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Barriers, limitations, and challenges to the implementation of artificial intelligence in Latin American healthcare systems: a scoping review

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Systematic Review

Keywords: artificial intelligence, digital health, implementation science, Latin America, health information systems, scoping review

Posted Date: November 17th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11156390/v1

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Additional Declarations: Competing interest reported. The authors are affiliated with Nebula Medical, a health-technology company developing an ambient AI clinical documentation tool. This review concerns the general regional evidence base and no Nebula Medical product was assessed. Several measures limit the influence of this interest on the findings. The protocol was registered prospectively before screening began, and screening was performed in duplicate with third-reviewer adjudication. Barrier instances were charted in full against the source text by one reviewer and reviewed in full by a second, and the count matrices were audited by a third. The charting dataset with its verification flags is publicly deposited. No Nebula Medical product, and no ambient documentation technology, was among the technologies charted. The review's principal finding, that the regional evidence describes implementation barriers more often than it measures them, does not favour the commercial interest of an AI implementation vendor. The authors declare no other competing interests.

Barriers, limitations, and challenges to the implementation of artificial intelligence in Latin American healthcare systems: a scoping review

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ABSTRACT

Background. Artificial intelligence (AI) and digital transformation are promoted as ways to close gaps in Latin American health systems, but the obstacles to routine clinical use are scattered across a multilingual literature.

Objective. To map evidence on barriers to implementing AI, and the digital infrastructure it depends on, in Latin American healthcare, 2016 to 2026.

Methods. Joanna Briggs Institute methodology, PRISMA extension for Scoping Reviews reporting, Open Science Framework registration. Five databases were searched in English, Spanish and Portuguese, with duplicate screening. Sources were charted under a manual frozen before charting: verified against the full text by one reviewer, reviewed by a second. Barriers traceable to data the source collected were counted as empirically studied.

Results. Of 2,742 records, 43 sources were included, contributing 1,031 barrier instances concentrated in Brazil, Peru, and Colombia. Sixteen of the 43 sources measured none of the barriers they reported; all 13 primary empirical studies measured something, 11 of the 12 narrative reviews nothing. At instance level 328 (31.8%) were empirically studied, 703 (68.2%) asserted without supporting data. Instances clustered at the health-system (374) and regulatory/political (217) levels, dominated by infrastructural (140) and regulatory (165) barriers. The pattern held among the 813 AI-specific instances (63.3% asserted) and strengthened among the 16 exclusively Latin American sources (76.8%).

Conclusions. The regional evidence describes implementation barriers far more often than it measures them: more than a third of the included sources measured none of what they reported. Prospective implementation studies, not further assertion, will close the gap.

Keywords: artificial intelligence; digital health; implementation science; Latin America; health information systems; scoping review

RATIONALE

The claim that artificial intelligence (AI) will transform medicine is now made so often that it can pass without examination. In Latin America the claim carries particular weight, because the region enters the current wave of clinical AI with a documented set of structural disadvantages: fragmented financing, uneven digital infrastructure, specialists concentrated in a few urban centers, and health information systems that were rarely designed to talk to one another [1]. Against that backdrop, tools that promise earlier diagnosis, lighter administrative load, or triage where no specialist is available are unusually attractive; for many institutions they are the only plausible route to closing gaps that decades of conventional investment have left open [2].

What is far less clear is whether these tools reach the bedside. A model that performs well on a retrospective dataset has crossed only the first of several thresholds. The harder thresholds are organizational, ethical, regulatory, financial, infrastructural, and cultural, and they are where most health technologies in the region have historically stalled [3]. The distinction between technical performance and real-world implementation is familiar in the global literature, but its specific caveats in Latin America, where a public tertiary hospital in a capital and a rural primary-care post can operate under incompatible constraints inside one national system, have not been assembled in one place [4].

Several features of the regional evidence make that assembly difficult. The relevant work is genuinely multilingual, with important contributions in Spanish and Portuguese that are inconsistently indexed in the major English-language databases [5]. Much of the applied work appears as engineering conference proceedings rather than clinical studies, so implementation is often discussed inside papers whose primary framing is technical. Also, a large body of publications treats low- and middle-income countries as one undifferentiated category, folding Latin American realities into a global-South average that hides what is distinctive about the region. The result is a body of work that exists but is hard to search.

A scoping review is the design suited to a literature of this shape. Where a systematic review answers a narrow question about effect, a scoping review maps the extent, range, and nature of a body of evidence and shows where the gaps lie. Recent regional work has documented specific facets of the problem, including the acceptance and literacy of the health workforce [6, 7], the maturity of algorithmic governance [8], and the uneven development of regulation across countries [9], but these strands have not been drawn into a single map of implementation barriers.

This review therefore maps and synthesizes the literature on barriers, limitations, and challenges to the implementation of artificial intelligence technologies in Latin American healthcare between 2016 and 2026. We treat implementation as depending on more than model performance, focusing on the organizational, ethical, regulatory, financial, infrastructural, operational, and sociocultural factors that decide whether a technology is adopted and sustained in real care. Our objectives are to classify reported barriers by the level at which they operate, to characterize the technologies and settings in which they arise, to establish how much of what is reported rests on data collected for the purpose, and to identify gaps, including countries and care settings that remain underrepresented.

METHODS

This review followed the Joanna Briggs Institute methodology for scoping reviews [10] and is reported per the PRISMA extension for Scoping Reviews (PRISMA-ScR) [11]; the completed checklist is provided in Online Resource 1. The protocol was registered on the Open Science Framework before screening began (29 May 2026) [12]. Three departures from the registered protocol, all made after registration, are disclosed here rather than by amendment: the revision of the evidence-classification rule to admit qualitative data, stated under Selection, charting, and verification; the correction of an incomplete PubMed export, described under Information sources and search; and the full recharting of the corpus under the revised rule after editorial review.

Eligibility criteria

Eligibility used the Population–Concept–Context (PCC) framework.

- **Population:** healthcare systems, institutions, professionals, and patients in Latin American countries. Studies addressing low- and middle-income countries as an undifferentiated group, without data specific to one or more Latin American countries, were excluded.
- **Concept:** barriers, limitations, and challenges to the implementation or adoption of AI (machine learning, deep learning, clinical decision support, natural-language processing, predictive analytics, automation, and generative AI) or of broader digital transformation. Sources reporting only technical model performance, with no implementation component, were excluded.
- **Context:** real-world or prospective health-service environments. Sources were restricted to 2016–2026 and to English, Spanish, or Portuguese.

Both AI and broader digital transformation technologies were eligible, because the regional literature discusses the two together and because interoperability, data infrastructure, and health information system capacity are prerequisites for AI deployment rather than a separate subject. The distinction is kept visible by coding it on every instance, and it is reported as a result with a sensitivity analysis beside it.

Information sources and search

We searched PubMed/MEDLINE, Scopus, Web of Science, Embase, and LILACS on 3 June 2026, combining controlled vocabulary and free-text terms across three blocks (AI and digital transformation; implementation and its barriers; Latin America), adapted per database and expressed in the three languages. No grey literature source was searched and no reference lists were screened for further reports.

During the audit that followed initial editorial review, the PubMed export retained from that search was found to be truncated at 22 records. The PubMed strategy was therefore re-executed on 3 September 2026 and restricted to records that had entered PubMed by 3 June 2026, which reproduces the result set as it stood on the search date (184 records; 11 records entering PubMed after that date were set aside unscreened). Records already present in the original screening set carried their decisions forward and the 16 new records went through the same duplicate screening. Every included source was matched to the database export that retrieved it; the truncated export retrieved

none of the 41 sources included from the original search, which is why PubMed appears in no source's provenance. The PubMed string as executed, and the strings for all five databases, are given in Online Resource 2.

Selection, charting, and verification

Records were deduplicated and screened in duplicate at title and abstract and then at full text, with conflicts adjudicated by a third reviewer. Reports excluded at full text are listed in Online Resource 3 with the reason for exclusion, together with the five reports that were sought but could not be retrieved.

Charting was performed twice. A first round, with a piloted form, captured bibliographic details, country and setting, technology, study design, and each reported barrier with the level at which it applied; that round produced the version assessed at editorial review. After that assessment, every included source was recharted in full from its full text under a coding manual frozen before recharting began (version 1.10, Online Resource 4).

The manual fixes the unit of analysis, which is a distinct barrier statement: where one source states the same deficit more than once, the statements are linked and the deficit is counted once. It also fixes what counts as a barrier at all, the evidence rule stated below, the controlled vocabulary of five levels, seven domains and 25 sub-themes, the treatment of claims attributed to settings outside the region, and the verification protocol. Fourteen further sub-themes were admitted during charting under the manual's own procedure for a deficit no existing term named, each recorded with its motivating statements and a sweep of the charted corpus, so the vocabulary as applied carries 39 terms (Online Resource 4). Where a source scores several jurisdictions against a framework in a compliance matrix, the manual charts one instance per principle rather than one per cell. A completeness pass then re-read every source against its charted rows, and every instance from the first round was crosswalked to its recharted counterpart or to a documented disposition.

Each barrier statement was quoted verbatim before it was coded, and a validation script accepted a row only when the quotation matched the source text exactly; for 77 rows across 18 sources, whose printed sentence a two-column layout or an interleaved table leaves unrecoverable as continuous text, the quotation was checked against a layout-preserving extraction of the same document instead, and those rows are listed in Online Resource 4. Each instance was then classified by level of analysis (professional, institutional, health-system, patient, and regulatory or political), by thematic domain (organizational, ethical, regulatory, financial, infrastructural, operational, and sociocultural), and by sub-theme. Three further variables were coded on every instance: whether the statement concerned an AI-specific technology or the general digital infrastructure, whether the claim was the source's own primary finding, cited from another publication or unattributed, and whether the barrier was already experienced or was anticipated.

A barrier was classified as empirically studied when the source reported data collected for the purpose of characterizing it, whether quantitative (survey frequencies, measured indicators, performance or utilization data) or qualitative (interviews, focus groups, structured stakeholder consultation, or documented content or thematic analysis of primary material). The statement also had to be traceable to those data rather than to the authors' commentary. Statements made without reference to data collected in the source, including barriers cited from other

publications, were classified as asserted. This rule replaces the quantitative-only rule of the first round and was applied to the whole corpus in one pass; evidence type was not sub-classified, so the studied share under the previous rule cannot be recomputed here.

Two regional rules were applied at the level of the individual statement. A claim attributed specifically to a country outside the region, or whose setting was carried by a regulatory instrument that exists only outside it, was not charted; claims about low- and middle-income countries or the BRICS group, groupings to which the region belongs, were charted and labelled as pooled. Separately, and only after the barrier map had been built, each source was coded for regional specificity into one of three tiers: exclusive to Latin America, reported as a separate arm of a group analysis, or reported as a group or incidental finding.

The unit of counting was the barrier instance, not the study, because one source can report barriers across several levels and domains. Instance counts describe the composition of the published record and are not treated as independent observations. Two study-level denominators are therefore reported beside them: the number of sources reporting a given barrier at least once, and the number reporting at least one empirically studied barrier of that kind. Every source was assigned to one of five design groups (primary empirical study; systematic or scoping review; narrative review; document or legal analysis; perspective or opinion) by written rules applied to the design each source states for itself, deposited with the analysis scripts and reproducing the first round's design distribution exactly. Instance-level results are stratified by design and by evidence type so that the contribution of reviews, primary studies and commentary can be read separately.

Rows were extracted and verified in full against the source text by one reviewer, and reviewed in full by a second reviewer. Verification was corrective rather than adjudicative: a row accepted after correction was edited in place, so no charted row carries a rejection, and the corrections themselves are in the deposited dataset. The recharted count matrices were audited by a third reviewer. Consistent with the aim of a scoping review, methodological quality was not appraised and did not affect eligibility. Only verified instances entered the synthesis.

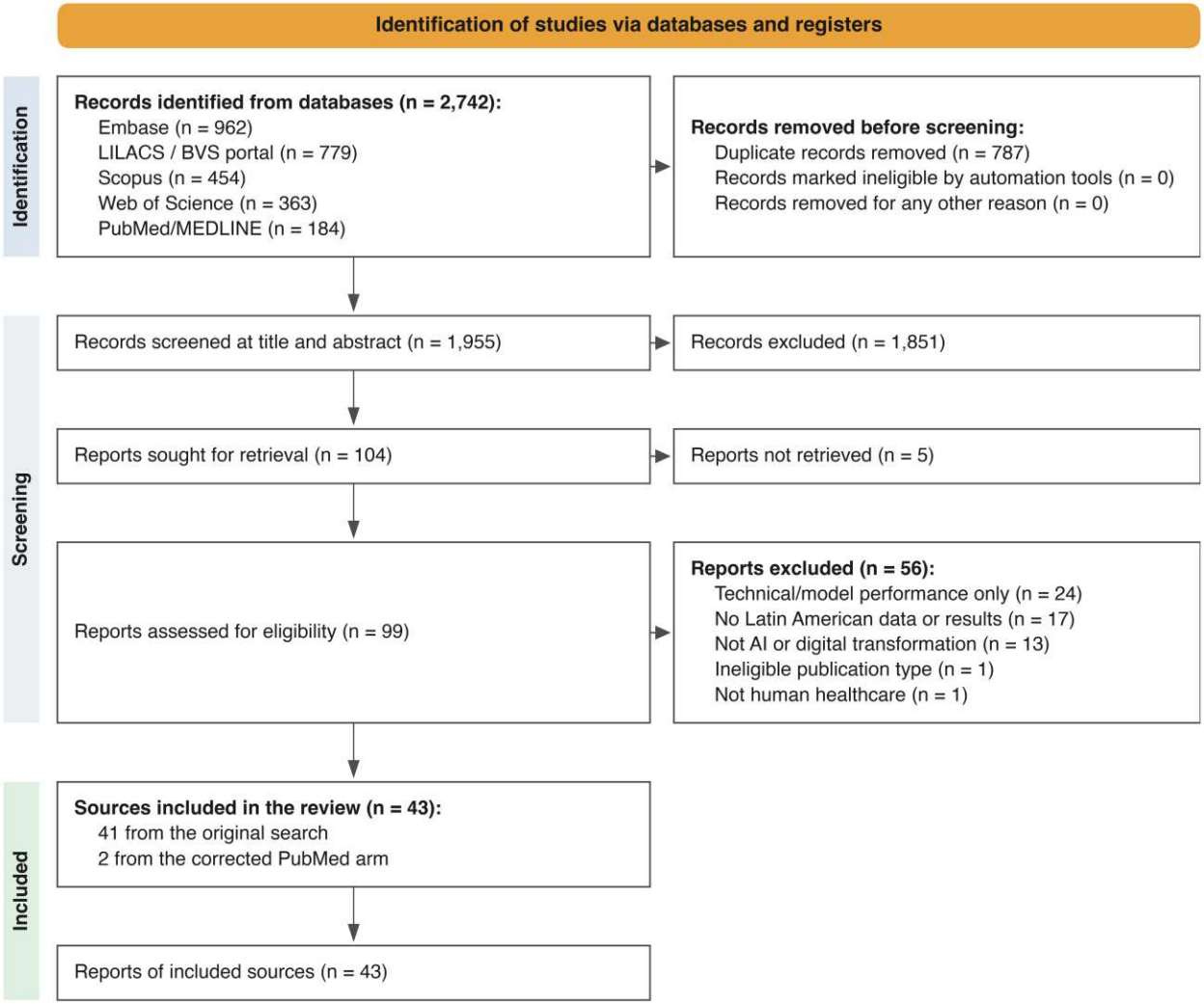
Synthesis

Verified instances were organized through the level-of-analysis framework and, within each level, by domain and sub-theme. Frequencies are reported at instance level and at study level, overall and stratified by study design and by evidence type. Two sensitivity analyses were performed: restriction to AI-specific instances and restriction to the cumulative regional-specificity sets. Characteristics of the included sources were summarized as frequencies. No statistical pooling was performed. Every count was computed by script from the deposited charting dataset, and each reported number names its denominator.

RESULTS

Selection of sources

The searches returned 2,742 records (Embase 962; LILACS 779; Scopus 454; Web of Science 363; PubMed/MEDLINE 184). After 787 duplicates were removed, 1,955 records were screened at title and abstract and 1,851 were excluded. Of 104 reports sought for retrieval, 5 could not be obtained and 99 were assessed at full text. Fifty-six were excluded with documented reasons (technical or model-performance only, 24; no Latin American data, 17; not AI or digital transformation, 13; excluded publication type, 1; not human healthcare, 1), leaving 43 included sources: 41 from the original search and 2 identified through the corrected PubMed arm [13, 14]. Five records were not retrieved due to a lack of institutional access. Figure 1 shows the selection process; the corrected PubMed arm is counted within the records identified.



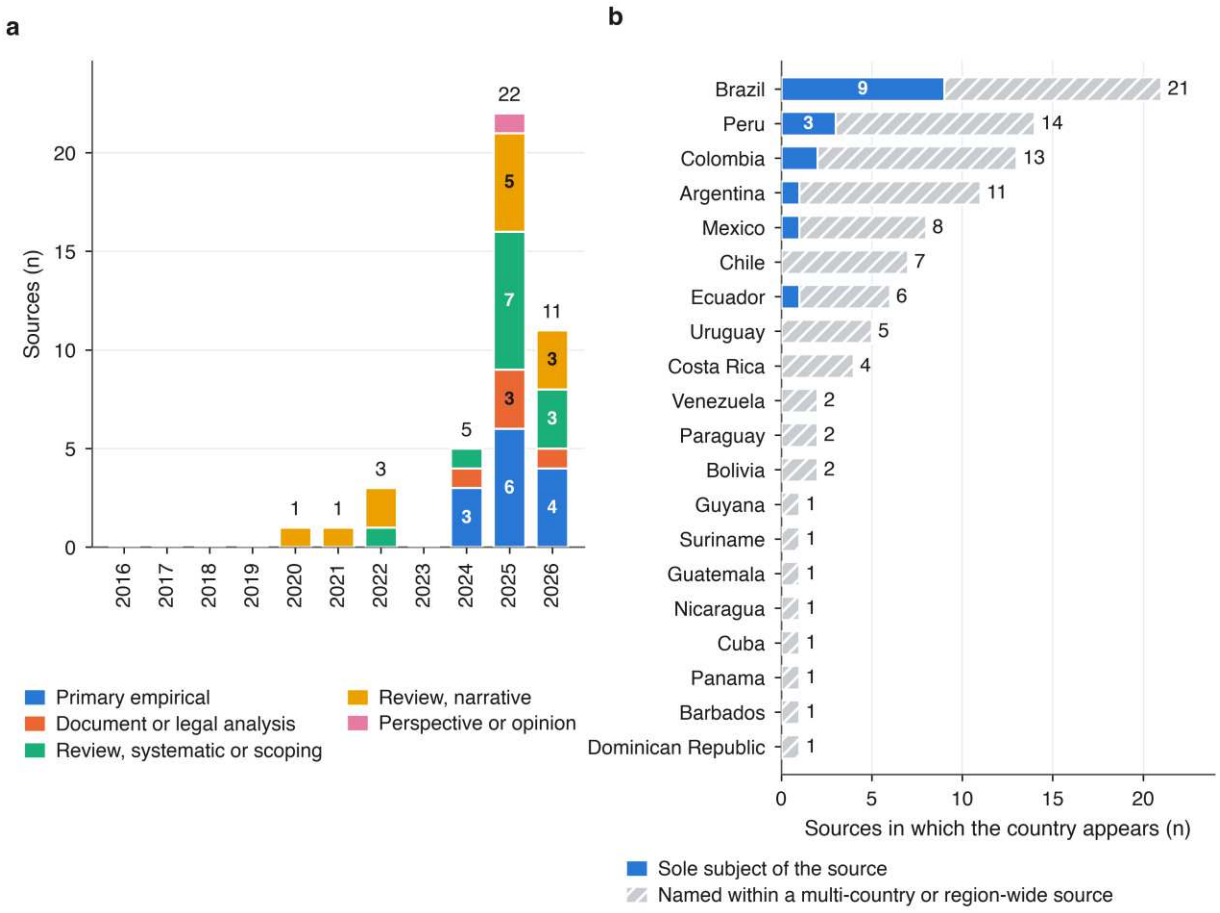
Charting the 43 sources under the frozen manual produced 1,097 verified rows, 1,031 of them distinct barrier instances and 66 restatements of an instance already counted. Every instance charted in the first round is accounted

for in the deposited dataset, whether it was carried forward, absorbed into another instance or set aside under the manual's eligibility rules, and Online Resource 4 gives the reconciliation.

Characteristics of the included studies

Table 1 profiles each of the 43 included sources. This is a young literature: 22 sources appeared in 2025 and 11 in 2026, so 33 of the 43 were published in the final two years of the eligibility window (Figure 2a). It is also a literature of reviews more than of studies: 12 systematic or scoping reviews and 12 narrative reviews, against 13 primary empirical studies, 5 document or legal analyses and one perspective piece. Most appeared as journal articles (37), with 5 conference papers and one master's thesis, and most were written in English (32), the rest in Spanish (6) or Portuguese (5).

Geographically the evidence is concentrated where the region's research capacity is. Brazil appears in 21 of the 43 sources and is the sole subject of 9 of them, followed by Peru (14) and Colombia (13); most other countries in the region surface only inside multi-country or region-wide commentary, and several do not appear at all (Figure 2b). The same unevenness shows in how much of a source is actually about the region: 16 sources report exclusively Latin American material, 17 carry a separately attributable Latin American arm or case inside wider material, and 10 place Latin American settings only inside pooled multinational results.



The barrier map

The map is unbalanced in two directions at once (Figure 3). More than half of the 1,031 instances sit at two of the five levels, the health system (374) and the regulatory or political level (217), ahead of the institutional (199), professional (134) and patient (107) levels. Two cells carry much of that weight: regulatory barriers at the regulatory/political level (165 instances) and infrastructural barriers at the health-system level (140). What the regional literature reports as blocking AI is, to a large extent, missing rules and missing infrastructure.

Domains behave differently from one another. Ethical barriers turn up at every level, between 18 and 42 instances, while operational barriers cluster where clinical work is organized, at the institutional (70), health-system (69) and professional (48) levels, and are absent from the regulatory/political level altogether. Sources contributed unevenly: the median source supplied 22 instances, the range ran from 6 to 66, and the five largest contributors between them accounted for 234 instances (22.7%).



Barriers by level of analysis

Health-system level

This level carried the largest share of verified barriers, driven mainly by infrastructure. Studies described fragmented information systems, weak connectivity, and poor data standardization as the ground on which any regional deployment must stand [15–18]; one regional review noted that information systems have low interoperability and that institutions store poor-quality data [16]. Financing and access inequities recurred, with advances concentrated in Brazil and Mexico while other countries lagged for economic and political reasons [16].

Regulatory and political level

Governance was the single most reported sub-theme in the whole map. Studies pointed to absent or immature legal frameworks, unclear approval pathways, and the regulatory heterogeneity that complicates cross-border tools [15, 16, 19]; regulatory barriers and the lack of clear legal frameworks were named as the principal obstacle to health-sector AI in more than one regional synthesis [1, 16, 20].

Institutional level

Inside institutions, the recurring barriers were operational and organizational: integrating tools into clinical workflow, procurement and cost, data quality, and organizational readiness, often compounded by resistant institutional cultures [17].

Professional level

At the level of the individual clinician, sociocultural and operational barriers led, mainly related to digital literacy and workforce capacity, trust in and acceptance of AI, and added workload. A shortage of experts was reported to affect the quality and interpretation of data in remote cardiovascular monitoring [16].

Patient level

Patient-level barriers were dominated by sociocultural and ethical concerns: acceptability, equity of access, and trust. Inequalities in access to advanced technologies were reported to limit adoption, especially in rural and disadvantaged communities [16], and privacy and data-security concerns were linked to distrust of a government AI initiative [15].

Evidence basis of the barriers

The barriers identified matter less than the evidence behind them, and that evidence tracks study design closely enough to be predicted from it. Across the corpus, 27 of the 43 sources reported at least one empirically studied barrier, and the remaining 16 reported barriers without supporting data of any kind.

Stratified by design, the deficit sits almost entirely in the sources that collected nothing (Table 2). Primary empirical studies measured 199 of their 317 instances, and every one of the 13 measured something. Narrative reviews measured 5 of 269, a rate of 1.9%, and 11 of the 12 measured nothing at all. Document and legal analyses (39.9%) and systematic or scoping reviews (22.3%) fall between those poles, and the single perspective piece measured none of its 17. The median within-source share of barriers resting on data the source itself collected is 57.1% among primary empirical studies and 0% among narrative reviews.

At instance level the ratio is close to one measured barrier in three. Only 328 of the 1,031 instances (31.8%) were empirically studied, against 703 (68.2%) asserted or discussed without reference to data collected in the source (Figure 4). The asserted majority is not one kind of claim: 397 instances repeat a barrier cited from another publication, 267 carry no attribution at all, and 39 come from sources that did collect primary data but did not tie the

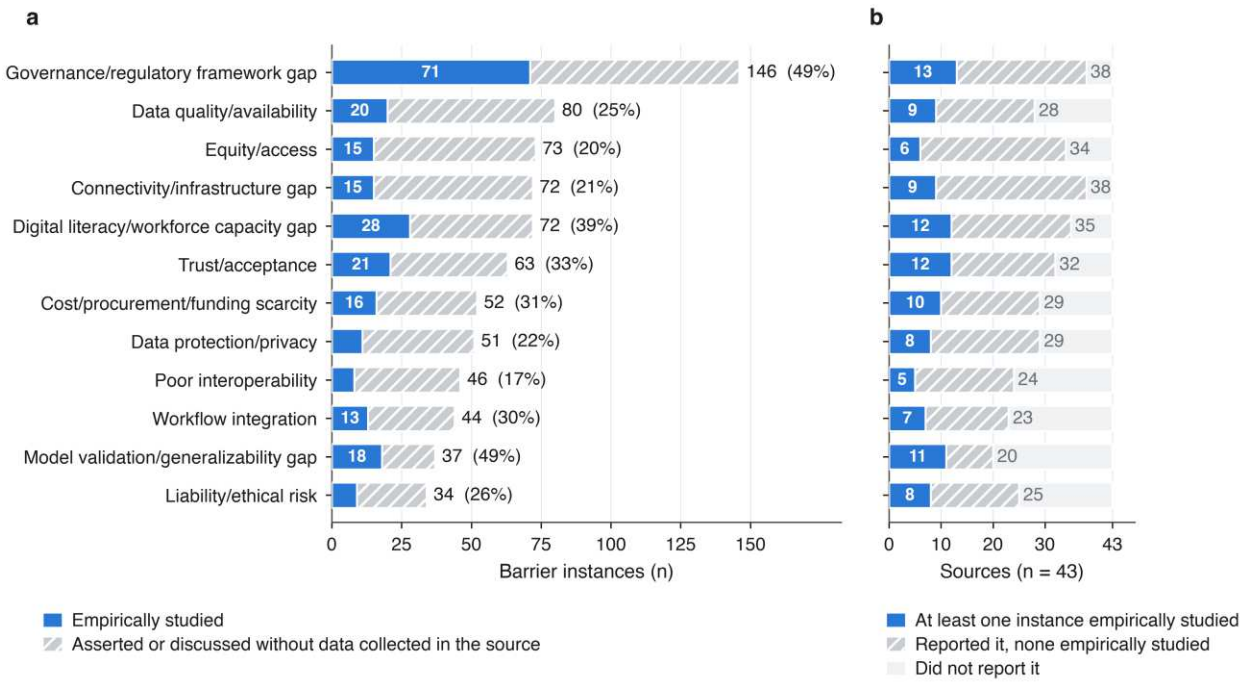
statement to it. Whether measured or not, most instances describe barriers already encountered (755, 73.2%) rather than anticipated ones (275, 26.7%), with one instance coded as both.

The deficit is not spread evenly across the barriers themselves, and it is sharpest where the literature sounds most confident. Governance and regulatory framework gaps, the most reported sub-theme in the map, appeared in 38 of the 43 sources, yet only 13 of those measured a governance barrier of any kind. Its studied rate of 48.6% (71 of 146 instances) is the highest among the large sub-themes and also the most concentrated: 42 of those 71 instances come from two documentary analyses of national instruments [21, 22], so what reads as a measured regional barrier is largely two sources scoring compliance gaps.

The same pattern holds for the two constraints most often named as the region's own. Equity of access was reported by 34 sources and measured by 6 of them (15 of 73 instances, 20.5%); connectivity and infrastructure gaps by 38 sources and measured by 9 (15 of 72, 20.8%). Data quality (20 of 80, 25.0%) and trust and acceptance (21 of 63, 33.3%) come off better without reversing the picture: each was still asserted about three times for every time it was shown. Online Resource 5 gives both denominators for all 39 sub-themes.

Separating AI from the infrastructure it runs on changes little. Of the 1,031 instances, 714 (69.3%) concern an AI-specific technology and 99 (9.6%) concern both AI and the general digital infrastructure, leaving 218 (21.1%) about digital infrastructure alone. Restricting the analysis to the 813 AI-specific instances, drawn from 38 of the 43 sources, moves no level share by more than 2.8 percentage points and no domain share by more than 3.8. The movements that do occur are the ones to expect: infrastructural barriers fall from 17.1% to 13.3% and interoperability from 4.5% to 2.5%. The asserted share falls from 68.2% to 63.3%, so the evidence finding is not an artefact of counting infrastructure problems as AI problems (Online Resource 6).

Restricting the analysis to the sources most specific to the region changes little either. The exclusively Latin American sources carry 370 instances, those with a separately attributable regional arm 400, and those reporting the region only inside pooled multinational results 261. Across the exclusively regional set, the cumulative set that adds the attributable arms, and the full corpus, no level share moves by more than 5.6 percentage points and no domain share by more than 7.4, the largest being organizational barriers, which are more prominent in the exclusively regional sources. The asserted share is 76.8% in the exclusively regional set and 76.2% in the cumulative set, against 68.2% across all 43 sources, because the pooled multinational primary studies carry the largest share of measured barriers (55.6% of their instances). The evidence finding therefore sharpens as regional specificity tightens (Online Resource 6).



Among the gaps, primary care, insurance and payer settings, and public-health administration are thinly represented; most non-Brazilian countries appear only inside regional commentary; and prospective, real-world implementation studies are scarce relative to reviews and model-development papers. Policy-relevant sub-themes such as algorithmic bias, explainability, and language or cultural adaptation each account for fewer than 3% of instances (Online Resource 5).

CRITICAL SYNTHESIS

This review mapped the published evidence on barriers to implementing AI and digital transformation in Latin American health systems between 2016 and 2026. Three patterns stand out. The evidence is recent and concentrated, clustering in the last two years and in Brazil, Peru, and Colombia. Its center of gravity sits at the health-system and regulatory levels, where infrastructure and governance dominate, rather than at the level of the individual model. And it is, for the most part, asserted rather than measured. Read against the wider literature, these patterns place the region as a local intensification of a universal constraint set rather than a regional anomaly.

The concentration of the regional evidence mirrors a documented global asymmetry rather than a purely regional publication artifact. A global review of bias in clinical AI found datasets and authorship dominated by the United States and China, with data-poor regions largely absent [23], and an analysis of mature, real-world models showed that the large majority of deployment cohorts originate in high-income or upper-middle-income countries [24]. Within Latin America the same pattern repeats, with a landscape review identifying only a few dozen open health datasets across the region, most drawn from a single Brazilian source [25]. The clustering we observe in Brazil, Peru, and Colombia is therefore the regional face of a worldwide concentration of data and scholarship.

The center of gravity at the health-system and regulatory levels is at once convergent with the global pattern and distinct from it. The barrier categories are shared: a theory-based review of predominantly high-income implementations identified interoperability and data quality as the most cited obstacles [26], the same headings that dominate our map. What differs is the floor beneath them. High-income systems debate these barriers on top of largely solved infrastructure, whereas the region does not. The clearest evidence that data, rather than the algorithm, can be the binding constraint comes from a cross-country study in which a United Kingdom model deployed unchanged in two Vietnamese hospitals fell to near-chance discrimination and recovered only after local retraining [27].

Governance shows a parallel contrast: against the European Union's dense body of binding health-AI policy [28], the region regulates AI largely through data-protection law, as in Brazil where the operative instrument is the general data-protection statute rather than a device or clinical-performance regime [29], while national AI strategies remain rare across low- and middle-income countries more broadly [30].

The last pattern matters most, and it is not a regional deficiency. Where most claims about barriers rest on no supporting data, consensus can be mistaken for evidence, the mechanism documented in citation networks in which a belief expands through papers that present no data bearing on it [31]. Three features of the recharted data sharpen the point. The deficit is a property of sources rather than of statements: 16 of the 43 sources measured none of the barriers they reported. It tracks study design: sources that collect data measure most of what they report, while the narrative reviews that make up more than a quarter of the corpus measure almost nothing. And it is concentrated in the barriers named most often: governance, infrastructure and equity were each reported by more than three quarters of sources and measured by between a sixth and just over a third of those reporting them. Nor is the shortfall speculation about technologies not yet in use, since most instances describe barriers already encountered rather than anticipated ones, so what goes unmeasured is an obstacle the region is already meeting. That is the wider field's habit as much as the region's, well-tested quantitative measures of implementation determinants being available but little used [32].

The same shortfall is documented globally. A systematic review and meta-analysis of predictive clinical decision-support systems across seventeen specialties found that only a minority of studies involved prospective deployment and most reported technical metrics alone, at modest pooled discrimination [33], and a companion analysis argues that trials of AI decision support rarely incorporate implementation outcomes, so the field cannot explain why bedside translation succeeds or fails [34]. What is distinctive about the region is not that it asserts more than it measures, but that it reproduces a worldwide deficit in prospective, deployment-level evidence while being largely absent from the source data that would let it measure at all. The graded analysis puts a number on that: the asserted share rises to 76.8% among the sources reporting exclusively Latin American material, and the measured material is carried disproportionately by the pooled multinational studies in which the region is one setting among several.

IMPLICATIONS FOR RESEARCH, POLICY AND PRACTICE

Four implications follow, and each connects to evidence from beyond the region. First, the priority is prospective implementation research that measures barriers rather than asserting them, sited in the countries and settings the current record overlooks, especially primary care and public-health administration outside Brazil; because the measurement deficit is global [33, 34], such studies would contribute well beyond Latin America. That agenda should also reach what the regional record barely raises: algorithmic bias, explainability, and language or cultural adaptation are among the least represented sub-themes in the map, and for explainability the global field disputes whether current methods deliver the trust and bias mitigation claimed of them [35].

Second, shared governance and interoperability standards would address the two dominant cells of the barrier map directly, and regional feasibility work suggests political alignment can matter more than hardware, since a Brazilian project federating municipal and federal records through open standards attributed its success to political will [36], consistent with the broader lesson that national-scale digital-health systems are sustained by government ownership and by designing interoperability in from the outset [37].

Third, the concentration of evidence in a few countries argues against transferring models trained on high-income or single-country data without local validation, given the documented collapse of transported models [27]. A fourth consideration is sustainability, as much digital-health investment in low- and middle-income settings stalls as short-lived pilots [38], and analysis of the financing layer suggests survival depends less on a favorable cost-effectiveness ratio than on integration with public financial management [39].

Lastly, the pattern of reported barriers suggests that digital transformation capacity conditions what AI implementation is feasible. Interoperability gaps and weak data infrastructure were among the most frequently reported barriers at the health-system level, and model training and deployment depend on data assets that those gaps withhold. Brazil, the country appearing in the largest number of included sources, is also the setting of the one account of successful large-scale interoperability [36]. On the evidence mapped here, strengthening digital transformation capacity is a plausible precondition for AI deployment across the levels this review identifies, though no included study tested that sequence directly.

LIMITATIONS

As a scoping review, this review maps the literature without appraising the quality of individual sources, so the barriers reported should be read as those present in the published record, not as a validated ranking. Restricting eligibility to three languages, while it captured the region's principal scientific languages, may have missed work elsewhere. A substantial share of the evidence appears in conference proceedings, whose reporting of implementation is often brief. The boundary between a source that examines implementation and one that reports model performance with passing context required judgement, applied in duplicate but still partly subjective.

Of the 41 sources included from the original search, no single database returned more than 23, and 25 were returned by exactly one of the five. The multi-database design was therefore load-bearing: a single-database replication would not reproduce this corpus. Twenty-three of the 41 have a PubMed record and the strategy as executed

retrieves 14; every one of the nine it misses was captured through another database. Those nine carry a higher proportion of empirically studied instances than the rest, so a search that had lost them would have reported 71.0% of instances as asserted against 68.2%.

Counts refer to verified barrier instances, not sources, so one source contributes to many cells; the study-level denominators and the design stratification reported beside them are the guide to how much of the map rests on sources that collected data. The largest single contributor, an unpublished master's thesis, supplies 66 instances, 6.4% of the corpus. No charted instance was traced to another included source, so no barrier is double-counted through citation, though that is a lower bound rather than a measurement, because 224 of the 397 instances citing another publication carry a bare numeric marker identifying no work outside its own source. The recharting was performed after editorial review and therefore with the first-round result known; the coding manual was frozen before it began and every rule applied is deposited, but the recharting was not blind to that result.

Eligibility turned on whether a source reported data specific to at least one Latin American country, not on how much of the source that was. Regional specificity was therefore coded post hoc, after screening and after the barrier map had been built, one coder per source against the full text under a fixed brief, and verified. At the far end is a multinational interview study in which Chile is one of eleven countries and one of the 46 interviews, with no finding attributed to any single country [40]. The graded results are reported in the Results and in Online Resource 6.

Two further caveats concern the comparison drawn here. The contrast with high-income and other low- and middle-income settings rests on syntheses of differing scope rather than a head-to-head study, so the relative ordering of barriers across income levels should be read as inference, and the one direct empirical high-income versus low-income contrast available concerns model generalizability rather than barrier frequency [27]. Several of the region-specific comparators also sit low in the evidence hierarchy, including narrative reviews, expert workshops, and one non-peer-reviewed technical report [41], which reinforces rather than weakens the review's central claim about an asserted evidence base.

CONCLUSION

The regional literature on AI and digital-transformation implementation in Latin American health systems describes its barriers far more often than it measures them: 16 of the 43 included sources measured none of the barriers they reported, and the shortfall tracks study design rather than subject matter. The map itself concentrates on a few countries and on health-system and regulatory concerns, with infrastructure and governance the two dominant fault lines. Read against the global and low- and middle-income literature, the region reads as an intensified instance of a shared pattern. The main contribution of this map is to show where the evidence is thin and asserted, and thereby to set an agenda of prospective, context-specific implementation research in the settings and countries the current record leaves out.

STATEMENTS AND DECLARATIONS

Funding. This scoping review received no specific funding from any agency in the public, commercial, or not-for-profit sectors.

Competing interests. The authors are affiliated with Nebula Medical, a health-technology company developing an ambient AI clinical documentation tool. This review concerns the general regional evidence base and no Nebula Medical product was assessed. Several measures limit the influence of this interest on the findings. The protocol was registered prospectively before screening began, and screening was performed in duplicate with third-reviewer adjudication. Barrier instances were charted in full against the source text by one reviewer and reviewed in full by a second, and the count matrices were audited by a third. The charting dataset with its verification flags is publicly deposited. No Nebula Medical product, and no ambient documentation technology, was among the technologies charted. The review's principal finding, that the regional evidence describes implementation barriers more often than it measures them, does not favour the commercial interest of an AI implementation vendor. The authors declare no other competing interests.

Ethics approval. Not applicable. This review analyses published literature only; no human participants, human data, animals or biological materials were involved, so no ethics approval was required.

Consent to participate and for publication. Not applicable; the review involved no human participants.

Data availability. The charting dataset (1,097 verified rows with the crosswalk to the first-round instances, the source-level table with design group and regional specificity, and the verification flags), the coding manual, and every count matrix reported here are deposited on the Open Science Framework project for this review (https://osf.io/kf6bn/), from which the protocol registration [12] was made.

Code availability. The Python scripts that compute every reported count from the deposited dataset are included in the deposit.

Author contributions. VVM and JDNS conceived the review. VVM, JDNS, PPS, DVJ, LGT, MUG, and SASG performed screening and the first round of charting and verification. PPS verified the recharted dataset in full and JDNS reviewed it in full; DVJ audited the count matrices. PPS and JDNS conducted the analysis and drafted the manuscript. LMA supervised the methodology. All authors reviewed and approved the final manuscript.

Use of AI. Generative AI tools were used in the preparation of this review and are declared here. Claude (Anthropic; Opus 5, accessed through the Claude Code command-line interface, June to September 2026) was used for data-charting support under the frozen coding manual, for the analysis scripts that compute every reported count from the deposited dataset, and for revising manuscript text. NotebookLM (Google; the product carries no version number, accessed September 2026) was used as fact-check support during verification, comparing charted rows against the uploaded full texts. SciSpace (accessed September 2026) was used to improve the readability of the manuscript text. The coding manual and the prompts under which the tools operated are deposited with the dataset; default sampling

settings were used. No AI tool screened records, decided eligibility, or acted as a reviewer. The authors reviewed all AI-assisted content and take full responsibility for it.

Registration. Open Science Framework, 29 May 2026 (https://osf.io/6byqz/overview). The three departures from the registered protocol postdate registration and are described in the Methods.

Clinical trial number: Not applicable.

Table 1. Characteristics of the 43 included sources.

Ref.	First author (year)	Country / countries	Design group (specific design)	AI / digital technology	Setting	Language	Barrier instances (n)	Predominant domains (n)	Regional specificity
[15]	Alencar et al (2025)	Brazil	Review, systematic or scoping	ML/predictive; computer-vision/imaging; telehealth/digital-health platform; EHR/HIS/interoperability; robotics/automation; wearables/monitoring; other	Hospital, Primary care, Public health, Administrative	English	17	infrastructural (6), organizational (4), regulatory (2)	Separate arm
[16]	Arcos Huamán et al (2025)	Region-wide	Review, systematic or scoping	ML/predictive; CDSS; telehealth/digital-health platform	Hospital	Spanish	22	operational (6), infrastructural (5), regulatory (4)	Separate arm
[14]	Baka et al (2026)	Mexico, Colombia, Argentina; multinational LMIC	Primary empirical (qualitative interviews)	AI in health broadly; generative AI/LLM	AI research institutes and start-ups	English	42	organizational (11), sociocultural (10), regulatory (8)	Group
[17]	Bellei et al (2025)	Brazil	Review, systematic or scoping	ML/predictive; CDSS; EHR/HIS/interoperability; telehealth/digital-health platform;	Hospital, Primary care, Public health,	English	28	operational (8), infrastructural (8), organization	Exclusive

				other	Administrative			al (5)	
[19]	Bentes et al (2024)	Brazil	Document or legal analysis	generative AI/LLM; NLP; other	Not specified	Portuguese	24	ethical (11), regulatory (9), sociocultural (2)	Separate arm
[42]	Botero et al (2025)	Brazil	Review, systematic or scoping	ML/predictive; computer-vision/imaging; generative AI/LLM; EHR/HIS/interoperability	Primary care, Public health	English	13	infrastructural (3), organizational (3), operational (2)	Separate arm
[43]	Chatterjee et al (2020)	Brazil, Colombia, Argentina, Chile, Peru, Ecuador, Uruguay, Bolivia, Venezuela, Paraguay, Guyana, Suriname	Review, narrative	telehealth/digital-health platform; EHR/HIS/interoperability; CDSS; ML/predictive; wearables/monitoring; other	Public health, Hospital, Primary care, Administrative	English	6	infrastructural (3), regulatory (1), operational (1)	Exclusive
[44]	Ciecierski-Holmes et al (2022)	Mexico, Peru, Ecuador; region-wide	Review, systematic or scoping	ML/predictive; CDSS; computer-vision/imaging; NLP; telehealth/digital-health platform;	Hospital, Primary care, Public health	English	32	operational (15), infrastructural (8), regulatory (4)	Separate arm

				EHR/HIS/interoperability; robotics/automation; other				
[18]	Dantas et al (2025)	Peru; region-wide	Primary empirical (cross-sectional survey)	ML/predictive; CDSS; EHR/HIS/interoperability; other	Hospital, Public health, Administrative, Insurance	English	40	regulatory (11), ethical (6), infrastructural (6)	Group
[45]	De Andrade et al (2026)	Brazil, Peru; region-wide	Review, narrative	telehealth/digital-health platform; EHR/HIS/interoperability; ML/predictive; CDSS; wearables/monitoring; other	Hospital, Primary care, Public health, Administrative	English	30	sociocultural (7), organizational (7), ethical (5)	Group
[46]	De Morais Rodrigues et al (2025)	Brazil; region-wide	Review, systematic or scoping	EHR/HIS/interoperability; ML/predictive; telehealth/digital-health platform; other	Public health, Administrative, Hospital	English	9	infrastructural (4), operational (3), organizational (1)	Group
[47]	Alburuqueque Arana et al (2025)	Chile, Uruguay; region-wide	Review, systematic or scoping	ML/predictive; CDSS; EHR/HIS/interoperability; telehealth/digital-health platform; wearables/monitoring; other	Hospital, Public health, Administrative	Spanish	16	infrastructural (5), regulatory (3), organizational (2)	Group

[48]	Fagundes et al (2024)	Brazil; region-wide	Review, systematic or scoping	ML/predictive; EHR/HIS/interoperability; robotics/automation	Public health, Administrative	Portuguese	17	infrastructural (10), ethical (3), organizational (2)	Separate arm
[49]	Garcia Alonso et al (2022)	Brazil, Mexico, Colombia, Argentina, Chile, Peru, Ecuador, Costa Rica; region-wide	Review, narrative	ML/predictive; computer-vision/imaging; NLP; telehealth/digital-health platform; EHR/HIS/interoperability; robotics/automation; other	Hospital, Primary care, Public health, Administrative	English	24	sociocultural (8), organizational (6), infrastructural (3)	Exclusive
[50]	Garcia Arias et al (2025)	Colombia	Primary empirical (case study)	wearables/monitoring; telehealth/digital-health platform; ML/predictive	Primary care, Public health, Hospital	English	14	sociocultural (6), infrastructural (4), operational (2)	Exclusive
[51]	Gonzales Aste (2025)	Peru	Review, narrative	ML/predictive; CDSS; computer-vision/imaging; generative AI/LLM; telehealth/digital-health platform; EHR/HIS/interoperability; wearables/monitoring	Hospital, Public health	Spanish	25	ethical (9), organizational (4), sociocultural (3)	Separate arm

[1]	Lemes et al (2025)	Brazil, Mexico, Colombia, Argentina, Chile, Uruguay, Cuba; region-wide	Review, narrative	ML/predictive; CDSS; computer-vision/imaging; telehealth/digital-health platform; EHR/HIS/interoperability; wearables/monitoring	Hospital, Primary care, Public health	English	20	infrastructural (6), operational (6), ethical (3)	Exclusive
[52]	Luna et al (2026)	Argentina	Primary empirical (case study)	CDSS; NLP; computer-vision/imaging; generative AI/LLM; EHR/HIS/interoperability; other	Hospital, Administrative	English	18	operational (9), organizational (3), infrastructural (2)	Exclusive
[21]	Machado (2025)	Brazil	Document or legal analysis	AI/ML (national policy — EBIA/PBIA); digital transformation/interoperability; other	Policy/governance	Portuguese	66	organizational (20), regulatory (15), infrastructural (9)	Exclusive
[40]	Marco-Ruiz et al (2024)	Chile; region-wide	Primary empirical (qualitative interviews)	ML/predictive; NLP; CDSS; computer-vision/imaging; EHR/HIS/interoperability; other	Hospital, Administrative	English	46	organizational (11), operational (10), regulatory (10)	Group
[53]	Marey et al (2026)	Colombia, Peru; region-wide	Primary empirical (expert consensus workshop)	computer-vision/imaging (radiology AI: CXR, CT, MRI, ultrasound,	Hospital, Public health, Policy/	English	27	operational (10), ethical (6), infrastructural (3)	Separate arm

				PACS); ML/DL; foundation models/federated learning; telehealth/digital-health platform; other	governance				
[54]	McLennan et al (2024)	Mexico, Colombia, Argentina; region-wide	Primary empirical (qualitative interviews)	ML/predictive; CDSS; EHR/HIS/interoperability; robotics/automation	Hospital	English	24	operational (6), organizational (6), ethical (4)	Group
[55]	Mendez-Avila et al (2025)	Brazil, Colombia, Argentina, Chile, Ecuador, Uruguay, Costa Rica, Bolivia, Venezuela, Guatemala, Nicaragua; region-wide	Primary empirical (cross-sectional survey)	ML/predictive; computer-vision/imaging; other	Hospital, Public health	English	20	sociocultural (6), organizational (5), operational (4)	Exclusive
[56]	Moreno-Fernandez et al (2025)	Peru	Primary empirical (case study)	NLP; generative AI/LLM; EHR/HIS/interoperability; other	Hospital, Administrative	English	6	operational (3), infrastructural (2), financial (1)	Separate arm

[13]	Portilho et al (2026)	Brazil	Primary empirical (cross-sectional survey)	Generative AI/LLM; NLP; workflow automation	Primary care, Hospital, Public and private facilities	English	18	ethical (5), infrastructural (5), sociocultural (3)	Exclusive
[57]	Puig-Bosch et al (2024)	Peru; region-wide	Primary empirical (co-creation workshops)	ML/predictive (AI-driven HF risk/prognosis prediction); CDSS; other	Hospital	English	15	operational (5), sociocultural (4), ethical (2)	Separate arm
[58]	Hamú Ribeiro et al (2026)	Brazil	Document or legal analysis	Generic: AI, IoT and ICTs mentioned as enabled by the legal framework (no focal or evaluated technology)	Public health, Policy/ governance	Portuguese	12	regulatory (4), organizational (4), sociocultural (2)	Exclusive
[8]	Rocha et al (2025)	Brazil, Peru, Dominican Republic; region-wide	Perspective or opinion (opinion piece)	AI/ML for public health: AutoML, automated epidemiological & bioinformatic analysis, outbreak-prediction models (Aedes/dengue), cough-sound classification for respiratory infections, misinformation	Public health	English	17	ethical (6), regulatory (5), infrastructural (3)	Separate arm

				countermeasures					
[59]	Sánchez-González et al (2025)	Mexico	Primary empirical (cross-sectional survey)	ML/predictive; other	Hospital, Administrative	English	31	organizational (8), ethical (7), regulatory (7)	Exclusive
[60]	Santa et al (2025)	Colombia	Primary empirical (cross-sectional survey)	ML/predictive; EHR/HIS/interoperability; telehealth/digital-health platform; robotics/automation; other	Hospital, Administrative	English	16	operational (5), organizational (5), infrastructural (2)	Exclusive
[30]	Shahid et al (2026)	Brazil; region-wide	Review, systematic or scoping	AI in health broadly: predictive ML, CAD/CXR (qXR for TB), NLP, LLMs, CDSS, EHR (OpenMRS), telemedicine	Public health	English	32	ethical (7), sociocultural (6), regulatory (6)	Separate arm
[61]	Silva et al (2025)	Brazil	Document or legal analysis	Digital health transformation broadly: data science, processing of sensitive personal data, EHR, tele-assistance/tele-consultations, learning health systems; AI	Public health	Portuguese	21	sociocultural (6), regulatory (5), organizational (5)	Exclusive

				appears only marginally (mentions the Brazilian AI Plan and ML-based decisions as out of scope)					
[62]	Soares et al (2026)	Brazil	Review, narrative	ML/predictive; computer-vision/imaging; NLP; generative AI/LLM; telehealth/digital-health platform; EHR/HIS/interoperability	Public health, Hospital, Primary care, Administrative	English	18	operational (5), infrastructural (3), sociocultural (3)	Separate arm
[63]	Solari (2025)	Peru	Review, narrative (essay)	ML/predictive; CDSS; computer-vision/imaging; generative AI/LLM; EHR/HIS/interoperability; other	Hospital, Public health, Administrative	Spanish	26	operational (10), ethical (7), infrastructural (4)	Separate arm
[64]	Sussman et al (2022)	Region-wide	Review, narrative	ML/predictive; CDSS; computer-vision/imaging; other	Hospital	English	37	operational (10), infrastructural (8), ethical (8)	Separate arm
[65]	Valli et al (2026)	Brazil, Mexico, Colombia, Argentina, Ecuador; region-	Review, systematic or scoping	ML/predictive; computer-vision/imaging; NLP; EHR/HIS/interoperability; other	Hospital, Primary care, Public health	English	17	operational (4), infrastructural (4), sociocultural (3)	Group

		wide							
[66]	Vasconez-Gonzalez et al (2025)	Ecuador	Review, narrative	EHR/HIS/interoperability; telehealth/digital-health platform; wearables/monitoring; other	Public health, Hospital, Primary care, Administrative	English	25	infrastructural (8), organizational (4), sociocultural (4)	Exclusive
[67]	Vidal et al (2025)	Region-wide	Review, systematic or scoping	ML/predictive; CDSS; computer-vision/imaging; generative AI/LLM; other	Hospital, Public health	Spanish	30	regulatory (10), ethical (6), operational (5)	Group
[68]	Villamarín Marrugo et al (2026)	Region-wide	Review, systematic or scoping	ML/predictive; CDSS; computer-vision/imaging; telehealth/digital-health platform; other	Hospital, Primary care, Public health	English	32	operational (18), infrastructural (5), ethical (4)	Separate arm
[69]	Werutsky et al (2021)	Brazil, Mexico, Colombia, Argentina, Chile, Peru, Uruguay, Costa Rica, Panama, Barbados; region-	Review, narrative	ML/predictive; computer-vision/imaging; telehealth/digital-health platform; EHR/HIS/interoperability; wearables/monitoring; other	Hospital, Primary care, Public health, Administrative	English	30	infrastructural (12), financial (5), regulatory (4)	Exclusive

		wide						
[70]	Xiques-Molina et al (2025)	Colombia, Argentina, Peru; region-wide	Review, narrative	computer-vision/imaging; ML/predictive; telehealth/digital-health platform; other	Primary care, Public health	English	7	operational (2), ethical (2), infrastructural (1)	Group
[20]	Yepes-Barreto et al (2026)	Brazil, Colombia, Argentina, Peru, Paraguay; region-wide	Review, narrative (expert consensus, SWOT analysis)	ML/predictive; other	Hospital, Administrative	Spanish	21	organizational (7), financial (3), operational (3)	Exclusive
[22]	Zavaleta-Monestel et al (2025)	Costa Rica; region-wide	Document or legal analysis (documentary analysis of national instruments, with survey)	ML/predictive; CDSS; other	Hospital, Administrative	English	40	regulatory (27), ethical (7), sociocultural (3)	Separate arm
	43 sources						**1031**		

Design group is the category used in the stratified analysis. Barrier instances are distinct verified instances, restatements excluded. Predominant domains gives the three most frequent domains with their instance counts. Regional specificity: exclusive, exclusively Latin American material; separate arm, a separately attributable Latin American arm or case within wider material; group, Latin American settings only inside pooled multinational results. Included sources are numbered within the single continuous reference list; 14 are also cited in the narrative text and 29 appear only here. AI, artificial intelligence; CDSS, clinical decision support system; EHR, electronic health record; HIS, health information system; ML, machine learning; NLP, natural language processing.

Table 2. Evidence basis of the barrier instances by study design group.

Design group	Sources (n)	Instances (n)	Empirically studied, n (%)	Asserted (n)	Sources with at least one studied instance, n (%)
Primary empirical	13	317	199 (62.8)	118	13 (100.0)
Document or legal analysis	5	163	65 (39.9)	98	4 (80.0)
Review, systematic or scoping	12	265	59 (22.3)	206	9 (75.0)
Review, narrative	12	269	5 (1.9)	264	1 (8.3)
Perspective or opinion	1	17	0 (0.0)	17	0
All sources	**43**	**1,031**	**328 (31.8)**	**703**	**27 (62.8)**

Empirically studied instances are those traceable to data the source collected, quantitative or qualitative. The last column gives the number of sources in the group reporting at least one empirically studied instance. 43 sources, 1,031 instances.

FIGURE LEGENDS

Fig. 1 PRISMA-ScR flow diagram of record retrieval, deduplication and screening. Identification was through databases and registers only; the other-methods arm of the PRISMA 2020 template is omitted because no grey literature source, website, organisation or reference list was searched. The PubMed/MEDLINE count is the corrected export and is counted within the 2,742 records identified; a further 11 records that entered PubMed after the search date of 3 June 2026 were set aside unscreened and fall outside the diagram

Alt text: A single-column flow diagram. Of 2,742 records identified in five databases and deduplicated (787 removed), 1,955 were screened at title and abstract and 1,851 excluded; 104 reports were sought, 5 not retrieved, 99 assessed at full text, and 56 excluded with the reasons shown, leaving 43 included sources contributing 1,031 distinct verified barrier instances. The diagram has no other-methods arm.

Fig. 2 Characteristics of the 43 included sources. (a) Sources by publication year and design group; no source was published between 2016 and 2019 or in 2023, and the 2026 count is partial, covering publications retrieved up to the search date of 3 June 2026. (b) Number of sources in which each Latin American or Caribbean country appears, distinguishing sources of which the country is the sole subject (solid) from those naming it within multi-country or region-wide material (hatched); a source may appear under several countries, so appearances (103) exceed the number of sources (43)

Alt text: Among the included sources, publication is concentrated in the last two years of the window, and reviews, narrative and systematic together, are the most frequent design group overall. Most countries appear only inside multi-country or region-wide sources; Brazil, Peru and Colombia are the most frequent, and Brazil accounts for most of the sources devoted to a single country.

Fig. 3 Barrier map cross-tabulating the 1,031 verified barrier instances by five levels of analysis and seven thematic domains. Cell values are counts of instances, not sources; a cell holding no instance is printed as zero. Shading encodes the cell count, and rows and columns are ordered by their own totals

Alt text: When cross-tabulating barrier instances by level of analysis and thematic domain, regulatory barriers at the regulatory/political level and infrastructural barriers at the health-system level dominated, and several combinations, among them operational barriers at the regulatory/political level, were reported by no source at all.

Fig. 4 Evidence basis of the twelve most frequent barrier sub-themes, which together account for 770 of the 1,031 verified barrier instances. (a) Instances of each sub-theme, split between those empirically studied (solid) and those asserted (hatched), annotated with the total and the proportion empirically studied. (b) The same split counted at source level, on a fixed denominator of all 43 sources: those with at least one instance empirically studied (solid), those reporting the sub-theme with none empirically studied (hatched), and those not reporting it (unshaded), with the number marking where the reporting sources end. Across all 1,031 instances, 328 (31.8%) were empirically studied and 703 (68.2%) asserted

Alt text: The most frequently reported barrier sub-themes concern governance and regulatory frameworks, data quality, equity of access, connectivity and workforce capacity. Most instances of each were asserted rather than measured, and the same pattern holds at source level: for all but one of the sub-themes shown, most of the sources reporting it measured none of its instances.

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