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Bridging the Digital Divide in Rural SADC: A Scoping Review of Barriers to AI-Integrated Health Information Systems

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Abstract: *Health Information Systems (HIS) and telehealth technologies have been promoted across sub-Saharan Africa to improve healthcare access, yet adoption in rural areas remains low and implementations frequently fail. The Southern African Development Community (SADC) region faces conditions that systems designed for well-resourced settings were never built to handle: unreliable electricity, intermittent connectivity, absent technical support, limited digital literacy, and linguistic diversity. Although artificial intelligence has been proposed to address these barriers, no AI-integrated HIS has been rigorously evaluated in rural SADC settings. This scoping review synthesizes evidence from SADC countries to identify barriers to AI-integrated HIS deployment, derive design requirements, and propose theoretical extensions to technology acceptance models reflecting rural African realities. A systematic search of five databases covered studies published between 2010 and 2026, with country-specific terms for all SADC member states. The search yielded 447 records; after screening, 120 underwent full-text review and 85 met the synthesis criteria. Four interconnected gaps emerged: infrastructure, language, diagnostic support, and theoretical limitations in UTAUT2 for rural African contexts. Three design requirements follow: infrastructure resilience, linguistic adaptability, and diagnostic support. The review proposes three constructs — Infrastructure Resilience Expectancy, Local Language Expectancy, and Disease Pattern Recognition Expectancy — as candidate extensions to UTAUT2.*

Keywords: Health Information Systems; Artificial Intelligence; Rural Healthcare; SADC; UTAUT2

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1. Introduction

Researchers have studied health information systems since the 1970s, but almost entirely in well-funded settings. Early investigations concentrated on technical feasibility within well-resourced settings (Winter et al., 2023). That work says little about rural realities and the distinctive barriers characterizing these regions. They face a persistent challenge in the form of geographic isolation. This is the most obvious barrier, but it's not the only one, as unreliable infrastructure and socioeconomic constraints compound the problem.

A village health worker entering a symptom description in Shona or Ndebele receives no intelligent response. Despite this Zimbabwe operates over eleven distinct HIS, including DHIS2 for aggregate reporting, Impilo EHR for electronic patient records, and LabIMS for laboratory data (Moyo et al., 2020). These systems operating in a rural setup in Zimbabwe neither recognize indigenous languages nor

checks for local disease patterns. The SADC region as a whole also typifies these challenges. Their systems collect and store data, but they do not possess learning capabilities.

The problem is not the absence of health information systems, but the absence of AI-integrated HIS with specific capabilities that resonates with their settings. So, what rural Zimbabwe needs is not just another database. It needs a system that understands local languages like Shona and Ndebele. It needs a system that can predict a disease based on a prevalence in a particular local area. That system should work when the power is out or if there is a network failure (Mangundu et al., 2020; Furusa & Coleman, 2018). No empirically validated framework appears to exist that systematically addresses the simultaneous barriers of sporadic electricity, limited digital literacy, unreliable connectivity, and language differences in rural Zimbabwe.

This scoping review addresses the following research question: What AI-integrated HIS have been deployed in the SADC region, and what gaps remain in addressing language barriers, infrastructure failures, and disease pattern recognition? The review maps what has been deployed. It then identifies what's missing and proposes design requirements for future systems across the SADC region with respect to AI-integrated HIS in rural settings.

2. Literature Review

2.1 Theoretical Literature Review

This section reviews the theoretical models that underpin technology acceptance in healthcare, establishing the framework that the empirical literature then tests in low-resource settings.

2.1.1 Technology Acceptance Models

Technology acceptance models explain why users adopt or reject technology. The Technology Acceptance Model (TAM), developed by Davis (1989), proposes that two beliefs determine a person's intention to use a technology. Perceived usefulness is the degree to which a person believes using the system will improve their job performance. Perceived ease of use is the degree to which a person believes using the system will be free of effort.

TAM has been widely used in healthcare information systems research. Holden and Karsh (2010) conducted a systematic review identifying 68 studies that applied TAM to healthcare settings. These covered electronic health records, clinical decision support systems, telehealth, and patient portals. The review found that TAM explains between 40% and 50% of variance in behavioral intention. Perceived usefulness consistently emerged as a stronger predictor than perceived ease of use (Holden & Karsh, 2010).

However, Holden and Karsh (2010) also identified important limitations. TAM does not account for social influence, such as a doctor adopting a system because colleagues and supervisors expect it. It does not account for facilitating conditions, such as a nurse wanting to use a system but being unable because the internet is down. It does not account for infrastructure constraints. A critical limitation of their review is that only 3 of the 68 included studies were conducted in low-income or middle-income countries, and none were conducted in rural sub-Saharan Africa (Holden & Karsh, 2010). The review's conclusions about TAM's explanatory power therefore apply primarily to well-resourced healthcare settings.

Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) by reviewing and synthesizing eight competing models. UTAUT has four core constructs. Performance expectancy is similar to perceived usefulness. Effort expectancy is similar to perceived ease of use. Social influence is the perception that important others believe one should use the system. Facilitating conditions is the perception that organizational and technical infrastructure exists to support system use. UTAUT also includes four moderating variables: gender, age, experience, and voluntariness of use (Venkatesh et al., 2003).

Dwivedi et al. (2019) conducted a systematic review of over 1,000 UTAUT studies and found that UTAUT explains between 50% and 70% of variance in behavioral intention. Performance expectancy is consistently the strongest predictor. Critically, facilitating conditions matter more in contexts where users have limited control over their environment (Dwivedi et al., 2019). This matters for rural African settings because users have very limited control over power cuts, internet availability, or broken computers (Mangundu et al., 2020). This suggests that a construct related to infrastructure resilience may be a strong predictor of user acceptance. A limitation of the Dwivedi et al. (2019) review is that fewer than 2% of the included studies were conducted in sub-Saharan Africa. The finding that facilitating conditions matter more when users lack environmental control is theoretically plausible but has not been empirically tested in settings where users have extremely low control.

Venkatesh et al. (2012) extended UTAUT to create UTAUT2 for consumer contexts. UTAUT2 adds three constructs. Hedonic motivation is the fun or pleasure

derived from using the technology. Price value is the trade-off between benefits and monetary cost. Habit is the extent to which behaviors become automatic. In healthcare settings where the HIS is provided free of charge, price value is less relevant. In new implementations where users have no prior experience, habit is less relevant in the initial adoption phase (Venkatesh et al., 2012).

UTAUT2 has been validated across multiple well-resourced countries including Hong Kong, and the United States (Venkatesh et al., 2012). A critical gap is that no validation study has been conducted in a low-income country, let alone a rural setting within a low-income country (Dwivedi et al., 2019). The factor structure of UTAUT2 has not been tested in contexts where facilitating conditions are highly variable. It is possible that the four core constructs collapse into fewer factors when infrastructure dominates the user experience, or that new factors emerge that are not captured by the existing model.

Despite its popularity, UTAUT has received criticism. Bagozzi (2007) argued that UTAUT is overly complex, with four core constructs and four moderators whose interactions are difficult to interpret. This criticism is particularly relevant for rural African settings where sample sizes are often small due to the limited number of healthcare workers at rural clinics (Mangundu et al., 2020). A study with 50 to 100 participants may lack statistical power to test interaction effects (Bagozzi, 2007). No identified study has established minimum sample sizes for UTAUT studies in small-population settings.

Other researchers have argued that UTAUT focuses too narrowly on individual beliefs, ignoring organizational, social, and cultural factors (Holden & Karsh, 2010). In rural Zimbabwe, a nurse may not adopt the HIS because the Ministry of Health has not endorsed it. A patient may not trust the AI because they do not understand how it works (Mangundu et al., 2020). A limitation of the UTAUT literature is that it has not been extended to include constructs for trust in algorithmic decision-making. This may be particularly important when AI provides diagnostic suggestions that conflict with a nurse's clinical judgment (Holden & Karsh, 2010). No identified study has measured whether trust in AI moderates the relationship between performance expectancy and behavioral intention in healthcare settings.

Holden and Karsh (2010) argued that technology acceptance models need adaptation for healthcare contexts because the consequences of technology failure are higher. A software crash in a bank is an inconvenience, but in a hospital, it could be a matter of life and death. This argument suggests that existing UTAUT2 studies conducted in non-healthcare consumer contexts may not generalize to healthcare. However, no identified study has systematically compared UTAUT2's explanatory power across healthcare versus non-healthcare settings (Dwivedi et al., 2019).

2.1.2 Artificial Intelligence in Healthcare

Machine learning algorithms offer potential solutions to the diagnostic support gap. Breiman (2001) developed random forest algorithms that work by creating many decision trees and averaging their predictions. Random forests offer three characteristics suitable for rural contexts. They perform well with small datasets. A rural clinic may see only a few hundred patients per month. There is also the production of interpretable results. The algorithm can explain which features were most important for its prediction (Breiman, 2001). The end result is robustness to missing data and outliers (Breiman, 2001).

Deep learning, in contrast, requires thousands or millions of examples and demands significant computational resources. Deep learning also produces results that are difficult to interpret (Winter et al., 2023). For rural healthcare settings, random forests are often more appropriate than deep learning (Holden & Karsh, 2010).

2.2 Empirical Literature Review

This section reviews the theoretical models that underpin technology acceptance in healthcare, establishing the framework that the empirical literature then tests in low-resource settings.

2.2.1 Health Information Systems in Low-Resource Settings

Moyo et al. (2020) documented the fragmentation of Zimbabwe's HIS landscape. Each system serves a specific purpose, received funding from a different donor, and has its own login credentials with data formats and reporting requirements. The result is fragmentation without integration (Mangundu et al., 2020). This creates significant problems for healthcare workers. A nurse at a rural clinic may need to enter the same patient information into three or four different systems (Mangundu et al., 2020). Nurses spend considerable time manually entering data because the systems do not share information with each other. A patient's record in the HIV system cannot be accessed by the laboratory system. A tuberculosis patient's information remains invisible to the pharmacy system (Moyo et al., 2020).

2.2.2 Language Barriers in Healthcare

Africa is one of the most linguistically diverse regions in the world, with estimates indicating that between 1,500 and 2,000 languages are spoken across the continent (Hammarström, 2018). Zimbabwe has sixteen official languages. The most widely spoken are Shona, with approximately 10 million speakers, and Ndebele, with approximately 2 million speakers. Yet most digital systems in Africa operate in colonial languages spoken by a minority of the population: English, French, or Portuguese. In rural areas, English proficiency is low. Patients speak local languages at home and at the clinic. They struggle to communicate with healthcare workers who use English as the best spoken means of communication.

All HIS operating in Zimbabwe are designed exclusively with English-language interfaces. Menus, data entry forms, system prompts, error messages, and training materials are all presented in English. This design choice assumes that every healthcare worker possesses sufficient English proficiency to navigate interfaces and interpret system feedback. It also assumes accurate clinical data entry.

In rural Zimbabwe, Mangundu et al. (2020) documented that many nurses and village health workers have limited English proficiency. Their primary languages are Shona, Ndebele, Kalanga, or Tonga. A nurse who is not fluent in English cannot effectively navigate system menus and will misunderstand error messages. This often leads to incorrect data entries. Village health workers serve as the first point of contact between rural communities and the formal health system, and the language barrier here is more pronounced. These workers collect patient data in local languages at the community level but must translate that information into English when entering it into the HIS. This introduces delays. It also increases cognitive burden and creates opportunities for transcription errors. The literature therefore establishes that language is a structural barrier in HIS design, and that empirical measurement of its clinical consequences remains scarce. A significant portion of the rural healthcare workforce is effectively excluded from fully utilizing these systems.

3. Methodology

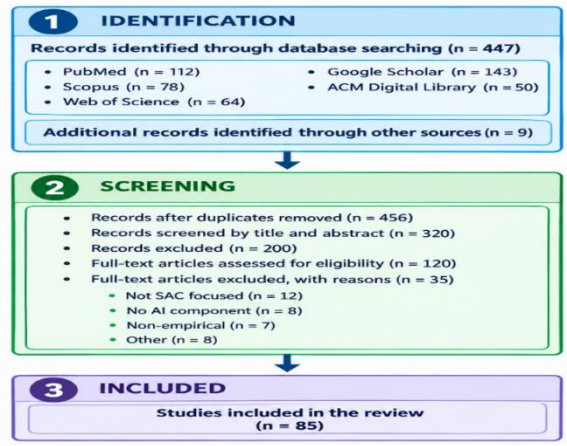
3.1 Search Strategy

Systematic searches of multiple academic databases yielded the literature reviewed in this paper. The databases searched included PubMed, Scopus, Web of Science, Google Scholar, and the ACM Digital Library. The search was conducted between January and March 2026.

Search terms combined the following keywords using Boolean operators: “Health Information System,” “Telehealth,” “Telemedicine,” “Artificial Intelligence,” “Machine Learning,” “Natural Language Processing,” “Indigenous Language,” “Technology Acceptance,” “UTAUT,” “Rural Healthcare,” “Sub-Saharan Africa,” and “SADC.” Additional terms included specific country names: Zimbabwe, South Africa, Botswana, Malawi, Mozambique, Zambia, Lesotho, Eswatini, Namibia, and Angola.

The search strategy employed the following primary search string for PubMed:

(“Health Information Systems” [Mesh] OR “Telemedicine”[Mesh] OR “Artificial Intelligence”[Mesh]) AND (“Rural Health Services”[Mesh] OR “Developing Countries” [Mesh]) AND (“Africa South of the Sahara”[Mesh] OR Zimbabwe OR South Africa OR Botswana OR Malawi OR Mozambique OR Zambia OR Lesotho OR Eswatini OR Namibia OR Angola)



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3.2 Inclusion and Exclusion Criteria

Studies were included if they met the following criteria. First, they addressed HIS, telehealth, or telemedicine in low-resource settings and discussed AI applications such as machine learning, Natural Language Processing (NLP), or computer vision. Second, they examined technology acceptance in developing countries using models such as TAM, UTAUT, or UTAUT2. Third, they provided empirical evidence from SADC countries. Fourth, they were published between 2010 and 2026.

Studies were excluded if they focused exclusively on well-resourced settings in North America, Europe, or East Asia. Studies not presenting original research, such as opinion pieces, editorials, and commentaries, were excluded. Studies published before 2010 were excluded, except for foundational theoretical works by Davis (1989) and Rogers (2003).

A limitation of this search strategy is that it included only English-language publications. This may have excluded relevant studies published in Portuguese or French that address SADC countries such as Mozambique and Angola. Grey literature from ministries of health and donor organizations may contain valuable implementation data not captured by academic databases. The reliance on peer-reviewed literature alone may therefore underrepresent on-the-ground experiences of digital health failures and successes.

3.3 Screening and Data Extraction

The search generated 447 potentially relevant articles. After screening titles and abstracts, 120 articles underwent full-text reading. Eighty-five of these are cited in this review. The remaining 35 provided background context but lacked direct relevance to the specific gaps addressed by the literature and therefore were not cited.

Data extraction followed a standardized form capturing the following information: author(s), year, country, study design, sample size, barriers identified, AI technologies discussed, technology acceptance constructs measured, and key findings.

3.4 Quality Assessment

For quantitative studies, the following criteria were assessed: sample size adequacy, validity of measurement instruments, appropriateness of statistical analysis, and generalizability of findings. For qualitative studies, the following criteria were assessed: credibility of findings, transferability to other settings, dependability of data collection methods, and confirmability of interpretations. Mixed-methods studies were assessed against both sets of criteria. No studies were excluded based on quality assessment alone, but limitations were documented and considered in the synthesis.

4. Results and Discussion

4.1 Overview of Included Studies

The 85 included studies span multiple SADC countries and cover diverse topics including HIS implementation, telehealth pilots, AI applications, and technology acceptance. The geographical distribution reveals that Zimbabwe, South Africa, and Botswana have the highest number of studies, while Angola, Eswatini, and Namibia have fewer studies. This uneven distribution reflects differences in research capacity and funding across the region.

Temporal analysis shows increasing research activity over the past decade. Studies from 2010 to 2015 focused primarily on barriers to HIS adoption. Studies from 2016 to 2020 examined telehealth feasibility and identified infrastructure challenges. Studies from 2021 to 2024 have begun to explore AI applications, though empirical deployments remain rare.

The following sections synthesize findings according to four thematic areas: infrastructure barriers, language barriers, diagnostic support gaps, and technology acceptance model limitations.

4.2 Infrastructure Barriers in HIS and Telehealth

4.2.1 Electricity Supply

Electricity reliability constitutes a fundamental prerequisite for digital health systems. Without continuous power, servers, workstations, and network equipment cannot function. Evidence from across the SADC region reveals that this prerequisite is frequently absent in rural areas.

In Zimbabwe, power cuts last four hours per day on average, with some clinics experiencing outages lasting days (World Bank, 2023). An IRENA assessment (2025) found that 32.5% of Zimbabwe's health facilities lack access to reliable electricity. Among grid-connected facilities, 42% experience outages exceeding twelve hours daily. When power fails, HIS stop working immediately. Data being entered at the moment of power loss may be

corrupted or lost entirely. Paper registers become the only alternative, but they cannot be queried for decision support and do not generate alerts for drug interactions or follow-up reminders. Manual re-entry into digital systems is required when power is restored. This results in duplicate work, incomplete electronic records, and a healthcare workforce that has lost confidence in the reliability of digital tools.

The Malawi Ministry of Health (2019) reported that 55% of rural health facilities experience at least four hours of power cuts per day. Chipunga et al. (2021) documented that only 12% of rural clinics in Malawi have any form of digital health system that functions offline. The majority of clinics still rely on paper registers. When power fails, even basic digital functions cease.

A strength of the (International Renewable Energy Agency [IRENA] & SELCO Foundation, 2025) assessment is that it conducted facility-level audits rather than relying on self-reports. However, a limitation is that the assessment did not distinguish between scheduled load-shedding and unplanned outages. These have different implications for system design. Scheduled outages can be anticipated and prepared for, while unplanned outages require more robust resilience mechanisms.

4.2.2 Internet Connectivity

Most HIS deployed in Zimbabwe require a continuous internet connection to function. These systems are architected on a cloud-first model. User interfaces fetch data from remote servers, forms submit entries to cloud databases, and authentication verifies credentials against centralized directories. When internet connection is interrupted, these systems either cease functioning entirely or revert to limited offline modes that risk data loss upon reconnection.

In rural Zimbabwe, Moyo and Ncube (2023) found that 43% of rural clinics have no internet connection at all. The remaining clinics experience frequent and unpredictable outages. Where connectivity exists, it is often provided through mobile broadband networks (3G or 4G). Signal strength varies depending on topography, weather, and network congestion. When a nurse enters patient data during an online session and the connection drops mid-transaction, data may be partially saved, corrupted, or lost entirely. Where offline data entry is supported, it requires manual synchronization procedures that are often forgotten or performed incorrectly. During prolonged outages that can last days in some rural areas, clinics abandon digital systems entirely and revert to paper registers.

The 2018 telemedicine pilot in the Manicaland province of Zimbabwe illustrates how the absence of offline functionality leads to failure. The Postal and Telecommunications Regulatory Authority of Zimbabwe (POTRAZ) installed computers, webcams, and satellite internet terminals in fourteen clinics (Machengete, 2018). The government pronounced the pilot a success, but independent research by Furusa and Coleman (2018) found that infrastructure failed repeatedly. Satellite terminals lost connection during rain, power cuts damaged equipment, staff lacked training, and no technical support was available. The result was equipment that sat unused after the pilot ended.

Similar patterns appear across the region. Kgathi et al. (2021) found that only 18% of rural clinics have consistent internet connectivity sufficient for telehealth in Botswana. The country continues to experience shortages and an uneven distribution of healthcare professionals, particularly medical specialists. Recent government reports indicate that shortages of medical specialists and medical officers persist in the public sector, while efforts are being made to strengthen the distribution of healthcare personnel across district facilities and improve access to services in underserved areas (Government of Botswana, 2024, 2025). The rural patients often travel more than 100 kilometers to see a specialist. Telehealth could bridge this gap, but the necessary connectivity is absent.

Phiri et al. (2022) found that 65% of digital health systems in Zambia cannot operate during power outages. Two-thirds of all digital health investments become electronic waste whenever the electricity grid fails. Battery backup systems add approximately 15% to 20% to the cost of each workstation. This seemingly modest increase is often eliminated during budget-conscious procurement processes. A methodological strength of Phiri et al. (2022) is that they conducted site visits to verify offline functionality rather than relying on administrator reports. However, their study was limited to 20 clinics in two provinces.

A methodological limitation of the Moyo and Ncube (2023) study is that it relied on facility surveys rather than direct measurement of connectivity. Clinics may report “having internet” when a staff member has a personal mobile data connection, which is not equivalent to reliable HIS connectivity. The study also did not measure the duration or frequency of outages.

4.2.3 Technical Support and Maintenance

Even when equipment is installed and functioning, lack of technical support leads to failure. The Manicaland pilot had

no provision for ongoing technical support after launch (Furusa & Coleman, 2018). When equipment malfunctioned, there was no one to repair it. Staff who had received initial training forgot their skills without reinforcement.

In Botswana, Mutsvangwa et al. (2023) found that although telemedicine awareness and knowledge remain low, acceptance and willingness are high. A study at 12 public healthcare facilities found that only 42% of doctors and 10% of nurses had actively used telemedicine. However, 100% of professionals and 94% of patients expressed willingness to use it in the future. The study identified resource shortages as the most significant barriers, followed by cultural beliefs, privacy concerns, and security issues. A limitation of the study is its small sample size, with 12 facilities out of approximately 300 in Botswana. Willingness was measured by a single yes/no question rather than a validated scale.

The Ministry of Health in Lesotho launched the HIV and Health Situation Room in 2018 with UNAIDS support. An October 2020 evaluation found the platform not functioning. There were no active users in the prior 30 days, several key dashboards contained no actual data, and the live business matrix had no DHIS2 indicators (UNAIDS, 2020). The evaluation concluded that the Situation Room was "not clearly embedded in a wider government strategy" and that the Ministry had "limited capacity to resource" it. A strength of this evaluation is that it was conducted independently of the Ministry of Health. A limitation is that it was conducted only three months after launch, with no follow-up to determine whether usage improved over time.

4.2.4 The Infrastructure-Adoption Paradox

When findings are compared across countries, a contradiction emerges. Botswana demonstrates high willingness to use telemedicine alongside severe infrastructure constraints. In contrast, South Africa has better infrastructure, yet Mars and Scott (2020) conducted a systematic review revealing that adoption rates remain below 15% in rural areas. Their review screened 45 relevant studies and found that unreliable electricity, poor internet connectivity, and lack of training were consistently cited regardless of the specific telehealth application.

Infrastructure alone does not determine adoption. Training, digital literacy, and design likely matter equally - but no study in this review examined their interaction. The literature has not adequately explained this contradiction, as most studies examine infrastructure and adoption separately rather than investigating their interaction.

4.3 Language Barriers in Healthcare Communication

4.3.1 Evidence from Across the SADC Region

The problem appears across the region. In Mozambique, Cuinhane et al. (2020) surveyed 500 patients and 200 healthcare workers across 40 clinics. They found that language barriers between Portuguese-speaking clinicians and local language speakers (Makua and Sena) lead to misdiagnosis in approximately 20% of outpatient visits. Seventy percent of rural clinics lack any digital diagnostic support. Community health workers act as informal translators despite having no medical training. A limitation of this study is its cross-sectional design, which cannot establish causality between language barriers and misdiagnosis. However, its large sample size strengthens generalizability.

In South Africa, Levin et al. (2020) studied rural clinics in the Eastern Cape Province using timed observations of consultations rather than self-reports. They found that 40% of patient consultations are delayed because of language barriers between Xhosa-speaking patients and English-speaking nurses. The researchers identified language barriers as the root cause of misdiagnosis, poor treatment adherence, and patient dissatisfaction. A limitation is that the study was conducted only in the Eastern Cape where Xhosa is dominant. The findings may not generalize to KwaZulu-Natal or Limpopo.

In Angola, Silva et al. (2025) found that over 20% of the population speaks only autochthonous languages. 87.5% of healthcare professionals identified low patient education and digital literacy as the primary barrier to telemedicine adoption. This finding explicitly links language to digital literacy in ways that other SADC studies have not. A limitation is that the study did not measure which specific languages create the greatest barriers.

A methodological limitation of the evidence on language assumptions is that no identified study has quantified the proportion of rural Zimbabwean nurses with limited English proficiency. Neither has any study measured whether English proficiency correlates with data entry error rates. The claim that nurses are "excluded" from system use is based on qualitative interviews rather than direct observation of system usage or error analysis.

4.4 Diagnostic Support Gaps

4.4.1 Current State of Diagnostic Support

Rural clinics across the SADC region lack diagnostic support. The evidence from multiple countries documents this gap consistently. In Mozambique, 70% of rural clinics lack any digital diagnostic support (Cuinhane et al., 2020). In Zambia, digital diagnostic tools are absent in most rural facilities. In Zimbabwe, Chikwanha et al. (2018) documented that the nation has approximately 20 radiologists serving a population of 15 million people, with nearly all practicing exclusively in Harare or Bulawayo. A patient attending a rural clinic cannot access a radiologist's expertise without undertaking lengthy and costly travel.

This gap extends beyond imaging, laboratory services are similarly absent. Rural nurses must make diagnostic decisions based on symptoms alone, without access to diagnostic tools or decision support systems. The result is misdiagnosis, delayed treatment, and poor health outcomes.

4.4.2 Disease Surveillance versus Diagnostic Support

Existing HIS in Zimbabwe are designed for surveillance rather than diagnostic support. DHIS2 collects aggregate data on clinic visits, vaccinations, and disease outbreaks (Moyo et al., 2020). However, DHIS2 was designed for data aggregation, not for clinical decision support (Mangundu et al., 2020). A nurse entering patient symptoms receives no intelligent response. The literature has not adequately evaluated whether aggregate data from DHIS2 improves clinical decision-making at the point of care. Neither has it tested whether the system's design assumptions (stable internet, English proficiency, trained users) exclude the very clinicians who need decision support most.

Beyond mere inconvenience, fragmentation creates genuine clinical risks. Consider a patient diagnosed with hypertension at one clinic, with that diagnosis recorded in Impilo EHR. If the patient later visits a different clinic for a different complaint, the second clinic cannot see the hypertension diagnosis because they use a different system. This may lead to contraindicated treatment (Mangundu et al., 2020). Moyo et al. (2020) documented multiple cases of medication errors caused by fragmented HIS. However, a limitation of their study is that it was conducted in 2018 and 2019, prior to the significant economic deterioration that has further fragmented Zimbabwe's health system (World Bank, 2023). The study also did not quantify the time nurses spend on duplicate data entry, nor did it measure the clinical outcomes of medication errors attributed to fragmentation.

4.4.3 Machine Learning as a Potential Solution

As outlined in Section 2.2, random forests are well suited to small datasets and interpretable outputs. Several studies have applied machine learning to disease prediction in Africa, but most used retrospective data from urban hospitals. These studies did not deploy algorithms in real clinical settings and did not test whether nurses could use them effectively, nor did they measure whether patient outcomes improved (Mars & Scott, 2020; Moyo et al., 2020). A methodological limitation across this literature is that studies rarely report the prevalence of missing data or the characteristics of patients excluded from analysis (Winter et al., 2023). If rural patients with incomplete records are systematically different from those with complete records, model performance reported in retrospective studies may not generalize to real-world clinical settings. No study in this review measured whether machine learning predictions changed clinician behavior or patient outcomes in SADC settings.

4.5 Technology Acceptance Model Limitations

4.5.1 The Missing Constructs

The literature reveals no study that has extended UTAUT2 to include constructs for local language processing, infrastructure resilience, or disease pattern recognition in rural African contexts (Mangundu et al., 2020; Moyo et al., 2020; Cuinhane et al., 2020; Levin et al., 2020). This gap matters since existing technology acceptance models were developed in contexts where infrastructure, language, and diagnostic support were not barriers (Venkatesh et al., 2003; Venkatesh et al., 2012).

Three candidate constructs emerge from the literature as potentially relevant for extending UTAUT2 in rural African settings. Infrastructure Resilience Expectancy (IRE) refers to the degree to which users believe that the AI-integrated HIS will function during predictable disruptions, including power cuts and network downtime. The justification for proposing this construct is that infrastructure resilience constitutes a major barrier to digital health in rural Africa (Mangundu et al., 2020; Furusa & Coleman, 2018).

Local Language Expectancy (LLE) refers to the degree to which users believe that the AI-integrated HIS will accurately understand and respond in their indigenous language. The justification is that language barriers cause misdiagnosis and reduce healthcare utilization (Levin et al., 2020; Cuinhane et al., 2020).

Disease Pattern Recognition Expectancy (DPRE) refers to the degree to which users believe that the AI-integrated HIS will correctly identify locally prevalent diseases from symptom data. The justification is that rural clinics lack diagnostic support (Chipunga et al., 2021; Phiri et al., 2022).

These constructs have not been empirically tested or compared in rural African healthcare settings, which represents an opportunity for future research. Together, IRE, LLE, and DPRE map onto the first three thematic gaps identified in Section 4.1 - infrastructure, language, and diagnostic support — and offer a way to extend technology acceptance theory to address them. Whether these constructs improve explanatory power over existing UTAUT2 constructs remains an empirical question.

4.6 Synthesis of Findings

This scoping review synthesizes evidence from across the SADC region on barriers to AI-integrated HIS deployment in rural settings. Four major gaps emerge from the literature.

First, infrastructure barriers are pervasive and severe. Electricity outages affect the majority of rural health facilities in Malawi and Zimbabwe. Internet connectivity sufficient for telehealth exists at only 18% of rural clinics in Botswana. Technical support is absent after pilot projects end. These barriers are not minor inconveniences. They fundamentally undermine the functioning of HIS and telehealth systems designed for stable, connected environments.

Second, language barriers are widespread and consequential. All HIS in Zimbabwe operate exclusively in English, despite most rural healthcare workers and patients having limited English proficiency. Language barriers lead to delayed consultations in 40% of visits in rural South Africa and misdiagnosis in 20% of visits in Mozambique. No HIS in the region can understand or respond in indigenous languages.

Third, diagnostic support is virtually absent. Rural clinics lack digital diagnostic tools. Existing HIS collect data for surveillance but provide no decision support to clinicians. Machine learning has been proposed as a potential solution, but no AI-integrated HIS has been rigorously evaluated in rural SADC settings.

Fourth, technology acceptance models have not been adapted for rural African contexts. UTAUT2 has been validated in well-resourced settings but not in low-income, rural settings where infrastructure dominates the user experience. No study has extended UTAUT2 to include constructs for infrastructure resilience, local language processing, or disease pattern recognition.

These four gaps are interconnected rather than independent. Infrastructure failures prevent the deployment of language processing and diagnostic support systems. Language barriers reduce the usability of HIS that assume English proficiency, while the lack of diagnostic support reduces the perceived usefulness of HIS that collect data but provide no clinical guidance. Technology acceptance models that do not capture these barriers cannot accurately predict adoption.

4.7 Implications for Design

The evidence from this review has direct implications for the design of future AI-integrated HIS in rural SADC settings. There are design requirements that emerge consistently from the literature.

Three design requirements emerge. Systems must be resilient to infrastructure failures — offline-first architecture, edge computing, battery backup. They must support indigenous languages through NLP, machine translation, and speech interfaces. And they must deliver diagnostic support using machine learning trained on local disease patterns.

Critically, these three requirements must be addressed simultaneously rather than in isolation. An offline system that cannot process local languages is of limited use. Equally, a language-support tool that dies during a power cut will not be adopted. And a diagnostic aid that requires English excludes its intended users. An integrated design is therefore required.

4.8 Implications for Theory

The findings have implications for technology acceptance theory. UTAUT2, developed in well-resourced contexts, does not capture the unique barriers present in rural African settings (Venkatesh et al., 2012; Dwivedi et al., 2019). Extension of the model is warranted.

The three candidate constructs identified in this review, Infrastructure Resilience Expectancy, Local Language Expectancy, and Disease Pattern Recognition Expectancy, address gaps in existing theory. Empirical testing of these constructs is needed to determine which one best explains user acceptance in rural African healthcare settings. Each construct has theoretical justification.

Infrastructure Resilience Expectancy extends the concept of facilitating conditions. UTAUT defines facilitating conditions as organizational and technical infrastructure that supports system use (Venkatesh et al., 2003). However, in rural settings, the question is not whether infrastructure exists, but whether it can be relied upon. IRE captures this distinction by focusing on resilience during disruptions.

Local Language Expectancy addresses a gap in technology acceptance research on linguistic diversity. Existing models assume that users share a common language with the system. In linguistically diverse settings, this assumption does not hold. LLE captures users' beliefs about whether the system can bridge language barriers.

Disease Pattern Recognition Expectancy addresses a gap specific to healthcare. Healthcare workers adopt technology not for its own sake, but to improve patient outcomes. DPRE captures beliefs about whether the system can provide clinically useful diagnostic support.

Extension of UTAUT2 with these constructs should be accompanied by validation of the measurement instruments. This requires survey development, factor analysis, and structural equation modeling. The contribution of each construct to explained variance in behavioral intention should be assessed.

4.9 Limitations of the Review

This scoping review has several limitations that must be acknowledged. First, the review included only English-language publications. As noted in Section 3.2, the English-language restriction may have excluded Portuguese- and French-language studies from Mozambique and Angola.

Second, the quality of evidence from included studies varies. Some studies use rigorous methods with validated instruments and adequate sample sizes. Others rely on small samples or self-reported measures. The review did not exclude studies based on quality, but limitations of individual studies were documented and considered in the synthesis.

Third, the review synthesizes evidence from multiple countries with different contexts. Findings from South Africa may not fully apply to Zimbabwe, and findings from Malawi may not fully apply to Angola. However, the consistency of barriers across countries strengthens the generalizability of the findings.

Fourth, the review focused on barriers rather than successes. This may present a one-sided picture of AI-integrated HIS in the region. However, the limited number of successful deployments documented in the literature suggests that barriers currently dominate the landscape.

4.10 Future Research Directions

The gaps identified in this review point to several directions for future research. First, empirical studies are needed that design, deploy, and evaluate AI-integrated HIS in rural SADC settings. These studies should use Design Science Research (DSR) methodology to build and evaluate artifacts that address infrastructure resilience, language processing, and diagnostic support simultaneously.

Second, studies are needed that extend UTAUT2 for rural African contexts. The three candidate constructs identified in this review (IRE, LLE, DPRE) require empirical testing. Survey instruments need development and validation. Structural equation modeling can assess the explanatory power of each construct and determine which one best predicts user acceptance.

Third, comparative studies are needed that test offline-capable versus online-only versions of the same system. The magnitude of the offline functionality effect on adoption and outcomes is unknown. Controlled trials or quasi-experimental designs could provide evidence to guide investment decisions.

Fourth, studies are needed that measure the clinical consequences of language barriers in healthcare. It is unknown whether language-discordant patients have higher rates of medication errors, follow-up non-attendance, or adverse outcomes. Quantifying these consequences would strengthen the case for investment in language-support systems.

Fifth, studies are needed that develop and evaluate NLP resources for SADC indigenous languages. Corpus development, machine translation, and speech recognition for Shona, Ndebele, and other languages are underdeveloped. Medical terminology translation requires domain-specific resources.

5. Conclusions and Recommendations

5.1 Conclusion

This scoping review examined the barriers to AI-integrated HIS deployment in rural SADC and identified four interconnected gaps. Infrastructure is unreliable: electricity

outages and intermittent internet connectivity disrupt systems designed for stable environments, and technical support rarely survives beyond the pilot phase. Language is a structural barrier: every HIS in Zimbabwe operates exclusively in English, excluding most rural healthcare workers and patients from full participation. Diagnostic support is virtually absent, with rural clinics relying on symptoms alone while machine learning applications remain confined to urban, retrospective settings. And technology acceptance models such as UTAUT2, developed and validated in well-resourced contexts, have not been adapted to the conditions that prevail in rural African healthcare.

Three design requirements follow from these findings. Systems must be resilient to infrastructure failure, which in practice means offline-first architecture, edge computing, and battery backup. They must support indigenous languages through natural language processing, machine translation, and speech interfaces that reduce dependence on reading and writing. And they must provide diagnostic support using machine learning trained on locally prevalent disease patterns, with interpretable outputs that clinicians can trust. These requirements are interdependent: an offline system that cannot process local languages is of limited use, and a diagnostic tool that dies during a power cut will not be adopted. Integrated design is therefore necessary, not optional.

The review also proposes three constructs — Infrastructure Resilience Expectancy, Local Language Expectancy, and Disease Pattern Recognition Expectancy — as candidate extensions to UTAUT2. Each addresses a barrier the existing model does not capture. Empirical testing is needed to determine which construct best explains user acceptance in rural African healthcare settings, and to establish whether the extended model improves on the explanatory power of UTAUT2 in low-resource contexts.

Existing HIS and telehealth implementations in rural SADC fail because they were designed for conditions that do not exist. Systems assume stable electricity, reliable internet, English proficiency, and trained users — none of which hold in rural areas. Successful implementations will require design grounded in local realities rather than imported assumptions. Investment should prioritize systems built for the conditions that exist, not the conditions that developers wish existed.

5.2 Recommendations

Based on the findings of this scoping review, the following recommendations are made for ministries of health, international donors, researchers, practitioners, and technology developers.

5.2.1 For Ministries of Health in SADC Countries

Ministries of Health should prioritize investment in HIS designed for offline functionality, indigenous language support, and diagnostic assistance rather than importing systems designed for well-resourced settings. All digital health pilots and implementations should include provisions for ongoing technical support and maintenance, and procurement policies should adopt a total-cost-of-ownership approach that budgets for training, technical support, and infrastructure adaptation alongside hardware costs. Finally, ministries should establish minimum standards for infrastructure resilience, including battery backup and offline functionality, as prerequisites for HIS deployment in rural facilities.

5.2.2 For International Donors and Implementing Organizations

International donors and implementing organizations should align funding with locally identified needs and priorities rather than donor-driven agendas, and should support co-design processes that involve healthcare workers and communities in system development. Evaluation frameworks should be required to measure not only technical performance but also user acceptance, health outcomes, and long-term sustainability. Donors should also fund the creation of NLP corpora and model development for SADC indigenous languages as a precondition for future language-capable HIS.

5.2.3 For Researchers

Researchers should conduct empirical studies that design, deploy, and evaluate AI-integrated HIS in rural SADC settings. They should develop and validate survey instruments to test the three candidate constructs identified in this review — Infrastructure Resilience Expectancy, Local Language Expectancy, and Disease Pattern Recognition Expectancy — and conduct comparative studies testing offline-capable versus online-only versions of the same system. Researchers should also measure the clinical consequences of language barriers, including rates of medication errors, follow-up non-attendance, and adverse outcomes among language-discordant patients, and develop and validate NLP models for Shona, Ndebele, and other SADC languages, with a specific focus on medical terminology translation.

5.2.4 For Practitioners and Healthcare Workers

Practitioners and healthcare workers should engage in design and testing processes by providing expertise on clinical workflows and local conditions, and should participate in continuing professional development rather than single-session training. They should also provide structured feedback to system developers on usability challenges and the clinical relevance of AI-generated recommendations.

5.2.5 For Technology Developers

Technology developers should design systems with offline-first architecture that continues to function during power cuts and internet outages, and implement edge computing capabilities that allow AI models to process data locally on mobile or edge devices. They should develop interpretable machine learning algorithms that explain how predictions are generated, so clinicians can calibrate their trust to the system's actual reliability, and create user interfaces that support indigenous languages through natural language processing, speech recognition, and text-to-speech.

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