

The use of theories, models and frameworks to institutionalise routine data-driven decision-making in sub-Saharan African health facilities: a scoping review

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Abstract

Background

Limited use of routine data for decision-making plagues Sub-Saharan African (SSA) health facilities despite key investments in health system data infrastructure to harness routine health-data. Evidence remains limited on how theories, models, and frameworks (TMFs) guide, inform, and assess efforts to institutionalise routine data-driven decision-making in SSA health facilities. This review aimed to determine which TMFs have been used to institutionalise routine data-driven decision-making in SSA health facilities and examine how they have been applied.

Methods

We searched six databases (MEDLINE, Scopus, Web of Science, EMBASE, Global Health, and CINAHL). Publications on data use in SSA health facilities were included. Extracted data included year of publication, study location, study design and intervention type. We conducted framework analysis to assess TMFs use in strengthening data use for decision-making in SSA health facilities.

Results

44 papers (Qualitative = 23, quantitative = 7, mixed methods = 14) published between 2007 and 2025 across fourteen SSA countries were included. The fourteen identified TMFs for institutionalising routine data-driven decision-making were mostly determinant frameworks (29/44, 65.9%) which explored behavioural, technical and organisational data use factors. Few studies explained factor interaction over time to institutionalise data use. Common reported decision forums were performance monitoring (n = 13/44) and data/audit review (n = 7/44) meetings with 10/44 studies having unspecified decision-making forums. When featured, routine data use was operational (logistics, service delivery monitoring, target setting).

Conclusion

Determinant frameworks dominated the TMFs evidence-base of efforts to institutionalise routine data-driven decision-making and seldom explained their interaction over time. Institutionalisation requires understanding routine data use as a dynamic sociotechnical process where technologies, workflows, organisational structures and human behaviours interact over time. Routine data use across SSA health facilities remains operational rather than integrated into strategic and clinical decision-making. There's need for systems thinking to identify better ways to leverage TMFs to strengthen routine data-driven decision-making eco-systems in SSA health facilities.

Background

Globally, health system performance and patient outcomes depend on the availability and use of health data for disease surveillance, health system monitoring and decision-making to improve the efficiency, quality and equity of services [1]. Routine health data, generated through Health Management Information Systems (HMIS), include systematically collected clinical and administrative information from paper-based records, patient registers, electronic health records (EHRs) and other digital platforms [2, 3].

Investments in digital health infrastructure across sub-Saharan Africa (SSA), including EHRs, DHIS2 platforms, e-registries and mobile data-capture tools, have substantially increased the volume and availability of routine health data [4–6]. However, increased data availability has not necessarily resulted in their routine use for improving patient care or health system performance [7]. In many settings, data continues to be collected primarily to satisfy reporting requirements rather than being consistently interpreted and acted upon [8]. Rather than simply introducing new sources of information, digitisation can transform hospitals into increasingly complex data ecosystems; interacting technologies, platforms, records, workflows, professional roles, reporting relationships, governance arrangements and organisational practices [8, 9]. As digital and paper-based systems, registers and reporting channels accumulate, data may move through multiple organisational and technical processes before reaching those expected to act on them. Consequently, the availability of data does not guarantee that information becomes connected to clinical and managerial workflows, interpreted within local contexts, or translated into action [8]. Organisational integration of routine data use, rather than technology adoption alone, becomes the central challenge for strengthening health facilities data use eco-systems [10].

Institutionalising routine data-driven decision-making means embedding continuous use of patient-care data into routine health facility operations to inform clinical and managerial decisions, quality improvement, resource allocation, performance monitoring, and benchmarking [11–13]. Institutionalisation extends beyond individual staff occasional data access or use, by assessing whether data use is embedded and sustained within workflows, decision-making structures, governance arrangements, and organisational practices beyond externally supported programmes [12].

Achieving such institutionalisation is a difficult, non-linear and dynamic process shaped by interacting individual, organisational and wider health-system conditions [14–16]. At the individual level, health workers may have limited data literacy, inadequate training in interpretation and application of routine data, low motivation and competing clinical and data-entry responsibilities [17]. At the organisational level, fragmented HMIS, inadequate staffing, poorly designed digital infrastructure and underutilised decision-making forums can limit the integration of data into everyday practice [7, 18–20]. At county and national levels, inadequate investment, weak governance and accountability, fragmented platforms, limited interoperability and poor feedback structures may further constrain the institutionalisation of routine data use [7, 21].

These challenges may be particularly pronounced at lower levels of the health system, including hospitals and frontline facilities, where resources, analytical capacity and digital infrastructure may be more constrained despite these settings being closest to patient care [21, 22]. Consequently, routine data collection may remain secondary to immediate clinical demands -fragmented systems may prevent the integration of clinical information into everyday workflows; and weak coordination may limit organisational learning and resilience during health crises [17, 19, 21].

Theories, models and frameworks (TMFs) may help explain and guide how routine data use becomes embedded within these complex organisational environments [23]. TMFs can be used to conceptualise the mechanisms through which implementation occurs, identify contextual barriers and enablers, guide intervention design, inform implementation strategies and support the evaluation of implementation processes and outcomes [23, 24]. In the context of routine data-driven decision-making, they may help explain how data use is integrated into everyday workflows, decision-making structures, governance and organisational routines. However, their usefulness depends on how a TMF is selected, operationalised, adapted and applied within the implementation process [7, 21, 25].

Existing research has examined barriers and facilitators to health information use, digital health implementation, HMISs and learning health systems [21, 23]. However, it remains unclear how TMFs have been used to understand and support the institutionalisation of routine data-driven decision-making [23, 24]. Consequently, there is limited understanding of the theoretical approaches employed, how and why they were selected, how they informed the design, implementation and evaluation of data-use practices, and the mechanisms, facilitators and barriers they elucidated [17, 26, 27]. This gap is important given the complexity and contextual diversity of health facility data ecosystems in SSA, where a clearer understanding of how TMFs are applied may inform efforts to embed routine data use within everyday clinical and managerial workflows [28, 29]. We, therefore, conducted a scoping review to map the use and application of TMFs in efforts to institutionalise routine data-driven decision-making in SSA health facilities.

Objectives

The review sought to address the following questions:

1. What theories, models and frameworks (TMFs) have been used to inform the institutionalisation of routine data use for decision-making in SSA health facilities?
2. How have TMFs informed the design, implementation, and evaluation of routine data-driven decision-making practices in health facilities in SSA?
3. What mechanisms, facilitators, and barriers to the institutionalisation of routine data use for decision-making in health facilities in SSA have been identified or elucidated through the application of TMFs?

Methods

The review, charting and reporting process adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) extension for Scoping Reviews (PRISMA-ScR) checklist and PRISMA-P chart [30, 31] with detailed information provided in our published protocol [32]. A five-stage scoping review method recommended by Arksey and O'Malley framework with incorporated refinements proposed by Levac and colleagues was used. It included (1) formulating the research question, (2) identifying relevant peer reviewed articles, (3) selection of relevant studies, (4) data extraction and charting, and (5) synthesis and reporting of the result [33, 34].

Eligibility criteria

The eligibility criteria were guided by Joanna Briggs Institute's Population, Concept, Context (PCC) framework [31, 35]. Peer reviewed papers that reported primary data on use of TMFs to inform the design and implementation of institutionalisation practices of routine data-driven decision-making in SSA health facilities were included. To ensure inclusion of studies with sufficient methodological detail and peer-reviewed primary evidence to address the review questions, studies published in languages other than English, conference abstracts, preprints, systematic reviews, and study protocols were excluded (Supplementary Table 1).

Search Strategy

With an information specialist (EH), TT and AK conducted exploratory searches to gain familiarity with the literature, define key terms, and develop the search strategy. The search terms and information sources were selected based on keywords and available thesaurus headings, to identify relevant papers to answer the review topic. EH and TT piloted the search strategy to ensure inclusion of all relevant keywords and terms. EH searched Ovid Embase, Ovid MEDLINE, Ovid Global Health, CINAHL via EBSCOhost, Scopus, and the Web of Science Core Collection on 04/04/2025 for studies indexed since database inception. The full search terms can be found in Supplementary Table 2. All references were exported to EndNote 21 [36] and were deduplicated by EH using a method described by Falconer [37].

Data charting and synthesis

AK screened the titles and abstracts of retrieved articles using Rayyan. TT reviewed a random 10% sample of articles to refine the article inclusion and exclusion process with disagreements in the articles reviewed by AK and AE resolved through discussion by TT. Data extraction was primarily conducted

by AE and AK using NVivo v15, with the data later charted in excel. Emergent findings were discussed with the authors throughout data extraction and synthesis. We present the full results of the search and study selection in the results section and in Harvard Dataverse [38].

We conducted framework analysis underpinned by the MEASURE (Monitoring and Evaluation to Access and Use Results) logic model [39–41] organised under five key domains (a) data use context, (b) data demand, (c) data collection and reporting, (d) data quality and availability, and (e) data use [39–41] explained in detail in Supplementary Table 3.

The MEASURE logic model developed by MEASURE Evaluation guides efforts to strengthen health data demand and use for decision-making, addressing gaps between routine data collection and evidence-informed action [39, 40]. We used the MEASURE logic model because it specifically focuses on routine health data use, enabling synthesis of technical, behavioural and organisational factors and their interrelationships across domains, making it well suited to our study.

TMF use was considered explicit when studies named and applied a TMF to guide study design, data collection, analysis, or interpretation. TMF use was implicit when no specific TMF was named, but the study reflected an underlying theoretical logic consistent with TMF use. Each TMF application was coded as design, analysis, diagnosis or evaluation with studies allowed multiple codes. Mechanisms were identified by tracking author-described connections between determinants across domains and synthesised separately.

Quality appraisal of included studies

AE performed quality assessment of the methodological quality of studies using the Integrated quality Criteria for Review of Multiple Studies (ICROMS) tool with results independently checked by TT [42]. ICROMS assesses methodological quality across diverse study designs, enabling consistent appraisal of the heterogeneous evidence included in the review [42]. ICROMS considers studies methodologically maximum score: 16/26 for qualitative, 18/30 for quantitative, and 34/56 for mixed-methods studies [42]. The scoring framework is provided in Supplementary Table 4.

Results

Literature search results

The search yielded 13700 records from the databases (SCOPUS = 3429, Web of Science = 4694, MEDLINE = 1467, EMBASE = 1488, CINAHL = 998, Global Health = 1624). After removing 6165 duplicates, 7535 records remained. During title and abstract screening, 7393 articles were excluded for failing to meet the predefined eligibility criteria, leaving 142 for full-text review. Of these, 98 were excluded (5 were protocols/conference proceedings, 3 were not from SSA, 57 did not use TMFs and 33 were not in health facilities). Ultimately, 44 studies were included in the final analysis. Figure 1 summarises this process using a PRISMA-ScR flow diagram.

Figure 1: PRISMA-ScR flow diagram of selection of evidence sources.

All included articles were published between 2007 and 2025, with 38/44 (86.36%) of them published in the last 5 years (Fig. 2). Geographically, the papers spanned 14 SSA countries including Ethiopia (n = 21/44), Tanzania (n = 6/44), South Africa (n = 3/44), Rwanda (n = 3/44) with the remaining 8 countries having one study; Only 3/44 were multi-country studies (Fig. 2).

Figure 2: Geographical distribution and year of publication of identified studies

Approximately half of the papers were qualitative (n = 23/44), with 7/44 and 14/44 employing quantitative and mixed methods respectively. Detailed study characteristics are provided in this review's Harvard Dataverse repository [38].

Synthesis of Findings

Objective 1: What TMFs were used to inform the institutionalisation of routine data-driven decision-making practices in SSA health facilities.

Fourteen TMFs identified from the papers were used explicitly (43/44, 97.73%) or implicitly (1/44, 2.27%) and prospectively (13/44, 29.55%), retrospectively (14/44, 31.82%) or both (17/44, 38.64%). Across the studies, which were majorly descriptive, determinant frameworks (PRISM, socioecological and CFIR) accounted for 30/44 of all TMF applications hence a heavy weighted evidence base on factors that shape data use rather than explanation of how they factors interact to determine data use and sustain organisational changes. TMFs were primarily used to classify barriers and facilitators into pre-defined domain; as a coding structure for qualitative data and a scoring structure for quantitative data. Few studies used TMFs to capture a dynamic account of how the determinants interacted over time through implementation of theories and models in their application. Their application spanned conceptual use (9/44, 20.45%), diagnostic functions (31/44, 70.45%), analytical utilisation (14/44, 31.81%) and TMF-guided implementation and evaluation (6/44, 13.64%). Majority of TMFs were PRISM framework and its extensions being the most common (n = 20/44), followed by CFIR and its extensions (n = 9/44) and custom conceptual frameworks (n = 5/44) (Fig. 3) and described in detail in Supplementary Table 4. Studies using PRISM examined technical, organisational and behavioural determinants of routine data use by making comparisons across different health systems contexts to evaluate facilitators and barriers of effective use of data for decision-making among health care workers (HCWs) [28]. Studies applying CFIR identified barriers and facilitators across inner/outer settings, intervention and individual characteristics and gave insight into the stalling or success of performance-based incentive and quality-improvement programmes [43, 44].

Figure 3: Theories, models and frameworks used in studies to explain data use in health facilities and the research design.

Objective 2: How TMFs were used to inform the institutionalisation of routine data-driven decision-making practices in SSA health facilities.

Data use context

Formal data-use forums, including Performance Monitoring Teams, Health Management Teams and Quality Improvement teams, provided the main settings for routine data-driven decision-making [28, 40–46]. In most facilities, these forums often performed hierarchical data quality verification and reporting while structured closed-loop review of past actions, local problem diagnosis and clear HCWs responsibility allocation were rare and unevenly distributed across settings. Majority of the studies documented forums exhibited one function while a minority demonstrated a combination of several functions [28, 46–57]. The presence of these forums supported performance monitoring, target setting, quality improvement and planning. However, none was a proxy for institutionalised routine data-driven decision-making because they varied in functionality, frequency, and a closed data-action-review loop constrained by workload, limited clinical engagement and predominantly hierarchical, accountability-driven reporting structures [58–63].

Data demand

Data demand was variable as staff needed local, actionable data to solve immediate clinical problems yet the hospital level was driven by reporting requirements that demanded aggregate indicators and accountability to higher administrative levels i.e. national compliance [43, 45, 49, 54, 57, 60, 63–67]. Accountability gaps spanned under-enforcement to fear-driven concealment; no consequences for incomplete or false reporting [61] to fear of reporting outcomes that encouraged falsification and fabrication [47]. HCWs regarded hierarchical data demand as an obligation rather than a learning resource with decisions made independently of data reported i.e. Unkels et.al. reference to maternity care providers as “mere data producers” [44, 67, 68]. Training, mentorship and feedback were reported to strengthen data literacy, ownership and active engagement with data, while limited analytical capacity, competing priorities and poor infrastructure constrained demand for routine data workers [28, 43, 45, 46, 50, 55, 58, 61, 64, 65, 69–72].

Data collection and reporting

Routine data collection and reporting were frequently characterised by retrospective documentation, duplication and parallel paper and electronic systems [43, 45–47, 58, 62, 63, 69, 73, 74]. Across the studies, digitisation added onto paper-based documentation with data entry by a narrow subset of staff (designated nurses, midwives or data clerks) into multiple systems (register, tally sheet, reports) despite generation by clinicians [67, 70, 72, 75]. Data was commonly collected to meet standardised reporting requirements and rarely returned to frontline HCWs in a usable form to support local decision-making. Implementation of digital systems did not translate into institutionalisation as they were rarely embedded into actual organisational work processes [50, 67, 72, 76]. High workloads, inadequate training and poorly integrated systems contributed to incomplete, delayed and inconsistent data collection and reporting [44–46, 49, 57–60, 64, 68, 77–79].

Data quality and availability

Poor data quality and limited accessibility were recurrent constraints on routine data use. Incomplete, inaccurate, inconsistent and delayed data were associated with technical factors i.e. fragmented information systems, complex reporting tools, limited verification capacity, human-resource constraints and organisational factors such as prioritisation of completeness over accuracy in hierarchical reporting among HCWs with high data quality knowledge to avoid negative outcome reports [46, 47, 52, 54, 55, 57, 58, 66, 80, 81]. Poor quality data eroded HCWs trust and motivation hence discouraged data demand and use for accurate reporting, weakening the incentive to document carefully hence sustaining a self-reinforcing poor quality data cycle [28, 63, 65, 68, 73, 74, 76]. This cycle also reduced confidence in routine data and, in turn, weakened motivation to collect and use data for decision-making [28, 47, 50, 57, 74, 76, 81].

Data use

Routine data were most commonly used for operational purposes, including performance monitoring, target setting, service planning, resource management, outbreak identification and quality improvement [43–48, 58, 59, 64, 69]. Data production and reporting were near universal with successive levels of normalisation achieved by fewer facilities. There were inconsistent data reviews, skewed data-informed action towards operational decisions and rare evidence of organisational learning where follow-up and adaptation of actions and future decisions occurred [60–64]. Regular review meetings, feedback and supportive supervision enhanced utilisation, but use for clinical decision-making, strategic planning, policy development and research was less consistently reported, and translation of data into action was often constrained by limited resources, leadership support and accountability [28, 46, 48, 50, 53, 55, 58, 60, 61, 66, 76, 81, 82].

Table 1: Summary of how theories, models and frameworks informed the institutionalisation of routine data-driven decision-making in SSA hospitals.

Table 1

Summary of how theories, models and frameworks informed the institutionalisation of routine data-driven decision-making in SSA hospitals

MEASURE domain	TMF-informed finding	Examples of implementation practices	Studies	TMF role	Mechanism of Interaction examined	Evidence of sustained integration into routine workflow	Level of institutionalisation addressed
Data use context	<p>Formal forums existed but were often compliance-oriented</p> <p>Data engagement patterns were dependent on roles and duration in the practice</p> <p>Integration of community - level data into facility decision making was limited</p> <p>Variable complementary structures to formal meetings</p>	<p>PMT¹/HMT²/QI³/ program-specific meetings.</p> <p>Meeting frequency- weekly (facility), monthly (PMTs, Data review, managerial, quarterly quality audits, district performance reviews) and bi-annual (i.e. TB) or irregular meetings.</p> <p>Unclear venues and meeting duration in formal settings.</p> <p>Discussions led by facility managers, supervisors and focused on reporting requirements (performance indicators, service utilisation, disease trends)</p> <p>Data personnel had summarised RHIS data and occasionally led data quality discussions.</p> <p>Managers focused on aggregated data and reports, clinicians relied on informal clinical narratives and patient level-data.</p> <p>4/44 studies integrated community level data to facility decision-making.</p> <p>(9/44, 20.45%) studies had supportive supervision and mentoring</p> <p>(3/44, 6.82%) had informal data-sharing, follow-up and feedback</p>	[28, 44–49, 52, 54, 56–58, 61–63, 65, 67, 68, 71–76, 79, 83, 84]	<p>Predominantly descriptive (mapped forums, participants, meeting frequency)</p> <p>Some diagnostic (PRISM/CFIR identifying organisational determinants of forum functioning)</p>	<p>Interaction between forum functions and hierarchical accountability structures</p>	<p>Mixed: Structurally embedded data forums in most facilities but inconsistently sustained functional depth.</p> <p>Routine meetings that only served reporting functions.</p>	<p>Data reporting and data review forums captured as recurring events but not consistently as substantive interpretive activities.</p>
Data demand	<p>Demand driven mainly by reporting requirements</p> <p>Capacity building interventions strengthened data demand and ownership</p> <p>Systemic constraints limited data</p>	<p>Report specific indicators, National HMIS indicators drove managers' demand for aggregated data</p> <p>Target monitoring, performance reviews, analytical training reduced historical practices and operational pressures.</p>	[28, 43–49, 54–61, 64–67, 69–72, 75]	<p>Mostly diagnostic (PRISM constructs identification of data demand determinants i.e. training, motivation)</p>	<p>Interaction between externally driven reporting demand and internally generated local data demand</p>	<p>Weak: reactive data demand skewed to external reporting deadlines rather than routine clinical managerial workflow</p> <p>Strengthened ownership through capacity-</p>	<p>Data reporting normalised as compliance.</p> <p>Demand rarely translates into decision-making behaviour.</p>

MEASURE domain	TMF-informed finding	Examples of implementation practices	Studies	TMF role	Mechanism of Interaction examined	Evidence of sustained integration into routine workflow	Level of institutionalisation addressed
	demand and access	Unreliable infrastructure (electronics, power, internet, breakdown),				building interventions with rarely evidenced sustainability beyond intervention period	
Data collection/ reporting	Fragmented, retrospective and duplicative processes Collection and reporting capacity building Routine, structured aggregate report formats that negate local needs	Tedious, time-consuming and double burden attitude towards data collection HCWs (often)/ Data clerks(seldom) retrospective data collection Paper + electronic reporting HCWs trained in collection and hierarchical reporting Designated monthly varied facility reports standardised to meet HMIS and national requirements	[45, 46, 58, 69]	Largely descriptive with some implementation stage i.e. MRC ⁴ framing EMR requirements	Interaction between digitisation, workload and data collection Added digital steps interacted with existing paper-based routines to hence duplicates	Weak - moderate; digital system layered onto paper processes rather than replacing them hence incomplete workflow integration. A narrow set of clinical staff for data entry limited integration across wider clinical team.	Data production and data reporting routinised but not seamlessly integrated into part of clinical work - retrospective and fabricated data implied
Data quality/availability	Formal data quality assessment tools limited by implementation barriers Prioritisation of domains of data quality Varied data verification practices Recurrent data quality issues Quality problems undermined trust	DQA ⁵ /LQAS ⁶ , validation Constrained by complex registers, limited capacity and oversight, parallel documentation and fragmented sources. Completeness over accuracy to meet hierarchical needs. PMT data verification in data registers, tally sheets and reports, hierarchical transmission of data without verification. Missing values, over/underreporting, fabrication, register-report inconsistencies, late report submissions. Distrust, poor attitude and motivation in collection and use of data	[28, 46, 47, 49, 50, 52–58, 60, 61, 64–67, 70–72, 74, 76, 80–82, 85]	Mixed diagnostic and evaluation	Feedback loops of data quality in several studies Poor quality-reduced trust and use-reduced demand-weaker documentation incentives-persistent poor quality	Weak inconsistently utilised formal quality assurance tools Constrained by capacity and infrastructure Informal, absent data verification with hierarchical reporting	Data production and reporting – data submission despite poor quality. Data review – verification and poor data quality problems triggered systemic correction in few studies
Data use	Predominantly operational use Structural and socio-technical factors enhanced data utilisation	Performance and service monitoring, resource allocation, target-setting, outbreak identification and disease prioritisation, drug and supply	[28, 32, 46, 48, 50, 53, 54, 58, 60, 61, 66, 76, 81].	Diagnostic, analytical with limited evaluation	Interaction between the structures, and socio-technical factors of review meetings with	Weakest: Data informed decision present but often skewed for operational decisions.	Partial data - informed action Least normalised organisational learning

<i>MEASURE domain</i>	<i>TMF-informed finding</i>	<i>Examples of implementation practices</i>	<i>Studies</i>	<i>TMF role</i>	<i>Mechanism of Interaction examined</i>	<i>Evidence of sustained integration into routine workflow</i>	<i>Level of institutionalisation addressed</i>
	Basic compliance to sophisticated data use	<p>management, clinical decision making at point-of-care, resource allocation</p> <p>Community level linked root-cause problem identification</p> <p>Seldom policy development, advocacy and research.</p> <p>Frontline HCWs tracked treatment progress, missed care and interventions dependent on unique identifiers, records and capacity.</p> <p>Regular review meetings, feedback systems, supportive supervision, accountability systems, staff capacity, motivation, incentivisation and clarity of roles, available resources (electronic and human)</p> <p>Compliance-oriented, procedural tabulation of reports to decision-oriented analysis, trend analysis, performance comparisons</p>			their resulting action	Organisational learning rarely documented with very few studies displaying a closed loop process i.e. Kawakyu et al. 2024	
<p>Note:</p> <p>PMT¹: Performance Monitoring Team, HMT²: Health Management Meeting; QI³: Quality Improvement; MRC⁴: Medical Research Council; DQA⁵: Data Quality Assurance; LQAS⁶: Lot Quality Assurance Sampling;</p>							

Objective 3: The reported mechanisms, facilitators, and barriers of routine data use in hospitals in SSA from the use of the TMFs.

Across studies, institutionalisation was shaped by interacting technical, behavioural and organisational factors. Structured data-review forums, training and mentorship, feedback, supportive supervision, leadership engagement and incentives facilitated routine use [28, 45–48, 55–57, 59, 60, 63, 65, 71, 81, 83]. Conversely, fragmented HMISs, inadequate infrastructure, poor data quality, limited analytical capacity, high workloads, unclear responsibilities, weak feedback and accountability mechanisms constrained use [28, 45–48, 56, 57, 59, 60, 63, 65, 71, 81, 83]. These factors appeared to reinforce one another, with poor data quality and fragmented workflows undermining trust and motivation, thereby reinforcing reporting-oriented rather than decision-oriented data practices. The barriers and facilitators for the use of TMFs in institutionalising routine data-driven decision-making in SSA health facilities are provided in Table 2, and grouped by technical, organisational and behavioural determinants.

Table 2
Facilitators and barriers of institutionalisation of data driven decision-making in SSA health facilities

Type of factor	Facilitators	Barriers	Key interactions with other domains
Technical	<p>a) Well-trained frontline Health care workers [56, 58]</p> <p>b) Functional standardized HMIS tools and indicators [52, 84]</p> <p>c) Available data management tools e.g. DHIS2, EMRs with inbuilt validation and reporting tools</p>	<p>a) Inadequate in-depth training on HMIS [53, 74, 80]</p> <p>b) Limited indicator definitions, data elements comprehension and data analysis among staff [47, 52]</p> <p>c) Complex and poorly designed HMIS tools- poorly integrated paper-based and electronic systems [52, 57, 71]</p> <p>d) Inadequate infrastructure (limited computers, poor internet, power outages, system downtime, report stockouts, limited technical support resources) [47, 76, 79, 85]</p>	<p>Improvements in capacity, data management practices, and indicator standardization reinforce one another, creating a positive cycle that enhances data quality, strengthens trust in routine information, improves reporting performance, and promotes use of data for decision-making.</p> <p>System design and workload influence documentation burden, which in turn affects data quality and staff motivation.</p> <p>Reliable infrastructure supports timely reporting, data availability, and trust in information systems, reducing reliance on paper-based workarounds.</p>
Behavioural	<p>a) Good attitude towards data domains [58, 75]</p> <p>b) Perception of data collection and use as useful [51, 58]</p> <p>c) Motivation mechanisms i.e. training, mentorship, incentives (awards, certificates, education scholarships), performance-based recognition [28, 46, 57, 66]</p>	<p>a) Low motivation among HCWs [55, 68]</p> <p>b) Perception of data collection as tiresome [50, 79]</p> <p>c) Negligence and forgetfulness [50, 54]</p>	<p>Motivation influences documentation effort and data completeness, reinforcing the perceived usefulness and subsequent use of data.</p> <p>Perceived documentation burden and competing clinical demands influence a shift of attention toward clinical care, reducing the quality of routine data recording.</p> <p>Incentive structures and accountability mechanisms promote diligent documentation, strengthen data quality and trust in routine information.</p>
Organisational	<p>a) Formal platforms for regular data reviews as PMTs, HMTs, Quality Audits [46, 69, 73]</p> <p>b) Supportive supervision [45, 57, 73]</p> <p>c) Active feedback mechanisms and mentorship [48, 86]</p> <p>d) Implementation of national HMIS frameworks that promote standardisation and accountability [44, 46]</p> <p>e) Healthy decision-making environment [58]</p> <p>f) Leadership commitment and structured planning processes to guide data driven discussions [48]</p> <p>g) Implementation of national HMIS frameworks [44, 46]</p> <p>h) Involvement of management in data reviews [46]</p> <p>i) Senior and middle management engagement in data reviews [51, 73]</p>	<p>a) Insufficient training [53, 74, 80]</p> <p>b) Human resource constraints [47, 52, 54]</p> <p>c) Weak accountability systems for poor data quality [44, 55]</p> <p>d) Prioritization of completeness over accuracy [65, 69]</p> <p>e) Nearly non-existent feedback mechanism from higher health systems levels [87]</p> <p>f) Lack of dedicated HMIS budget at local hospital level [46, 84]</p> <p>g) Unclear roles among HCW on data management [52, 67]</p> <p>h) Poor data use culture [47, 54]</p> <p>i) Hierarchical reporting than decision making [47, 87]</p>	<p>Forum functionality influences whether data are merely reported or actively reviewed and used to drive institutional change.</p> <p>Staffing levels and workload influence documentation quality, supervisory capacity, and the frequency of feedback within routine data systems.</p> <p>Weak accountability weakens reporting integrity, creating a cycle of poor data quality, low trust, and limited data use.</p> <p>Hierarchical reporting structures coupled with limited feedback can discourage local engagement with data and weaken demand for its use in decision-making.</p> <p>Budget allocation influences investments in infrastructure and workforce capacity, shaping system functionality and the effectiveness of data collection, reporting, and use.</p> <p>Clear role definitions strengthen accountability and ownership, promoting more consistent data management and reporting practices.</p> <p>Organizational culture shapes data demand and diligence, influencing the perceived value of data and its routine use.</p> <p>Hierarchical reporting structures can limit local data review and action, thereby weakening organizational learning and continuous improvement.</p>

Table 2: Facilitators and barriers of institutionalisation of data driven decision-making in SSA health facilities

Critical appraisal within sources of evidence

Of the included studies, 43/44 met ICROMS' minimum global quality score and mandatory criteria for their respective study designs. The median score for qualitative, quantitative and mixed-method designs was 22/26, 22/30 and 45.5/56 respectively. Detailed quality appraisal information for individual studies is available in the study's Harvard Dataverse repository [38].

Discussion

Summary of process and findings

This review searched 6 databases, found 13,700 eligible articles, retained 44 after duplicate removal, title, abstract and full text screening and inclusion and exclusion criteria adherence. Critical appraisal using ICROMS showed 43/44 studies to be of good quality. This review identified 14 identified TMFs used predominantly to showcase determinants of routine data-driven use (behavioural, technical, organizational) in SSA health facilities rather than interactions within the determinants to normalise data-driven decision-making. Majority were implementation science determinant frameworks (PRISM and CFIR) based on Nilsen's taxonomy [29] forming the bulk of the TMFs at 65.91% (29/44).

Comparison to other studies

Previous reviews examining TMFs in digital health, clinical decision support, knowledge mobilisation and health system interventions have reported substantial diversity in the frameworks used, although their emphasis has differed according to the interventions and settings examined [84–88]. Unlike previous studies where models predominated, this review found determinant frameworks, particularly PRISM and CFIR, were most commonly used to guide institutionalisation of routine data-driven decision-making [85]. Similar to Rouleau et al., this indicates a predominance of frameworks designed to identify factors influencing implementation [87]. The key finding concerns TMF use; Across this and previous reviews, TMFs commonly identified barriers and facilitators or structured data collection and interpretation but rarely explained how these interact over time to produce sustained organisational change [23, 89].

Previous reviews have largely focused on the adoption, implementation or evaluation of discrete interventions, including digital health technologies and computerised decision-support systems [84, 85, 88]. In contrast, this review examined routine data use as an organisational process embedded within hospital systems. It therefore shifts attention from whether a specific intervention is implemented to how data generated across routine hospital processes become integrated into ongoing clinical and managerial decision-making. This distinction is particularly relevant to digitisation, as implementation of EHRs and other digital systems does not necessarily mean that the data they generate become routinely incorporated into organisational decision-making. The increasing availability of digital data may coexist with fragmented data systems, parallel reporting processes and weak integration of information across hospital workflows [90, 91].

The review also highlights limitations in how TMFs have informed understanding of routine data use. Determinant frameworks can identify factors such as infrastructure, analytical capacity, leadership and data quality, but their predominant use to describe barriers and facilitators provides limited explanation of how these factors combine to sustain or undermine routine data use [84, 85, 87, 88]. Relationships between data quality, trust, reporting behaviour, accountability and data use may therefore be interconnected rather than independent [84, 88]. When TMFs are applied primarily as classificatory tools, such dynamic relationships and feedback processes may remain insufficiently theorised [86].

The contribution of this review is therefore not only its focus on SSA but its conceptual shift from intervention-specific implementation towards the normalisation of routine data-driven decision-making within hospital systems. Compared with previous reviews across high-income, global and mixed settings, this review focuses on how TMFs have been used to understand the continuous integration of routine data into organisational decision-making [86]. It also highlights the limited attention given to the interactions between technologies, data practices and organisational processes through which routine data use is embedded, maintained or disrupted over time [8, 86, 92].

Implications of findings

Data use context

The findings suggest that the data-use context should be understood as a complex system rather than a collection of separate technical, organisational or behavioural barriers. Fragmented information systems, weak data-use cultures, limited analytical capacity, high workloads and compliance-oriented reporting can interact to reinforce reactive and report-driven practice [28, 53, 55, 73]. Formal decision-making forums alone are therefore insufficient if the surrounding system does not support trust, ownership and locally relevant action [28, 47]. Systems thinking is needed to understand how these determinants interact and generate reinforcing cycles of poor data quality, low trust and limited use [13]. This has particular relevance for digital and AI-enabled systems: technologies introduced into weak organisational environments may reproduce or amplify existing deficiencies unless they are integrated into workflows, supported by appropriate governance and designed to strengthen rather than replace local data ownership and interpretation [28, 47, 53, 55, 73].

Data demand

Weak data demand appears to be produced by limited individual motivation and a system in which external reporting requirements, infrastructure constraints, poor data quality and weak accountability shape how staff experience and respond to data [45, 56, 58, 72, 74, 82]. In this context, the lack of repercussions for incomplete, late or inaccurate reports, combined with limited follow-up, may reduce incentives to improve data quality [48, 51, 53, 73]. Conversely, fear-related data manipulation suggests that accountability can also become counterproductive when staff perceive reporting primarily as punitive [44, 47, 50, 53, 54, 65, 74, 82]. The implication is that accountability systems should support learning, verification and improvement while maintaining clear responsibility for data quality [93]. Systems thinking can help identify these feedback loops and distinguish accountability mechanisms that promote transparent reporting from those that unintentionally encourage concealment or manipulation [56, 65]. EHRs, HMIS and AI systems relying on routine data will not resolve these underlying dynamics and may magnify their consequences if poor or strategically distorted data are used at scale [4, 8, 44, 47, 53, 54, 57, 65, 92].

Data collection and reporting

The findings suggest that data collection and reporting should be understood as organisational workflows rather than isolated technical activities [72, 74, 82]. Fragmented and duplicative documentation, parallel paper and electronic systems, high workloads and unclear responsibilities can separate data generation from the clinical and managerial processes in which the information is subsequently used [56, 57, 65]. Strengthening routine data use therefore requires data capture, reporting, review and feedback to be embedded within everyday hospital workflows and linked to clearly defined responsibilities and decisions [4, 93]. This systems perspective is particularly important as hospitals digitise and expand EHRs and other digital technologies. Digitisation may improve the availability and timeliness of information. However, it may also add new reporting requirements or parallel systems that further fragment the data ecosystem if technologies are introduced without redesigning underlying workflows [4, 8, 92]. The contribution of EHRs and other digital tools should therefore be assessed not only by their implementation or technical performance, but by the extent to which they become integrated into routine organisational processes for generating, sharing and acting on data [47, 52, 56, 65, 71, 74, 94].

Data quality and availability

Poor data quality should be interpreted as technical and organisational outcomes. Discrepancies, inaccuracies and delays are shaped by limited analytical skills and indicator knowledge but are also reinforced by high workloads, competing priorities, inadequate infrastructure, weak verification and insufficient feedback [52, 54, 80]. Improving data quality requires more than technical validation tools; it requires attention to the processes and incentives through which data are produced, checked and corrected [54, 60, 62, 63, 95]. Quality assurance, staff capability, supportive feedback and accountability should operate as connected components of a learning system, as weak data quality can reduce trust and demand for data, while limited use may in turn weaken incentives to improve documentation [62, 70]. This systems perspective is particularly important for AI-driven digitisation, because advanced analytical methods cannot compensate for systematically incomplete, inaccurate or poorly governed routine data [8, 92]. Digitisation i.e. EHRs operate under existing workflows and accountability structures that reproduces distortions i.e. weak and absent verification, inaccurate complete hierarchical data collection at greater speeds and scales rather than correcting them [92]. AI-driven digitisation may instead create an appearance of precision or scale existing weaknesses unless data quality and the organisational processes that generate and govern data are strengthened simultaneously [9].

Data use

The findings suggest that institutionalisation requires closing the feedback loop between data generation, interpretation, decision-making and action [47, 57, 63]. Regular feedback and local review forums can shift practice from producing reports towards collective problem-solving and continuous learning [70]. However, these mechanisms are unlikely to succeed if data remain disconnected from organisational priorities or if the consequences of using (or failing to use) data are unclear [47, 53, 57, 65]. This review suggests that many SSA hospitals achieved the two earlier mechanical stages of normalisation (data production and data reporting) while data review, data-informed action and organisational learning, which require interpretation, judgement and iterative adjustment grapple for sustainability [4, 93, 96]. Institutionalisation often stalls due to structurally open feedback loops that fail to utilise abundant data activity to make decisions that trigger action which are reviewed to shape data demand and use [47, 53, 57]. A systems perspective, therefore, requires attention to how decisions generate actions, how actions change performance and how those changes subsequently influence future data demand and use [43, 54, 60, 95]. AI could potentially support this cycle by improving analysis and timely access to information, but only when embedded within accountable organisational processes and should not be treated as a substitute for data use culture, human judgement, feedback or learning [8, 10]. Otherwise, it risks creating faster analytical systems without improving the underlying capacity of hospitals to interpret and act on evidence [9, 92].

Implications for research and practice

The findings suggest that future research and practice should move beyond treating the technical, organisational and behavioural determinants of routine data use as separate problems [97, 98]. Determinant TMFs such as PRISM and CFIR are not conceptually flawed since they identify barriers and enablers, structure intervention designs, guide implementation and evaluation. However, their use is insufficient in achievement of a systems thinking approach for examining how determinants interact over time and generate reinforcing feedback loops, including those linking data quality, trust, accountability, reporting behaviour, data demand and decision-making to achieve or undermine sustained data use [28, 48, 64]. Systems thinking approach aids in examination of unintended consequences on interventions and study of interactions across technical, behavioural and organisational domains rather than in isolation and locate disproportionate system-wide effects of targeted changes [39, 98]. Longitudinal, prospective, implementation-focused studies are needed to examine these pathways and identify leverage points for change [44, 95].

In practice, hospitals should embed data generation, review and action within organisational workflows, strengthen learning-oriented accountability and ensure that formal decision forums connect data to locally relevant action [51, 73]. This has increasing importance as health systems adopt digital and AI-enabled technologies [28, 51]. AI cannot compensate for weak data governance, fragmented workflows, poor-quality data or limited organisational capacity to use evidence. Without addressing these underlying system conditions, Digitisation and AI use may reproduce or amplify existing weaknesses at greater scale [9, 10, 92]. Technology should therefore be implemented as part of a broader sociotechnical and learning system that strengthens human judgement, local ownership, accountability and continuous improvement [64, 80, 81, 95].

Strengths and limitations of this study

This review synthesised evidence across diverse TMFs, health information system maturity and facility settings, and applied ICROMS to assess methodological quality, strengthening confidence in the synthesis. However, exclusion of grey literature and non-English publications may have omitted relevant evidence. Publication bias may also have favoured successful initiatives, while short follow-up periods may limit understanding of sustained institutionalisation. Heterogeneity in study designs, settings and TMF applications also constrained direct comparison across studies. These limitations mean that the findings should be interpreted as mapping patterns and gaps in the evidence rather than estimating the effectiveness of TMFs. Because

most included studies used TMFs primarily to identify determinants, the review could map evidence on factors influencing institutionalisation more readily than establish causal pathways between them.

Conclusion

TMFs have increasingly been used to understand and support routine data-driven decision-making in SSA health facilities, but their application has focused mainly on identifying determinants rather than explaining how these determinants interact over time to sustain data use. Routine data use remains predominantly operational and is constrained by fragmented data systems, poor data quality, limited analytical capacity and weak organisational support. Sustainable institutionalisation therefore requires a systems-oriented approach that connects data quality, workforce capability, leadership, decision forums, accountability and feedback to locally relevant action. Future research should explicitly operationalise TMFs to examine causal and longitudinal pathways through which routine data use becomes embedded, maintained or disrupted within organisational practice. As EHRs and other digital technologies expand, their implementation should not be equated with the institutionalisation of routine data-driven decision-making. Their contribution will depend on how they are integrated with existing workflows, accountability structures, interpretation, feedback and organisational learning. The next challenge for SSA health systems is therefore not simply to generate more data or digitise more records, but to ensure that increasingly complex data ecosystems support the normalisation of routine data-driven decision-making within hospitals.

Abbreviations

EHRs
Electronic Health Records
HCWs
Health Care Workers
HMIS
Health Management Information System
MeSH
Medical Subject Headings
PCC
People Concept Context
PRISMA
Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PRISMA-P
Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Systematic Review Protocols
PRISMA-ScR
Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews
SSA
Sub-Saharan Africa
TMFs
Theories, models, frameworks

Declarations

Ethics and Consent

This is a scoping review of previously conducted research and therefore does not require ethical approval and consent for data collection.

Patient and public involvement

Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Data availability statement

All data relevant to the study are included in the article or uploaded as supplementary information and provided in full in the study's Harvard Dataverse repository: <https://doi.org/10.7910/DVN/B3SJ5D>

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Author Contributions

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Competing interests

The authors have declared that no competing interests exist.

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Figures

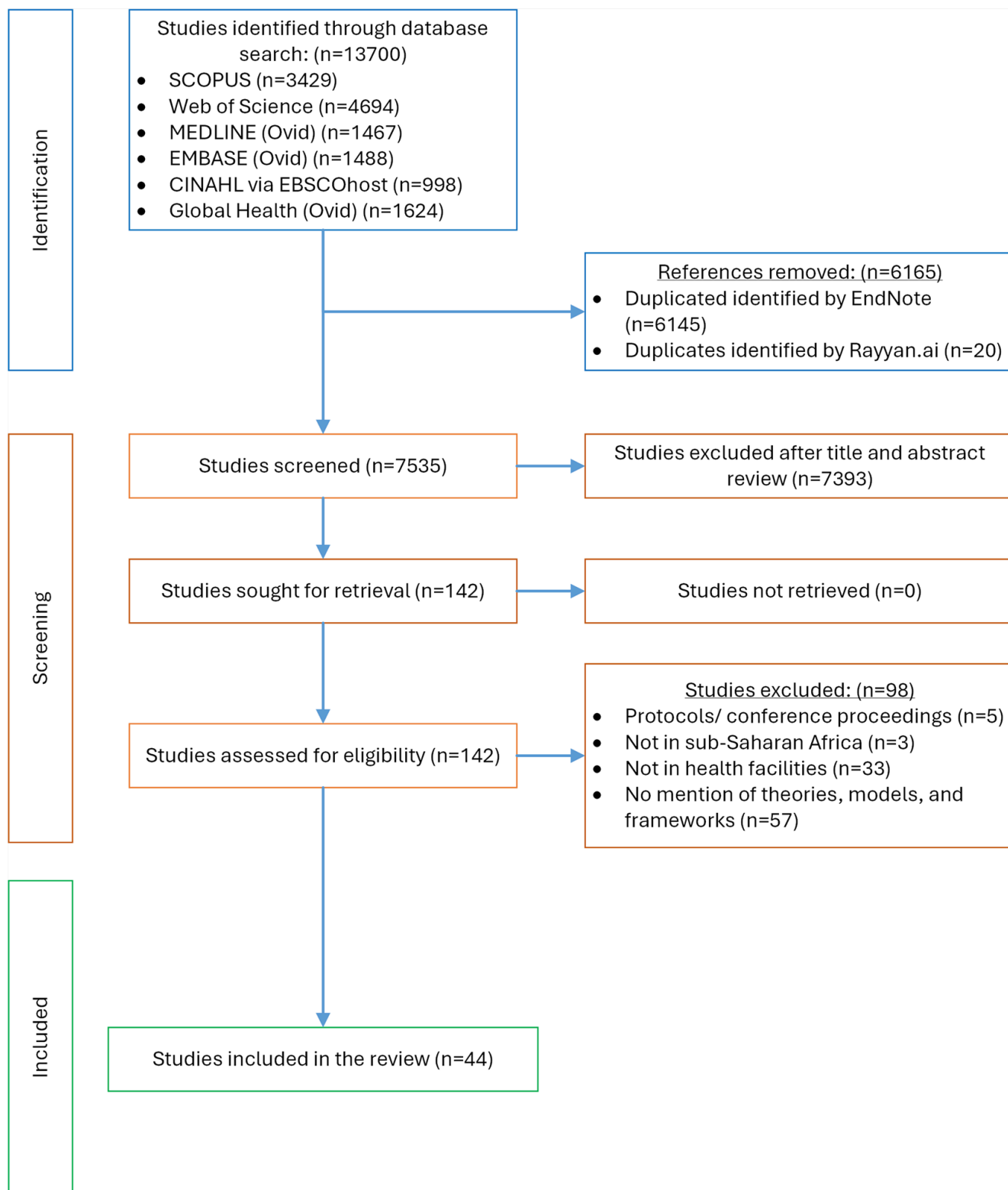


Figure 1

PRISMA-ScR flow diagram of selection of evidence sources.

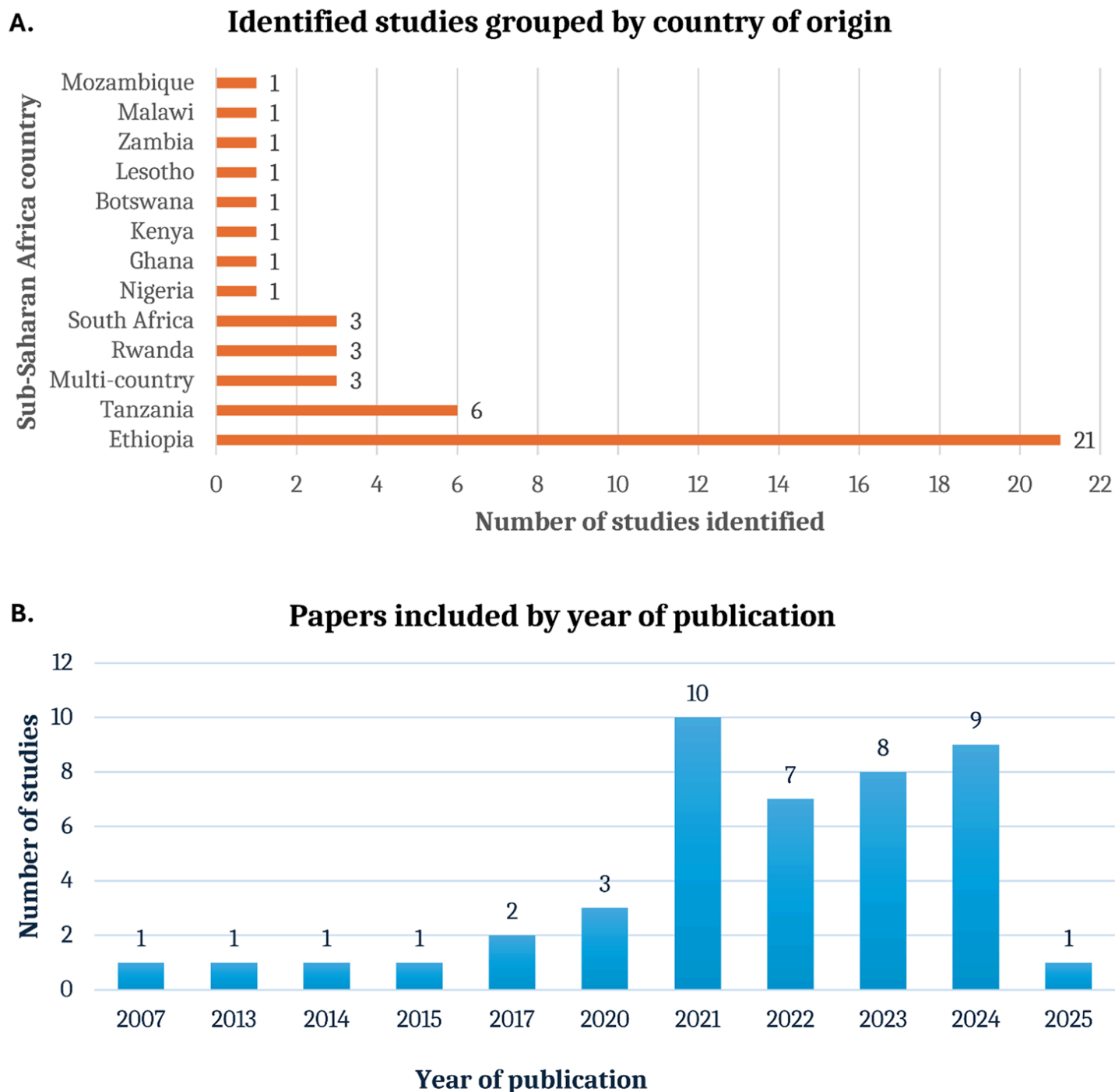
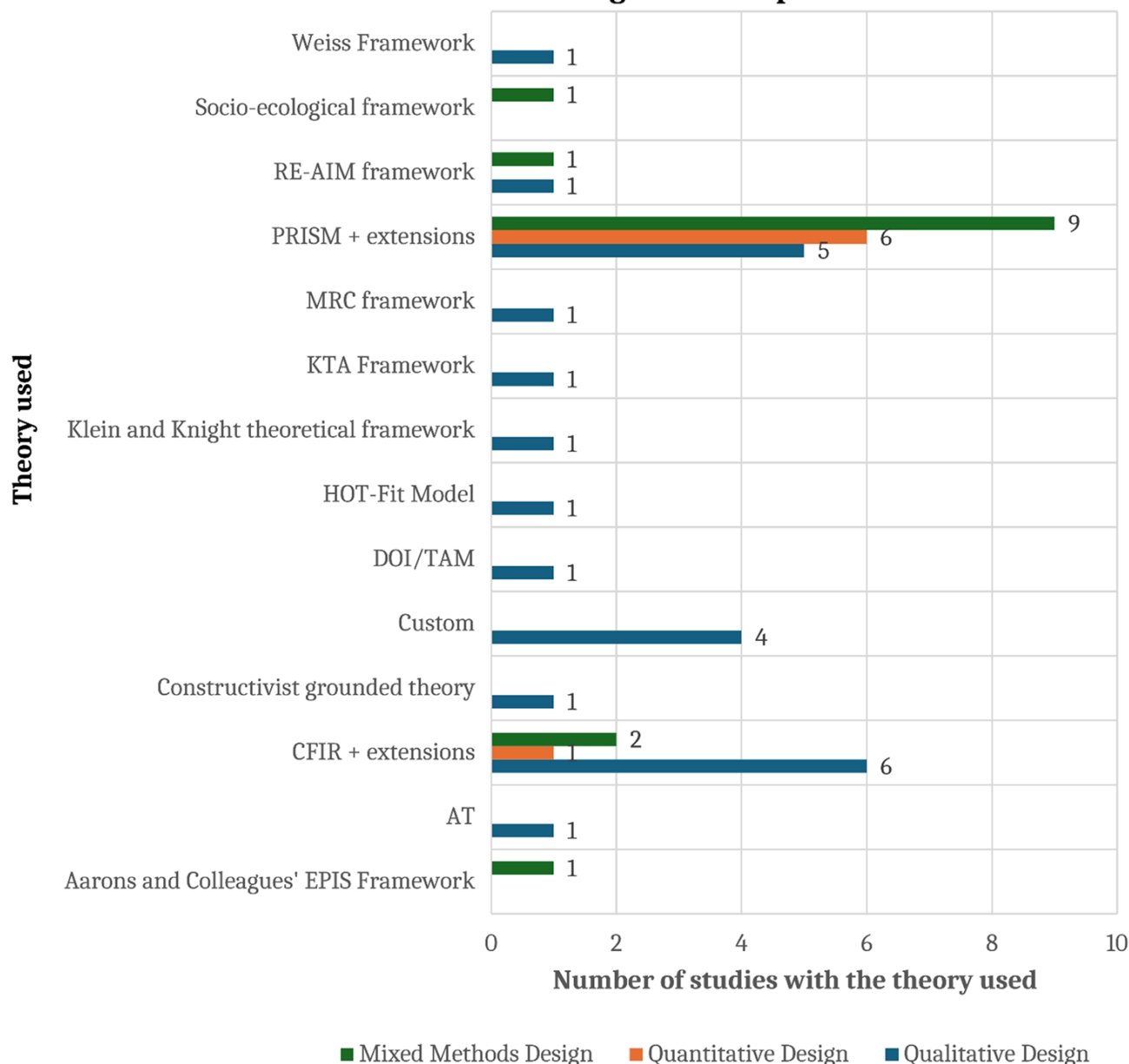


Figure 2

Geographical distribution and year of publication of identified studies

Theories used to inform institutionalisation of data driven decision making in SSA hospitals



KTA: Knowledge-to-Action Framework; **RE-AIM:** Reach, Effectiveness, Adoption, Implementation and Maintenance Framework; **CFIR:** Consolidated Framework for Implementation Research; **MRC:** Medical Research Council Framework; **HOT-fit:** Human Organization and Technology Model; **AT:** Activity Theory; **DOI:** Diffusion of Innovation; **TAM:** Technology Acceptance Model; **PRISM:** Performance of Routine Information System Management Framework; **CFIR:** Consolidated Framework for Implementation Research; **EPIS:** Exploration, preparation, Implementation, sustainment Framework; **Custom:** Unnamed and tailor-made frameworks and models for research projects.

Figure 3

Theories, models and frameworks used in studies to explain data use in health facilities and the research design.

Supplementary Files

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