative and health service hub of South Sudan, operates a network of 12 public health facilities spanning all service tiers. These facilities are expected to generate routine health data through the District Health Information System 2 (DHIS2) platform and to use that data for planning, monitoring, and decision-making. In practice, health information utilization at the facility level remains low, with data predominantly collected to satisfy national reporting requirements rather than to inform local action (Morris et al., 2024). The gap between data collection and data use is shaped by multiple factors, including data quality, organizational systems, and crucially, the capacities and behaviors of health workers themselves. Health workers are at the frontline of every step in the health information cycle. They record patient data, compile reports, and are expected to review and apply findings to improve the services they deliver. Whether they do this well depends heavily on the training they have received, their level of competence in information management, their access to the tools they need, and the degree of professional support they experience in their workplaces. This study was conducted to examine the specific health worker factors that influence health information utilization in Juba County, with the aim of generating evidence that can directly support targeted interventions to improve data use within the county's health system.

## 2. BACKGROUND OF THE STUDY

Health Management Information Systems (HMIS) are designed to support the collection, management, and use of health data for evidence-based decision-making at all levels of the health system (World Health Organization, 2024). The critical test of any HMIS is not whether data is collected, but whether it is used. In low-income settings across sub-Saharan Africa, this test is frequently failed, with data collection rates often far outpacing data utilization rates (Qian et al., 2023; Farnham et al., 2023). Research across the region consistently identifies health worker factors as among the most significant determinants of whether health information is effectively used. A study in Ketu North Municipality, Ghana, found that health workers who received feedback on their data were nearly four times more likely to use HMIS for decision-making compared to those who did not (Zeng et al., 2025). This finding underscores that the relationship between health workers and their data is not static; it responds to the professional environment in which they work.

In Ethiopia, a study on routine health information system utilization in Gofa Zone found that good information utilization was achieved by 52% of health workers, with data visualization competence, training, and management support identified as key predictors (Doka et al., 2025). A parallel study in Tanzania found that fewer than half of health facilities received district-level

supervisory visits in the three months prior to assessment, and that inadequate supervision was directly associated with poor data utilization (Rumisha et al., 2021). These patterns reflect a broader challenge: HMIS performance depends not only on the existence of digital platforms but on the human capacities and institutional behaviors that surround them. In South Sudan, the challenges are compounded by years of conflict, disrupted health systems, and chronic underinvestment in human resource development. A study in Maridi County, Western Equatoria State, identified inadequate training, limited supervisory visits, absent feedback mechanisms, and low staff motivation as the primary drivers of poor routine health information system performance (Morris et al., 2024). These findings are directly relevant to Juba County, where similar structural and human resource constraints shape day-to-day health information management. The WHO (2023) has highlighted that digital health literacy is a key barrier for health workers in many low- and middle-income countries, with workers lacking both the confidence and the skills to engage meaningfully with digital health tools. This challenge is particularly acute in settings where HMIS training is irregular, supervised practice is rare, and feedback loops are absent. Without addressing these human factors, investments in HMIS technology remain underutilized.

### **3. LITERATURE REVIEW**

#### ***Health Worker Factors and Health Information Utilization***

Health workers are the operational core of any HMIS. They generate the data, maintain the records, compile the reports, and in principle use the information to improve the services they deliver. Whether they perform these roles effectively depends on a constellation of individual and contextual factors: the training they have received, the supervision they experience, their professional competence, their access to tools, and the organizational culture around data use in their workplaces (Rendell et al., 2020). A well-designed information system is only as effective as the people who operate it. Health workers who understand how to interpret data, who feel personally committed to maintaining data quality, and who are supported by their organizations to act on information are essential to making HMIS work in practice (Addo & Agyepong, 2024). Where this understanding and commitment are absent, data tends to be recorded out of habit or obligation rather than with genuine purpose. The result is information that is collected but rarely used. This pattern is well documented across sub-Saharan Africa. A study in Tanzania found that only 60% of health facilities reported using HMIS data, and that inadequate training, lack of supervisory visits, and absence of feedback were the most commonly cited reasons for poor data utilization (Rumisha et al., 2021). A study in Ghana drew similar conclusions, finding that healthcare workers who received regular feedback on their data were significantly more likely to use it for local decision-making (Zeng et al., 2025). These studies collectively suggest that improving health information use requires interventions directed at the human dimensions of HMIS, not just its technological components.

#### ***Professional Training and Its Effect on Health Information Use***

Training is one of the most direct and modifiable factors affecting health information utilization. It builds the knowledge and practical skills that health workers need to collect accurate data, manage records appropriately, and translate information into action. The WHO (2023) has emphasized that digital health literacy, meaning the ability to engage confidently and competently with digital health tools, is a critical capability that must be actively developed through structured training programs. Evidence from across the region consistently shows that health workers who receive training in HMIS-specific skills are more likely to use health information for planning and decision-making. A cross-sectional study in Gofa Zone, Ethiopia, found that training was among the strongest predictors of health information system utilization, alongside management support and the provision of structured feedback (Doka et al., 2025). A study in Tanzania reported that more than 40% of facility-level health workers had received no HMIS training in the 12 months before the assessment, and that this gap was directly associated with poor data management practices (Rumisha et al., 2021). However, the type and content of training matters as much as its presence or absence. Research suggests that training specifically focused on data utilization, meaning not just how to collect and enter data but how to interpret it and apply it to decisions, has a stronger effect on actual information use than general data collection training (Qian et al., 2023). This distinction is important for designing effective capacity-building programs in settings such as Juba County, where training opportunities are limited and must be used strategically.

### ***Competence in Information Management***

Beyond formal training, the competence that health workers develop over time in managing health information has a direct bearing on whether that information is used. Competence encompasses a range of skills: the ability to calculate basic health indicators, prepare visual summaries of data, identify trends and gaps, interpret findings in the context of local service delivery, and present information to managers and colleagues in a way that supports decisions. Research in low- and middle-income countries has consistently shown that when health workers are not confident in their data management skills, they are less likely to engage with information beyond the minimum required for reporting (Owoyemi et al., 2022). A study reviewing digital health implementation in sub-Saharan Africa found that limited technical capacity among health workers, particularly in rural settings, was one of the most significant barriers to effective health information use (Owoyemi et al., 2022). These workers often possess basic data entry skills but lack the analytical capabilities needed to make health information actionable. Access to data is an equally important dimension of competence. Workers who can easily retrieve historical data, view trends, and compare their facility's performance against benchmarks are far better positioned to use information effectively. Where data access is limited by poor system design, inadequate infrastructure, or administrative restrictions, even highly competent workers cannot use information to its full potential (Addo & Agyepong, 2024).

### ***Information Technology Capacity and Computer Use***

The shift to digital HMIS platforms such as DHIS2 has created new demands on health workers' technological skills. Workers who use computers regularly and who are comfortable with

digital tools are generally better able to perform the analytical functions that support health information use. Conversely, workers with limited digital experience may find even basic data entry tasks challenging, and are less likely to engage with the more advanced analytical features of digital platforms. Research across sub-Saharan Africa has identified poor internet connectivity, inadequate computer availability, and limited digital competence as persistent barriers to HMIS utilization (Addo & Agyepong, 2024; Owoyemi et al., 2022). These barriers are not simply technical problems; they are human and organizational ones, requiring sustained investment in both infrastructure and workforce development. The WHO (2023) has called for digital health literacy programs specifically targeted at health workers in low-resource settings, recognizing that digital competence cannot be assumed and must be systematically built. The use of manual versus digital data management systems also shapes health workers' relationship with information. Facilities that rely primarily on paper-based recording often accumulate large volumes of data that are difficult to aggregate, analyze, or share, reducing the practical usability of the information generated (Farnham et al., 2023). Transitioning workers from manual to digital systems requires training, organizational support, and sustained follow-up to reinforce new practices.

#### **4.0 RESEARCH METHODOLOGY**

This study employed a quantitative descriptive cross-sectional research design to examine health worker factors influencing health information utilization among health workers in Juba County, South Sudan. The design enabled the collection of data at a single point in time and facilitated statistical analysis of relationships between variables. The study was conducted in 12 purposively selected public health facilities representing all levels of the county health system. The target population comprised 423 health workers involved in generating, managing, or using health information within the HMIS framework. Using the finite population correction formula and a 10% non-response adjustment, a final sample size of 220 participants was obtained. Multistage sampling, including purposive, proportional stratified, and simple random sampling techniques, was applied to ensure representativeness. Data were collected using structured self-administered questionnaires with closed-ended Likert-scale items. Additional facility observations assessed HMIS infrastructure availability. Ethical approval, informed consent, confidentiality, and voluntary participation were observed throughout the study. Data were coded, entered, cleaned, and analyzed using SPSS version 27. The findings were presented in tables and figures.

#### **5.0 RESEARCH FINDINGS AND DISCUSSION**

##### **Response Rate**

Two hundred and twenty (220) structured questionnaires were distributed to sampled health workers across the 12 selected health facilities in Juba County. The questionnaires were administered to health workers including facility in-charges, midwives, pharmacists, and health information officers. All 220 distributed questionnaires were completed and returned, yielding a 100% response rate, as presented in Table 4.1. According to Brick and Williams (2013), a

low response rate risks introducing bias in study findings. The high response rate achieved in this study therefore strengthens the reliability and internal validity of the results. Data were analyzed using descriptive statistics including means, standard deviations, frequencies, and percentages, as well as Pearson's chi-square and Fisher's exact tests. A significance level of  $\alpha = 0.05$  was applied throughout.

**Table 1: Response Rate**

| Response      | Frequency  | Percentage (%) |
|---------------|------------|----------------|
| Responded     | 220        | 100.0          |
| Not Responded | 0          | 0.0            |
| <b>Total</b>  | <b>220</b> | <b>100.0</b>   |

Source: Field Survey (2025).

## Health Worker Factors Influencing the Use of Health Information

### Continuous Professional Training

The study examined the extent to which health workers had received continuous training in areas associated with routine health data management and use. The training areas assessed included HMIS, data collection, data analysis, data utilization, data management, and HMIS software. Findings showed that 68.2% of respondents had received training in data collection, 63.6% in data analysis, 53.2% in data management, and 52.7% in data utilization. A chi-square test and Fisher's exact test were conducted to determine whether training in each area was significantly associated with health information utilization. The results, presented in Table 4.2, showed that training specifically focused on data utilization had a statistically significant association with actual health information use ( $p = 0.013$ ). Training in HMIS software was also significantly associated with utilization ( $p = 0.028$ ). In contrast, training in data collection ( $p = 0.572$ ), data analysis ( $p = 0.806$ ), and data management ( $p = 0.206$ ) did not show statistically significant associations with health information utilization.

These findings are consistent with evidence from other low-resource settings. A study in Gofa Zone, Ethiopia, demonstrated that training focused specifically on information use for decision-making was a stronger predictor of HMIS utilization than general data management training (Doka et al., 2025). Similarly, a systematic review of factors influencing data use in low- and middle-income countries found that governance, feedback structures, and training in data application were the most influential determinants of whether health information was acted upon (Mboera et al., 2021). The implication for Juba County is that capacity-building investments should prioritize training in data interpretation and application, not just data entry or collection procedures.

**Table 2: Continuous Professional Training and Association with Health Information Utilization**

| Variable               | Never    | Rarely     | Sometimes  | Always     | Significance |
|------------------------|----------|------------|------------|------------|--------------|
| HMIS – Trained (Yes)   | 3 (2.7%) | 11 (9.9%)  | 36 (32.4%) | 61 (55.0%) | p = 0.059    |
| HMIS – Trained (No)    | 4 (3.7%) | 24 (22.0%) | 36 (33.0%) | 45 (41.3%) |              |
| Data Collection – Yes  | 4 (2.7%) | 21 (14.0%) | 51 (34.0%) | 74 (49.3%) | p = 0.572    |
| Data Collection – No   | 3 (4.3%) | 14 (20.0%) | 21 (30.0%) | 32 (45.7%) |              |
| Data Analysis – Yes    | 4 (2.9%) | 20 (14.3%) | 47 (33.6%) | 69 (49.3%) | p = 0.806    |
| Data Analysis – No     | 3 (3.8%) | 15 (18.8%) | 25 (31.3%) | 37 (46.3%) |              |
| Data Utilization – Yes | 2 (1.7%) | 12 (10.3%) | 36 (31.0%) | 66 (56.9%) | p = 0.013*   |
| Data Utilization – No  | 5 (4.8%) | 23 (22.1%) | 36 (34.6%) | 40 (38.5%) |              |
| Data Management – Yes  | 3 (2.6%) | 14 (12.9%) | 37 (31.6%) | 63 (53.9%) | p = 0.206    |
| Data Management – No   | 4 (3.9%) | 21 (20.4%) | 35 (34.0%) | 43 (41.8%) |              |
| HMIS Software – Yes    | 3 (3.1%) | 11 (11.5%) | 25 (26.0%) | 57 (59.4%) | p = 0.028*   |
| HMIS Software – No     | 4 (3.2%) | 24 (19.4%) | 47 (37.9%) | 49 (39.5%) |              |

*Note. \* p < 0.05 indicates statistical significance.*

*Source: Field Survey (2025).*

### Competence in Information Management Tasks

Slightly more than half of respondents (52.3%) rated their competence in health information management tasks as moderate. A further 32.7% considered their competence high, 8.6% rated it very high, and 6.4% reported low competence. Additionally, 34.5% of participants reported experiencing difficulties accessing routine data whenever it was needed. The findings presented in Table 4.3 revealed a statistically significant association between competence level in information management tasks and health information utilization ( $p = 0.0001$ ). Access to routine data was equally strongly associated with utilization ( $p = 0.0001$ ). Workers who reported easy access to routine data used it consistently more often: 58.3% of those with easy

access always used health information, compared to only 28.9% of those who experienced access difficulties.

These findings support the conclusions of several comparable studies. Addo and Agyepong (2024), in a study evaluating HMIS implementation in Ghana, found that inadequate training and limited technical competence were among the most persistent barriers to effective health information use, even when digital platforms were nominally in place. The study found that many health workers possessed basic data entry skills but lacked the analytical capabilities needed to make information actionable. A study in Ethiopia similarly demonstrated that data visualization competence was one of the strongest predictors of routine health information system utilization (Tafere et al., 2026). These findings collectively underscore that competence in information management must be actively built and continuously reinforced, rather than assumed.

**Table 3: Competence in Information Management Tasks and Association with Health Information Utilization**

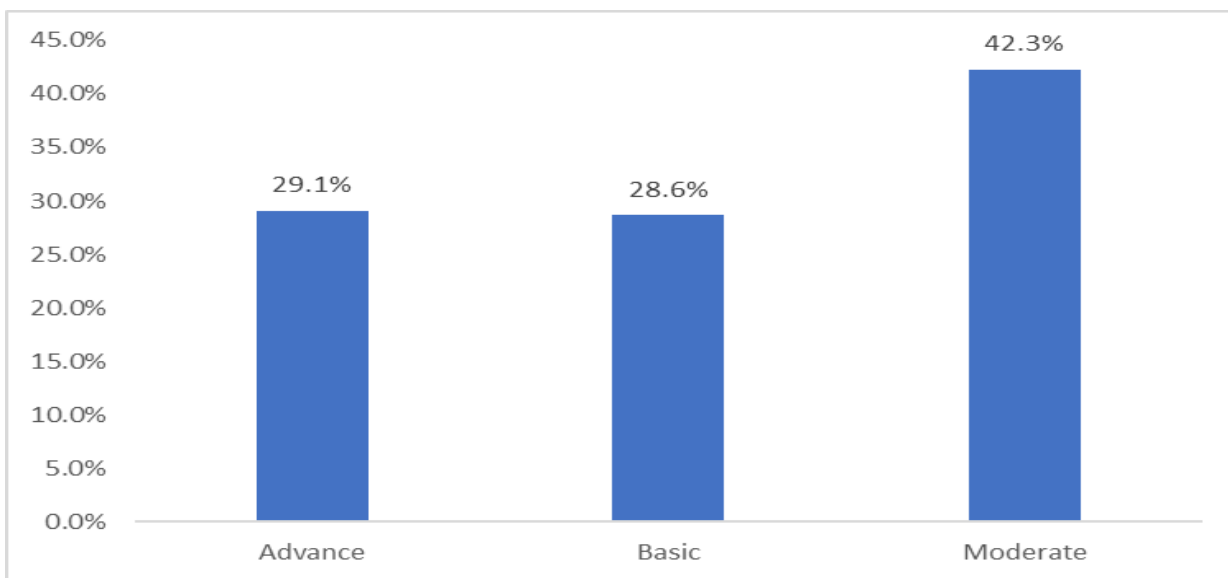
| Variable                         | Never    | Rarely     | Sometimes  | Always     | Fisher Exact |
|----------------------------------|----------|------------|------------|------------|--------------|
| Competence Level: Low            | 4 (1.8%) | 3 (1.4%)   | 3 (1.4%)   | 4 (1.8%)   | p = 0.0001*  |
| Competence Level: High           | 0 (0.0%) | 8 (3.6%)   | 19 (8.6%)  | 45 (20.5%) |              |
| Competence Level: Moderate       | 3 (1.4%) | 23 (10.5%) | 45 (20.5%) | 44 (20.0%) |              |
| Competence Level: Very High      | 0 (0.0%) | 1 (0.5%)   | 5 (2.3%)   | 13 (5.9%)  |              |
| Easy Access to Routine Data: Yes | 4 (2.8%) | 15 (10.4%) | 41 (28.5%) | 84 (58.3%) | p = 0.0001*  |
| Easy Access to Routine Data: No  | 3 (3.9%) | 20 (26.3%) | 31 (40.8%) | 22 (28.9%) |              |

**Note.** \* p < 0.001 indicates statistical significance.

**Source:** Field Survey (2025).

### Information Technology Skills

*Figure 1: Information technology Acquired*

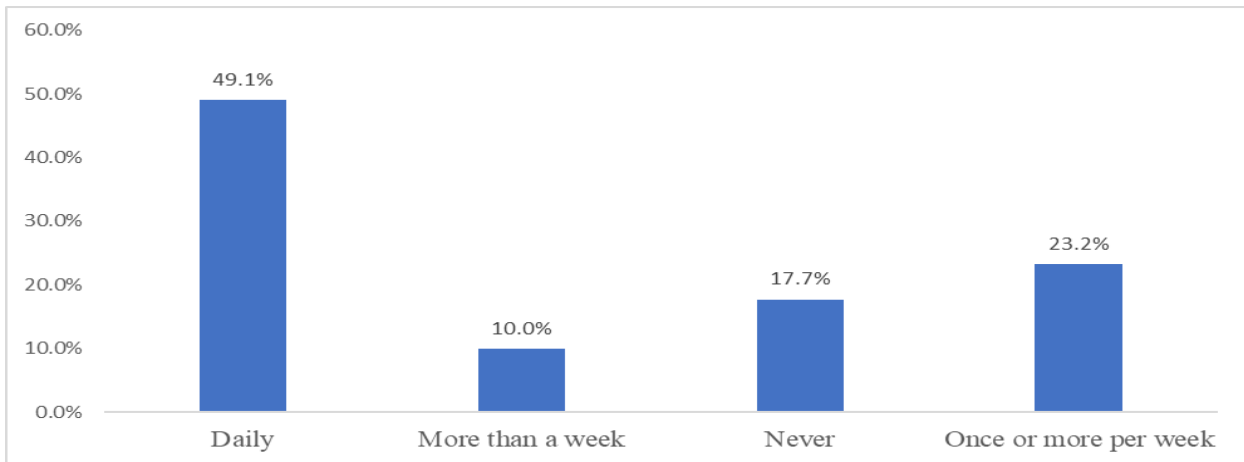


**Source: Field Survey (2025).**

The findings revealed that 42.3% of respondents possessed moderate information technology (IT) skills, while 28.6% had basic knowledge and 29.1% demonstrated advanced skills. Despite this variation, competence in IT was broadly recognized by respondents as important for effective health information system use. When asked to rate their ability to perform specific data-related tasks, including calculating percentages, preparing graphs, interpreting data, identifying service gaps, and setting targets, 50.9% rated themselves as competent. However, many workers reported lower confidence in interpreting findings and applying them to decision-making processes, reflecting a gap between technical and analytical skills. These findings align with the WHO's (2023) assessment that digital health literacy remains a significant barrier for health workers in low-resource settings, where many workers can operate digital tools at a basic level but struggle with higher-order analytical tasks. The Frontiers in Digital Health review by Okeke et al. (2025) similarly identified limited IT competence, combined with poor connectivity and power supply, as key barriers to digital health system effectiveness in African primary care settings.

### **Frequency of Computer Use**

*Figure 2: Frequency of Computer Use*

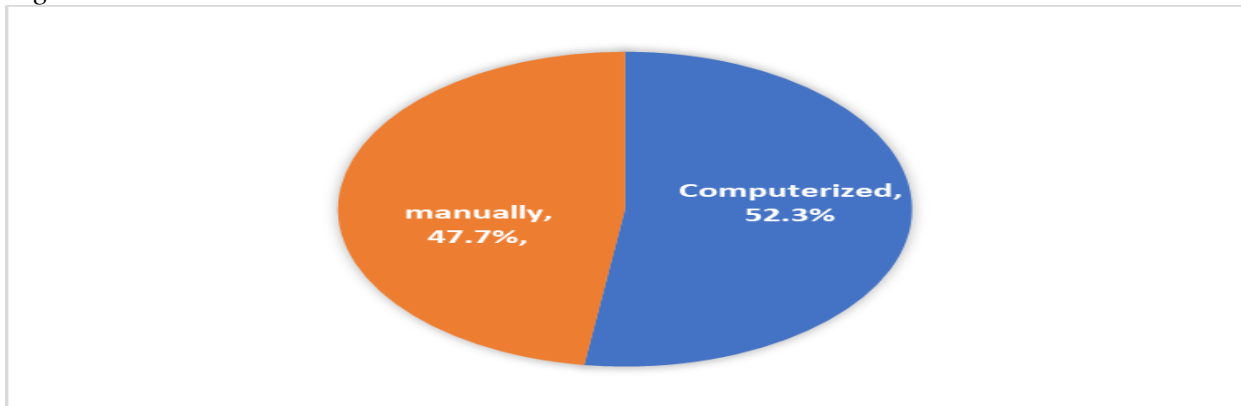


**Source: Field Survey (2025).**

The results showed that 49.1% of health workers used computers daily as part of their routine responsibilities. An additional 10.0% used computers several times per week, while 17.7% reported no computer use within their work environment. The remaining respondents fell between these categories. These patterns reflect the uneven availability of digital infrastructure across facilities of different types and sizes. High-volume facilities such as Juba Teaching Hospital had greater computer availability, while smaller primary health care centers had limited or no digital equipment. The relationship between regular computer use and health information utilization is well established in the literature. Kumasenu et al. (2023) found that poor computer network availability, unstable power supply, and infrequent system access were major deterrents to health information system utilization in Ghana, reinforcing the view that technology access and user behavior are inseparable from one another.

### **Routine Data Collection Methods**

*Figure 3: Routine Data Collection methods*

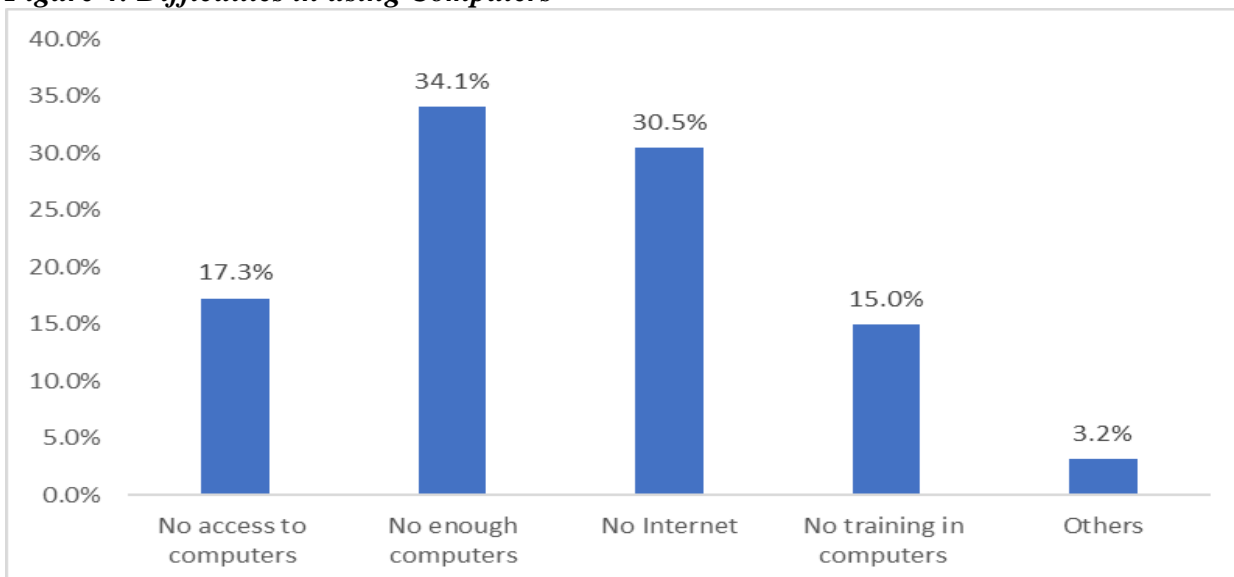


**Source: Field Survey (2025).**

The study found that 52.3% of respondents used computers for data analysis and storage, while 47.7% continued to rely on manual systems to manage routine health information. The continued prevalence of manual recording reflects the limited digital infrastructure across several facilities in Juba County, as well as habitual reliance on paper-based tools that predate the rollout of DHIS2. The persistence of parallel manual and digital systems creates inefficiencies and increases the risk of data inconsistencies. Wang et al. (2023) noted that the co-existence of paper and digital recording systems in low-income settings was one of the most commonly identified sources of data completeness and accuracy problems, as information recorded manually is not always transferred to digital platforms. This finding is directly relevant to Juba County, where ensuring data quality and utilization requires bridging these parallel systems through deliberate transition strategies.

### Barriers to Computer Use in Health Data Management

*Figure 4: Difficulties in using Computers*



**Source: Field Survey (2025).**

Health workers identified several challenges that limited their ability to use computers effectively for data management. The most commonly reported barriers were insufficient computer availability (34.1%) and poor internet connectivity (30.5%), both of which restricted data analysis and reporting capacity. Despite these obstacles, 55.9% of respondents reported using the internet daily for information sharing and communication, suggesting that personal or mobile access partially compensates for institutional shortfalls. However, such informal solutions do not substitute for structured facility-level HMIS infrastructure. These findings closely mirror those reported in comparable settings. Addo and Agyepong (2024) identified inadequate computer networks, unreliable internet, and power interruptions as the dominant

infrastructure barriers to HMIS use in Ghana, noting that these were problems not of digital platform design but of the physical and organizational environment in which platforms were deployed. For Juba County, addressing these barriers requires investments in hardware, connectivity, and power reliability alongside any software or training initiatives.

### Quality of Routine Health Data

The study examined health workers' perceptions of the quality of routine health data across six dimensions: timeliness, accuracy, reliability, completeness, relevancy, and credibility. The majority of respondents rated data quality as good or fair across most dimensions. All six quality dimensions showed statistically significant associations with health information utilization, as presented in Table 4. Timeliness of data was significantly associated with health information use ( $\chi^2 = 18.47$ ,  $df = 9$ ,  $p = 0.030$ ). Among respondents who rated data timeliness as very good, 63.3% reported always using health information, compared to only 25.0% of those rating timeliness as poor. Accuracy showed the strongest statistical association ( $\chi^2 = 26.29$ ,  $df = 9$ ,  $p = 0.002$ ), with 56.5% of those rating accuracy as very good reporting always using health information. Reliability ( $p = 0.008$ ), completeness ( $p = 0.048$ ), relevancy ( $p = 0.009$ ), and credibility ( $p = 0.007$ ) all demonstrated statistically significant associations with utilization. These findings are consistent with the broader evidence base. Rendell et al. (2020) identified data quality as one of three core categories of factors influencing health information use in low- and middle-income countries, noting that workers are reluctant to use information they perceive as unreliable or incomplete. Morris et al. (2024) found that in Maridi County, South Sudan, over-reporting and under-reporting, alongside inconsistencies between facility registers and submitted reports, were pervasive and directly undermined the usefulness of HMIS data. The Juba County findings reinforce the conclusion that data quality and data use are inseparable: improving one requires simultaneously addressing the other.

**Table 4: Quality of Routine Health Data and Association with Health Information Utilization**

| Variable   | Rating    | Never     | Rarely     | Sometimes  | Always     | Significance                                |
|------------|-----------|-----------|------------|------------|------------|---|
| Timeliness | Very Good | 2 (6.7%)  | 2 (6.7%)   | 7 (25.0%)  | 19 (63.3%) | $\chi^2=18.47$ ;<br>$df=9$ ;<br>$p=0.030^*$ |
|            | Good      | 2 (1.4%)  | 21 (15.1%) | 45 (32.3%) | 71 (51.0%) |   |
|            | Bad       | 0 (0.0%)  | 5 (21.7%)  | 9 (39.1%)  | 9 (39.1%)  |   |
|            | Poor      | 3 (10.7%) | 7 (25.0%)  | 11 (39.3%) | 7 (25.0%)  |   |
| Accuracy   | Very Good | 1 (2.2%)  | 5 (10.9%)  | 14 (30.4%) | 26 (56.5%) | $\chi^2=26.29$ ;<br>$df=9$ ;<br>$p=0.002^*$ |

|              |           |              |               |            |               |                                       |
|--------------|-----------|--------------|---------------|------------|---------------|---------------------------------------|
|              | Good      | 2<br>(1.5%)  | 17<br>(12.6%) | 44 (32.6%) | 72<br>(53.3%) |                                       |
|              | Bad       | 2<br>(7.7%)  | 9<br>(34.6%)  | 10 (38.5%) | 5<br>(19.2%)  |                                       |
|              | Poor      | 2<br>(15.4%) | 4<br>(30.8%)  | 4 (30.8%)  | 3<br>(23.1%)  |                                       |
| Reliability  | Very Good | 1<br>(2.4%)  | 4<br>(9.5%)   | 9 (21.4%)  | 28<br>(66.7%) | $\chi^2=22.29$ ;<br>df=9;<br>p=0.008* |
|              | Good      | 5<br>(3.5%)  | 19<br>(13.2%) | 49 (34.0%) | 71<br>(49.3%) |                                       |
|              | Bad       | 0<br>(0.0%)  | 7<br>(35.0%)  | 9 (45.0%)  | 4<br>(20.0%)  |                                       |
|              | Poor      | 1<br>(7.1%)  | 5<br>(35.7%)  | 5 (35.7%)  | 3<br>(21.4%)  |                                       |
| Completeness | Very Good | 2<br>(4.2%)  | 8<br>(16.7%)  | 12 (25.0%) | 26<br>(54.2%) | $\chi^2=17.08$ ;<br>df=9;<br>p=0.048* |
|              | Good      | 2<br>(1.6%)  | 16<br>(12.7%) | 41 (32.5%) | 67<br>(53.2%) |                                       |
|              | Bad       | 1<br>(3.2%)  | 7<br>(21.9%)  | 13 (40.6%) | 11<br>(34.4%) |                                       |
|              | Poor      | 2<br>(14.3%) | 4<br>(28.6%)  | 6 (42.9%)  | 2<br>(14.3%)  |                                       |
| Relevancy    | Very Good | 1<br>(2.3%)  | 5<br>(11.4%)  | 11 (25.0%) | 27<br>(61.4%) | $\chi^2=21.96$ ;<br>df=9;<br>p=0.009* |
|              | Good      | 3<br>(2.1%)  | 18<br>(12.8%) | 48 (34.0%) | 72<br>(51.1%) |                                       |
|              | Bad       | 2<br>(8.0%)  | 8<br>(32.0%)  | 10 (40.0%) | 5<br>(20.0%)  |                                       |
|              | Poor      | 1<br>(10.0%) | 4<br>(40.0%)  | 3 (30.0%)  | 2<br>(20.0%)  |                                       |
| Credibility  | Very Good | 2<br>(4.3%)  | 6<br>(12.8%)  | 10 (21.3%) | 29<br>(61.7%) | $\chi^2=22.86$ ;<br>df=9;<br>p=0.007* |
|              | Good      | 3<br>(2.4%)  | 19<br>(15.1%) | 37 (29.4%) | 67<br>(53.2%) |                                       |
|              | Bad       | 0<br>(0.0%)  | 6<br>(26.1%)  | 12 (52.2%) | 5<br>(21.7%)  |                                       |

|  |      |             |              |            |              |  |
|--|------|-------------|--------------|------------|--------------|--|
|  | Poor | 2<br>(8.3%) | 4<br>(16.7%) | 13 (54.2%) | 5<br>(20.8%) |  |
|--|------|-------------|--------------|------------|--------------|--|

*Note. \* p < 0.05 indicates statistical significance.*

*Source: Field Survey (2025).*

### Challenges of Routine Data Use

Respondents identified a range of challenges that hindered their use of routine health data. The most frequently cited challenge was lack of motivation and feedback to initiate corrective action (63.6%), followed by multiple reporting levels (60.9%), excessive volume of data requested (50.9%), inadequate training in data management (47.7%), insufficient time due to reporting burdens (47.3%), lack of incentives (45.9%), work overload (44.5%), and indicator systems with new additions but no deletions (44.5%). Fewer respondents cited limited understanding of the benefits of data use (43.2%) or duplication of reporting (40.9%) as challenges. Table 4.5 presents the complete distribution of challenges identified.

The prominence of motivation and feedback as the most reported challenge is particularly notable. Zeng et al. (2025) found in Ghana that health workers who received feedback on their data were nearly four times more likely to use it for decision-making than those who received no feedback. Rumisha et al. (2021) similarly found in Tanzania that fewer than 40% of districts routinely analyzed HMIS data, and that inadequate supervision and absence of feedback were the primary explanations. These findings align with a broader body of evidence demonstrating that feedback mechanisms are among the most cost-effective strategies for improving data quality and use in health systems (Rendell et al., 2020).

Multiple reporting levels and excessive data volume were also prominent challenges, suggesting that the reporting burden itself discourages meaningful engagement with data. When health workers spend large portions of their time completing forms for multiple reporting channels, they have less time for the analysis and reflection that data use requires. This challenge is compounded in Juba County by the parallel reporting systems maintained by approximately 25% of non-governmental organizations, which add to health workers' reporting obligations without contributing coherently to the national HMIS (Ministry of Health, South Sudan, 2022).

**Table 5: Challenges of Routine Data Use Reported by Health Workers**

| Challenge   | Response | Frequency | Percent (%) |
|---|----------|-----------|-------------|
| Poorly trained in data management                     | Yes      | 105       | 47.7        |
|   | No       | 115       | 52.3        |
| Lack of motivation and feedback for corrective action | Yes      | 140       | 63.6        |
|   | No       | 80        | 36.4        |

|   |     |     |      |
|---|-----|-----|------|
| Insufficient time due to reporting demands        | Yes | 104 | 47.3 |
|   | No  | 116 | 52.7 |
| Excessive workload and understaffing              | Yes | 98  | 44.5 |
|   | No  | 122 | 55.5 |
| Lack of incentives                                | Yes | 101 | 45.9 |
|   | No  | 119 | 54.1 |
| Limited understanding of the value of data use    | Yes | 95  | 43.2 |
|   | No  | 125 | 52.6 |
| Many reporting levels                             | Yes | 134 | 60.9 |
|   | No  | 86  | 39.1 |
| Inadequate guidelines                             | Yes | 56  | 25.4 |
|   | No  | 164 | 74.5 |
| Excessive data volume requested                   | Yes | 112 | 50.9 |
|   | No  | 108 | 49.1 |
| Duplication of reporting                          | Yes | 90  | 40.9 |
|   | No  | 130 | 59.1 |
| Indicators not regularly reviewed                 | Yes | 82  | 37.3 |
|   | No  | 138 | 62.7 |
| New indicator additions without removing old ones | Yes | 98  | 44.5 |
|   | No  | 122 | 55.5 |

Source: Field Survey (2025).

## 6.0 SUMMARY OF FINDINGS

This study examined the health worker factors influencing health information utilization in Juba County, South Sudan, among 220 health workers drawn from 12 public health facilities. A 100% response rate was achieved. The findings are summarized as follows. Professional training was significantly associated with health information use, but only when the training was specifically focused on data utilization ( $p = 0.013$ ) and HMIS software use ( $p = 0.028$ ). General training in data collection, analysis, or management did not show statistically significant associations with utilization. This finding suggests that the content and focus of training matter more than the volume of training received. Competence in information management tasks was strongly associated with health information utilization ( $p = 0.0001$ ). Workers who rated their competence as high or very high used health information more consistently. Ease of access to routine data was equally predictive ( $p = 0.0001$ ), with workers who could easily retrieve data being significantly more likely to use it regularly.

Information technology skills were moderately distributed across the workforce, with 42.3% reporting moderate IT competence, 29.1% advanced, and 28.6% basic skills. Fewer than half of workers used computers daily, and 17.7% reported no computer use in their work environment. Key infrastructure barriers included insufficient computer availability (34.1%)

and poor internet connectivity (30.5%). All six data quality dimensions assessed, namely timeliness, accuracy, reliability, completeness, relevancy, and credibility, were statistically significantly associated with health information utilization ( $p < 0.05$ ). Workers who perceived data quality as very good were consistently and substantially more likely to use health information than those who rated quality as poor. The most commonly reported barriers to routine data use were lack of motivation and absence of supervisory feedback (63.6%), multiple reporting levels (60.9%), and excessive volume of data requested (50.9%). These findings point to both structural and motivational dimensions of the challenge.

## 7.0 CONCLUSION

The study concludes that health worker factors play a decisive role in shaping the utilization of health information in Juba County, South Sudan. Training alone is insufficient; to meaningfully improve health information use, training must be specifically focused on data utilization and application in real-world decision-making contexts. Competence in information management and ease of access to routine data are among the strongest individual-level predictors of utilization, underscoring the need for sustained workforce capacity development. Data quality and health information use are mutually reinforcing: health workers are more likely to use information they perceive as accurate, timely, and credible, yet the quality of data also depends on the care and skill with which health workers collect and manage it. Addressing data quality therefore requires simultaneously addressing the human factors that produce it. The persistent absence of feedback mechanisms and the burden of multiple reporting levels are systemic challenges that require organizational as well as individual responses. Implementing structured, regular feedback sessions where health workers review their own facility's data is one of the most evidence-based and cost-effective strategies available for improving both data quality and utilization in low-resource settings.

## 8.0 RECOMMENDATIONS

Based on the study findings, the following recommendations are proposed:

The Ministry of Health and county health managers should redesign HMIS training programs to place greater emphasis on data utilization skills, specifically how to interpret data, identify performance gaps, and use findings to guide planning and resource allocation. Training in HMIS software operation should also be prioritized as a distinct and regularly updated component of health worker development. Structured supervisory feedback mechanisms should be established and maintained across all 12 health facilities. Monthly data review sessions at which health workers examine their facility's data together and develop action plans in response to identified gaps have been shown to significantly improve both data quality and utilization in comparable settings. The Juba County Health Department should invest in the physical infrastructure required to support HMIS use, including ensuring adequate computer availability, stable power supply, and reliable internet connectivity at all facility types, including primary health care centers.

The fragmented reporting system, in which approximately 25% of non-governmental organizations maintain parallel reporting structures outside the national HMIS, should be systematically addressed through a coordinated integration strategy led by the Ministry of Health, reducing duplication and the overall reporting burden on health workers. Health facility managers should cultivate a data-use culture in which health information is presented, discussed, and applied in routine operational meetings. Making data visible and relevant to everyday work decisions is one of the most effective non-technical strategies for improving health information utilization.

## 9.0 AREAS FOR FURTHER RESEARCH

Future research should examine the long-term impact of targeted HMIS training interventions on health information utilization in Juba County and similar low-resource settings. A longitudinal study tracking changes in utilization before and after structured training and feedback programs would provide stronger causal evidence than the cross-sectional design used in this study. Additionally, qualitative research exploring health workers' perspectives on what motivates or discourages data use would enrich the quantitative findings and support the design of more responsive interventions. Research comparing health information utilization across different service tiers, for example between national referral hospitals and primary health care centers, would also help to identify facility-level factors that can be targeted through differentiated support strategies.

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