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From Promise to Practice: AI-Enabled Telerehabilitation and the Evidence-to-Implementation Gap in Resource-Constrained Health Systems AI-Enabled Telerehabilitation – Evidence-to-Implementation Gap

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ABSTRACT

Background: Access to rehabilitation is still restricted in many low- and middle-income countries (LMICs) and artificial intelligence (AI) is becoming more widely used in remote rehabilitation. The main public health question is not about the feasibility of implementing AI-based telerehabilitation, but about the evidence base for safe, equitable and sustainable implementation at scale.
Methods: This critical narrative review collates literature from PubMed/MEDLINE, Scopus and additional web literature searches, focusing on literature from 2024 to 2026, with the inclusion of foundational implementation literature. Eligible interventions included remote/home-based rehabilitation plus a demonstrated AI, machine-learning or deep-learning element. The synthesis included clinical evidence, added value of AI, validity in real-world, implementation readiness, equity, safety and scale-up, in the context of Pakistan.
Results: Primary studies indicate positive outcomes with specific AI-supported telerehabilitation applications, such as computer vision exercise support and AI-guided programmes. Most studies are small and heterogeneous, and few studies sufficiently account for the effects of AI while controlling for remote delivery, therapist contact, monitoring, feedback, adherence support, and adherence dose. Home validation evidence, health-economic value, governance and sustainable scale evidence are significantly less robust. No Pakistan specific AI based Telerehabilitation trial was found.
Conclusions: AI-based telerehabilitation has strong potential but is not yet backed by robust evidence for widespread implementation within health systems with limited resources. Implementing should be done via evidence thresholds for clinical benefit, independent AI-added value, real-world validity, safety, equity, affordability, workforce compatibility and sustainability.

Keywords: AI, Telerehabilitation, Rehabilitation, Digital Health, ImplemEntation Science, Health Equity, LMC, Pakistan.

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Introduction

Rehabilitation is one of the least resourced areas of global health. A significant proportion of the population in most low- and middle-income countries (LMICs) have musculoskeletal, neurological and cardiopulmonary conditions that need rehabilitation, but have limited access to trained rehabilitation professionals outside of major urban centres. One way to increase reach without proportionately increasing the rehabilitation workforce is through telerehabilitation, the remote delivery of rehabilitation assessment, treatment, monitoring and education using telecommunications technologies, which has been proposed and increasingly implemented, especially since the COVID-19 pandemic drove rapid growth in remote care delivery. Real-time telerehabilitation has also provided evidence of its potential similarity to standard practice for selected musculoskeletal conditions [34].

In the same timeframe, artificial intelligence (AI) – and in particular machine-learning and deep-learning systems that can adapt, predict or classify – has been increasingly added to rehabilitation technologies: computer vision movement assessment, predictive adherence modelling, and AI personalised exercise prescription are now active fields of clinical research. The promise for health systems facing a critical workforce shortage is clear: AI can take over tasks that would otherwise be done by a therapist, enabling a limited rehabilitation staff to care for more patients [8].

But data from a controlled study showing that an AI-driven intervention is effective is not the same as data showing that it is ready for use in a health system. There is a series of distinct evidentiary questions that lie between technical demonstration and public-health-scale implementation: is the intervention clinically effective, is there a benefit specifically due to the AI component, does the intervention work in normal home conditions, can it be safely implemented with adequate human oversight, and is it affordable, equitable, and organisationally feasible at scale? Evidence at one stage of this pathway cannot substitute for evidence at another. The organising argument of this review is this distinction between a need for innovation, evidence for implementation, and evidence for scale.

A methodological issue present throughout the primary literature is that when an AI-enabled telerehabilitation arm performs better than a comparator, the improvement is frequently attributed to AI without adequate consideration of confounding. Patients receiving AI-supported interventions often also receive more frequent monitoring, richer feedback, novel-technology engagement effects, or simply a different rehabilitation dose than comparator groups. Without dose-matched, appropriately controlled comparisons, an observed benefit cannot be confidently attributed to the AI component specifically. These questions are particularly critical for health systems with limited resources.

The tension is further exemplified by Pakistan, where documented rehabilitation-workforce shortages, wide rural-urban disparities in the availability of rehabilitation services, and an underdeveloped telehealth-policy environment [11] suggest a genuine case for exploring AI-enabled telerehabilitation, while variable connectivity, inconsistent electricity supply, uneven access to devices, and limited digital literacy also raise the risk that evidence from well-resourced research settings may not transfer. Having an access problem does not, by itself, establish that a specific technological solution is ready for deployment. Recent reports from Pakistan have

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also highlighted workforce and service gaps in geriatric rehabilitation [12].

A recent 2026 umbrella review of AI-enabled rehabilitation broadly (Abdalla, El Arab and colleagues; hereafter the LAIR-REHAB synthesis) [6] has substantially advanced understanding of clinical effectiveness, real-world performance and equity across AI-rehabilitation modalities, while a related systematic review has examined clinical effectiveness, prognostic performance and pre-implementation feasibility across thirty studies [7]. Separately, scoping reviews of telerehabilitation have documented the current state of largely non-AI telerehabilitation services across LMICs, including Pakistan [9, 10]. What has not been synthesised is the intersection of these two bodies of evidence, read specifically through the lens of a resource-constrained health system, together with the growing number of primary AI-enabled telerehabilitation trials published since 2025 that these broader syntheses only partly capture.

This review therefore asks: what does current evidence establish — and fail to establish — about moving AI-enabled telerehabilitation from clinical promise to safe, equitable, and scalable implementation in resource-constrained health systems? A secondary question examines, specifically within telerehabilitation, whether current evidence isolates AI's independent contribution from other elements of digital care that are often bundled with AI interventions, such as remote monitoring, increased clinician contact, adherence support, and intervention dose.

Methods

This is a critical narrative review, NOT a systematic or scoping review, not pooled effect estimates, and NOT PRISMA compliant. Literature was identified using PubMed/MEDLINE, Scopus, and additional literature search via web sources in August 2026 with combinations of the following terms: artificial intelligence, machine learning, deep learning, telerehabilitation, remote/home rehabilitation, implementation science (non-adoption, abandonment, scale-up, spread, sustainability), equity, low and middle-income countries, and Pakistan. Searching focused on publications from 2024-2026, but included key implementation-science publications from all dates.

Literature was purposefully selected to include: recent high-level evidence syntheses of AI in rehabilitation; primary studies of AI-enabled telerehabilitation (randomised trials, feasibility studies, and validation of AI-based models for prognosis); implementation-science literature; LMIC digital-health and AI-implementation literature; Pakistan- and South Asia-specific rehabilitation, digital-health, and connectivity evidence; and relevant WHO guidance. Sources were weighted based on an explicit hierarchy that prioritised the randomized and controlled primary studies and systematic/umbrella reviews over narrative commentary, and were appraised for AI-specific contribution, dose- and contact-matching of comparators, and applicability to resource-constrained settings over being pooled and statistically analysed. References were cross-checked with original publications, especially those from the recent literature on AI/telerehabilitation and Pakistan-specific literature, discrepancies were rectified and sources that could not be verified were excluded. If there was no Pakistan-specific evidence for a claim, the lack of evidence is included as a finding, not as evidence that is extrapolated from other settings that are described as Pakistan-specific.

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Definitions and scope

The definition of Telerehabilitation is the delivery of rehabilitation assessment, treatment, monitoring, supervision, education, or follow-up remotely using telecommunications or digital technologies. AI-based telerehabilitation also needs to have a component that is actually AI, either in the form of machine learning, deep learning, or some other demonstrable machine-learning, deep-learning, or other genuinely AI-based task that is performing an adaptive, predictive, classification, personalisation, decision-support, or automated-assessment function. An intervention is not considered to be AI-enabled simply because it involves an app, a wearable sensor, a video-consultation platform, virtual reality, or a generic remote-monitoring software, as in the LAIR-REHAB synthesis taxonomy. This review thus focuses on remote or home-based, AI/ML-supported interventions in musculoskeletal, neurological, and cardiometabolic rehabilitation, and only considers purely in-clinic robotics, brain-computer interfaces without a remote-delivery component, AI-only diagnostic interventions, and conventional (non-AI) telerehabilitation as comparator or contextual evidence. The operational scope is presented in Table 1.

Table 1. Operational definition and scope of AI-enabled telerehabilitation

Source: authors' operational definition informed by the AI-versus-technology-assisted distinction in [6].

Category	Included	Excluded	Rationale
Delivery setting	Remote/home-based rehabilitation care	Purely in-clinic delivery with no remote component	Telerehabilitation is the exposure of interest, not rehabilitation in general
Technology component	Demonstrable ML/DL adaptive, predictive, classification or decision-support function	Apps, wearables, video-conferencing, VR or robotics with no genuine ML/DL component	Avoids taxonomy drift in which "AI" is applied to any digital or automated technology
Modality	Computer-vision movement assessment, predictive adherence/monitoring models, AI-personalised exercise prescription, AI-based remote monitoring	Brain-computer interfaces and imaging AI without a remote-delivery element	Keeps scope aligned with telerehabilitation rather than AI-rehabilitation broadly
Comparator evidence	Studies comparing AI-enabled to conventional or non-	Studies without any digital or telerehabilitation	Needed to address the AI-added-value question specifically

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Category	Included	Excluded	Rationale
	AI telerehabilitation, ideally dose-matched	comparator	
Population	Adult rehabilitation populations; paediatric evidence where directly relevant	General paediatric rehabilitation outside relevant subgroups	Keeps synthesis focused and consistent with the target evidence base

Conceptual model

This review is not intended to offer a new implementation-science model. It frames the narrative around an evidence-to-implementation pathway inspired by the staged logic used in the LAIR-REHAB synthesis [6] (including the laboratory-to-real-world performance gap, ΔReal), and by the multi-domain view of technology adoption in the Non-adoption, Abandonment, Scale-up, Spread and Sustainability (NASSS) framework [1-3] (where resource-constraint, such as infrastructure, workforce, affordability, and governance, is not a separate final step but is a cross-cutting layer that acts on every step). To avoid the "framework-listing for the sake of listing" effect, two frameworks were considered but not referenced: Reach, Effectiveness, Adoption, Implementation and Maintenance (RE-AIM) [4] and the Consolidated Framework for Implementation Research (CFIR) [5]. The pathway is clinical evidence, AI-added-value assessment, real-world/home validity, implementation readiness, equity, safety and governance, health-system integration, sustainable scale, and the impact of Pakistan/resource-constrained conditions on each of these steps (Figure 1).

Clinical promise

AI-driven telerehabilitation can help by providing personalised exercise prescription, remote movement assessment, adherence prediction, and decision support. These functions have been demonstrated to be technically deliverable in recent primary studies. In a small randomised trial, an AI-based pose-estimation system for multimodal home exercise for chronic non-specific low back pain (cLBP) was found to be superior at reducing pain compared with conventional video-guided telerehabilitation [21, 22]. An AI-recognition-based programme improved exercise capacity, physical activity, and systolic blood pressure in hypertension [23]. A Korean trial reported in 2025 found non-inferiority of self-guided AI cognitive telerehabilitation to therapist-supervised cognitive rehabilitation after stroke [24]; this is borderline evidence for the strict home/remote scope, as sessions were conducted in hospital rooms rather than participants' homes. Two trials in older adults with mild cognitive impairment (MCI) showed improved outcomes compared with a waiting-list control [25], and a feasibility study demonstrated technical feasibility without evidence of comparative AI-added value [26]. These findings are encouraging but condition- and outcome-dependent. Overall, the LAIR-REHAB synthesis reported inconsistent reporting of clinically important differences, responder proportions, and blinded assessment, with stronger signals in specific modalities and outcomes rather

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than across AI-enabled rehabilitation as a whole [6].

Does AI actually add value?

This is the main analytical question of this review. There are eight potential, but often confounded, effects that could account for the difference between an AI-enabled arm and a comparator: the AI effect, the remote-care/tele-delivery effect, more clinician contact, more frequent monitoring, richer feedback, better-supported adherence, novelty/engagement of new technology, and differences in rehabilitation dose between arms. To isolate the AI-specific contribution, dose-matched comparators, comparable therapist contact, symmetric adherence measurement, prespecified clinically important-difference thresholds, and blinded outcome assessment (where possible) are required.

Selected evidence for AI-enabled telerehabilitation against these criteria is summarised in Table 2, with one 2025 study retained as borderline, as it was conducted in a facility though its authors referred to it as telerehabilitation. The pattern is informative. The low-back-pain trial was a small, open-label trial (38 randomised, 34 analysed) comparing an AI-guided exercise group with a conventional video-guided group with matched exercise dose and frequency — a genuinely useful comparator for isolating the AI-specific signal — and found a significant benefit on the primary outcome (pain) but not on secondary outcomes (disability, catastrophising, muscle thickness) [21, 22]. The hypertension trial found an overall benefit for AI-assisted telerehabilitation compared with conventional exercise rehabilitation, but its publicly available reporting does not allow the effect of AI to be isolated from the effect of monitoring or therapist engagement [23]. The stroke cognitive-telerehabilitation trial was designed to compare self-guided AI with therapist-supervised care, and because therapist contact was, by design, asymmetric between arms, non-inferiority in this trial does not imply added value — rather, that self-guided AI is not inferior to some level of therapist contact, a different and arguably more policy-relevant question than whether AI adds value on top of existing care [24]. The mild-cognitive-impairment trial compared home cognitive rehabilitation delivered via AI with a delayed-treatment control, which can show the intervention is better than nothing, but cannot isolate AI's contribution from tele-delivery or novelty/engagement in general [25].

A separate category of AI function has strong technical potential but little evidence of independent clinical-effectiveness benefit: predictive and monitoring models. Machine-learning classification of data from an inertial sensor in a wrist-worn smartwatch has been shown to classify shoulder-physiotherapy exercises accurately in clinic, and reasonably though less accurately at home, directly demonstrating both the promise of automated adherence monitoring and the gap between laboratory and home performance [28, 29]. No completed outcome trial identified in this review tested whether deploying such a monitoring or adherence-prediction model as part of care changes clinical outcomes, unlike AI systems that directly adapt or guide rehabilitation. Responsible deployment of such tools also depends on trustworthy-AI principles covering validation, transparency, accountability, and human oversight [20].

Taken together, the honest conclusion at this stage is not that AI provides no

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independent value, but that current evidence is largely insufficient to confirm or exclude it for telerehabilitation specifically. Where a genuinely dose- or contact-matched comparator exists, the isolated AI-specific signal is real but modest and outcome-specific; where comparators are not dose- or contact-matched, or are passive controls, apparent benefit cannot be attributed to AI with confidence.

Table 2. Selected AI-added-value evidence: primary and borderline telerehabilitation studies

Source: authors' synthesis of [21-29].

Study	AI function	Comparator	Dose/contact matched?	Main finding	AI effect isolated? / key limitation
Xiao et al. 2025 (chronic nonspecific low back pain; 38 randomised, 34 analysed)	Computer-vision pose estimation guiding multimodal home exercise	Conventional video-guided telerehabilitation (WeChat)	Yes – dose and frequency matched	Significant pain-score reduction at 4 and 8 weeks vs video group	Partially – cleanest comparator in this table, but small, open-label, and no significant benefit on disability, catastrophising or muscle-thickness secondary outcomes
Yao et al. 2026 (hypertension; randomised trial)	AI movement-recognition-guided exercise/monitoring	Conventional exercise rehabilitation	Not clearly reported	Improved 6-minute walk distance, physical activity, self-efficacy and systolic blood pressure	No – therapist contact/monitoring frequency matching not established; benefit may reflect monitoring/engagement as well as AI
Kim et al. 2025 (facility-based asynchronous digital rehabilitation; n=63)	AI-driven adaptive difficulty and engagement monitoring	Therapist-supervised cognitive rehabilitation	No – asymmetric by design; facility-based rather than home delivery	Non-inferior to therapist-supervised care	Borderline for the strict scope: authors call it telerehabilitation, but sessions occurred in hospital rooms. It tests substitution for therapist contact, not AI added value on top of equivalent care.

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Study	AI function	Comparator	Dose/contact matched?	Main finding	AI effect isolated? / key limitation
Kim et al. 2026 (mild cognitive impairment; delayed-treatment randomised trial, 70 participants)	Self-guided AI home cognitive rehabilitation (Zenicog)	Delayed-treatment/waitlist (no active comparator)	No – passive control	Improved cognitive outcomes vs waitlist	No – cannot separate AI-specific effect from tele-delivery, novelty or general engagement
Burns et al. 2018 / Boyer et al. 2023 (shoulder physiotherapy; technical validation, 42 participants)	ML classification of wearable inertial-sensor data for adherence/exercise monitoring	Not a clinical-outcome comparator (technical validation only)	N/A	High in-clinic classification accuracy; reduced but usable accuracy at home	Not tested clinically – demonstrates the laboratory-to-home (ΔReal) performance gap directly; no outcome trial yet exists for this function

From controlled studies to real-world care

Another separate evidentiary issue is whether the performance exhibited in controlled environments is sustained when used in normal dwellings. The LAIR-REHAB synthesis revealed that models and devices that perform well in laboratory settings or convenience samples do not necessarily perform well in clinical use, and suggested staged validation: from internal or subject-wise validation splits, to multi-site external validation, to home-use validation with drift monitoring [6]. A directly relevant example for the field of telerehabilitation is the strong classification accuracy in the clinic that diminished, but remained usable, when the same models were used to classify at-home data collected in unsupervised settings [28, 29] (above). Home use also adds to the variation in lighting, camera positioning and background clutter not seen or better controlled in clinic based validation for computer-vision movement assessment [19]. Real-world validity should therefore be considered as a separate evidentiary criterion, rather than a foregone conclusion of clinical trial success, and none of the main AI-telerehabilitation trials found in this review included a prespecified comparison of home versus laboratory or multi-site external validation.

Implementation readiness

This review does not propose a new implementation framework, but rather uses a framework that is widely used to assess digital-health-technology adoption in rehabilitation and related areas, NASSS [1-3]. NASSS looks at the condition, the technology, the value proposition, the adopter system (patients and clinicians), the

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organisation, and the broader institutional and policy environment, and classifies each as simple, complicated, or complex. Several domains fall within the more complex-to-complex range, such as the adopter system, which necessitates the need for patients and limited rehabilitation professionals to adapt to the use of AI-powered telerehabilitation, as reported by the Pakistani physiotherapists themselves in the study [30] regarding the constraints of workload, supervision, and role-recognition in secondary-care settings; the organisational domain, which requires that the system be integrated with current, often fragmented, clinical records; and the wider context, which includes an underdeveloped regulatory and reimbursement landscape for AI-enabled digital therapeutics in Pakistan and similar LMICs. A recent qualitative policy analysis of rehabilitation prioritisation in the health system in Pakistan also mentions weak intersectoral coordination and limited dedicated financing as structural barriers that would apply and likely exacerbate for any AI-enabled technology added to the front of existing services [31]. While NASSS does not solve these problems, it helps to identify where implementation is likely to get stuck before resources are invested in scaling up.

Equity, safety and resource-constrained implementation

Equity is not a standalone piece but is integrated throughout the pathway. The equity issues of access, rather than the issues of representation in training data that are prevalent in high-income-country AI-equity literature, are the most salient for Pakistan and other LMICs: rural-urban differences in connectivity and provider availability, device ownership, electricity reliability, affordability of data and devices, digital literacy, and caregiver availability to support use of technology. National digital-access data show the extent of this constraint: well over half of Pakistan's population was not connected to the internet at the beginning of 2025, with connectivity and device quality significantly higher in Karachi, Lahore and Islamabad than in rural Balochistan, northern Khyber Pakhtunkhwa, and parts of Sindh [32]. Limited information and communication technology (ICT) skills and infrastructure are consistently reported as barriers to conventional, non-AI telerehabilitation across LMIC-focused evidence, including scoping reviews of LMICs, including Pakistan [9, 10]. Scale-up of AI-powered telerehabilitation in a resource-constrained health system can exacerbate existing access inequities if the system is not built with equity in mind, or if it is layered onto infrastructure that already excludes a significant portion of the population from conventional telerehabilitation.

Safety and governance aspects of AI outputs — human oversight, clear clinical accountability for incorrect recommendations, and data-privacy protections — are similarly under-specified in the primary AI-telerehabilitation literature identified in this review, despite WHO guidance on AI ethics and governance explicitly calling for such human oversight [13, 14]. None of the trials summarised in Table 2 reported a prespecified protocol for clinician review of AI-generated exercise or risk classifications.

From implementation to sustainable scale

The final question is not whether a proven, safe, fair intervention can be piloted successfully, but whether it can be sustained and scaled. This demands evidence

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around financing and procurement, workforce training and integration, regulatory clearance, data governance, interoperability and monitoring for model drift after deployment. The three claims of economic evidence (cost-saving, cost-effectiveness, and scalability) should be kept separate. This review did not find any trials of AI-enabled telerehabilitation that reported the health-economic detail required to differentiate these claims, nor could any cost data for AI-enabled telerehabilitation in Pakistan be identified. If there is no evidence to support this, then procurement based on the novelty of a new technology, rather than on evidence of value, risks the health system's limited resources being used before the evidence is available to support the decision. A 2026 protocol for an AI-assisted postdischarge telerehabilitation system explicitly calls for research priorities for implementation evaluation, but does not offer any outcome evidence to date [27].

Implications for Pakistan: three thresholds

The evidence presented here is supportive of the distinction between three claims that are often, and incorrectly, considered synonymous. Need is well defined: World Physiotherapy has reported 0.13 practising physiotherapists per 10,000 population in Pakistan, alongside significant rural-urban disparity in services and a substantial gap between rehabilitation and other health services [31, 35]. The second threshold, implementation, requires evidence that the intervention is effective, safe, feasible, equitable, and workable in the target setting; for AI-enabled telerehabilitation, this evidence remains limited and heterogeneous even globally, and no AI-specific telerehabilitation trial from Pakistan was identified in this review. A registered randomised trial of telerehabilitation for mobility impairment in rural Pakistan shows that rigorous telerehabilitation evaluation is feasible in this context, but its intervention is not AI-based, underscoring how much further research is needed before an AI-specific implementation trial exists [33]. The third threshold, scale, requires evidence that a model remains affordable, equitable, effective, and sustainable at health-system or population level — unestablished in any setting for AI-driven telerehabilitation, and entirely unestablished for Pakistan.

A system facing urgent need and limited resources has a strong incentive to move directly from the first threshold to the third. This review's synthesis suggests that doing so before generating the intervening evidence carries real risk: of adopting technologies whose apparent benefit reflects dose or engagement effects rather than AI-specific value; of deploying systems that succeed in the laboratory or in high-income settings but do not transfer to Pakistan's variable-connectivity home environments; and of committing limited resources to scale-up before affordability, workforce-integration, and governance questions have been answered locally.

A more defensible pathway would treat AI-enabled telerehabilitation as warranting carefully monitored, evidence-generating pilots: measuring its added value against dose-matched conventional telerehabilitation, testing performance under Pakistan's actual connectivity and device conditions, building in human-in-the-loop clinical oversight from the outset, and collecting the local cost and equity data currently missing from the evidence base before any decision to scale.

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Limitations

This review is limited in scope, reflecting in many ways the characteristics of a rapidly evolving evidence base. The definition of AI-enabled is not consistent, which is a potential for taxonomy drift. Populations and outcomes are heterogeneous and most primary AI-telerehabilitation trials are small, single-centre, and have a short follow-up. There are few dose-matched comparisons that isolate an independent AI added value, which makes it difficult to be certain about the added value of AI. No evidence specific to Pakistan was found, so the Pakistan discussion is based more on adjacent evidence than on AI-telerehabilitation evidence. The synthesis is not a systematic review, but a narrative synthesis, which is not intended to provide pooled effect estimates, but rather to map the evidence gaps and to synthesize in a way that is relevant for implementation.

Conclusion

AI-enabled telerehabilitation is a plausible response to a real and substantial rehabilitation-access problem, but promise and implementation-readiness are not the same thing, and current evidence does not yet allow them to be conflated. Recent primary trials demonstrate that AI-enabled telerehabilitation can be built and can, in some dose-matched comparisons, outperform conventional telerehabilitation on specific outcomes; they do not yet demonstrate that this benefit is general, that it survives real-world home deployment at scale, or that it is affordable and governable within resource-constrained systems. For Pakistan and comparable settings, scale-up decisions should be made contingent on locally generated evidence across the full pathway examined here: clinical benefit, independent AI-added value, real-world validity, safety and human oversight, affordability, equity, workforce compatibility, infrastructure feasibility, governance, and sustainability. Pakistan should be understood in this literature not as a demonstrated AI-telerehabilitation success story, but as a highly relevant and currently under-evidenced context in which each of these questions remains genuinely open. Table 3 summarises this evidence-to-implementation pathway, the associated evidence gaps, and their Pakistan/LMIC implications.

Table 3. Evidence-to-implementation pathway and critical questions
Source: authors' synthesis informed by [1, 6, 9, 10, 15-18, 30-35].

	Evidence question	Common evidence limitation	Implementation implication	Pakistan/LMIC implication
Clinical evidence	Does the intervention improve clinically meaningful outcomes?	Impairment/independence gains often not superior to well-delivered conventional therapy once bias is controlled	Benefit may be modality- and outcome-specific, not general	Local population/setting transferability of trial results is untested
AI-	Is any benefit	Dose, contact,	Cannot justify	Additional

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	Evidence question	Common evidence limitation	Implementation implication	Pakistan/LMIC implication
added value	attributable to AI specifically?	monitoring and engagement rarely matched or measured symmetrically	AI-specific investment on current evidence alone	infrastructure burden of AI may not be justified without local confirmation of added value
Real-world/home validity	Does performance hold outside controlled settings?	Laboratory/clinic performance often exceeds real-world, at-home performance (ΔReal)	Requires staged external and home validation before deployment	Connectivity, device and lighting variability in Pakistani homes likely more severe than in study settings
Implementation readiness	Can clinicians and health-system organisations realistically adopt it?	Adopter-system and organisational complexity rarely assessed prospectively	NASSS-style prospective assessment reduces risk of costly non-adoption	Underdeveloped regulatory/reimbursement environment for AI-enabled digital therapeutics
Equity, safety and governance	Who benefits, who is excluded, who is accountable for error?	Equity rarely stratified in underlying studies; accountability structures rarely specified	Equity and safety must be designed in, not evaluated after deployment	Rural-urban, connectivity, affordability and literacy gaps risk reproducing existing exclusion
Sustainable scale	Is it affordable and maintainable at scale?	Cost-saving, cost-effective and scalable are rarely distinguished	Procurement should follow evidence, not technological novelty	No Pakistan-specific AI-telerehabilitation cost data identified; scale-up currently unevidenced

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Figure 1

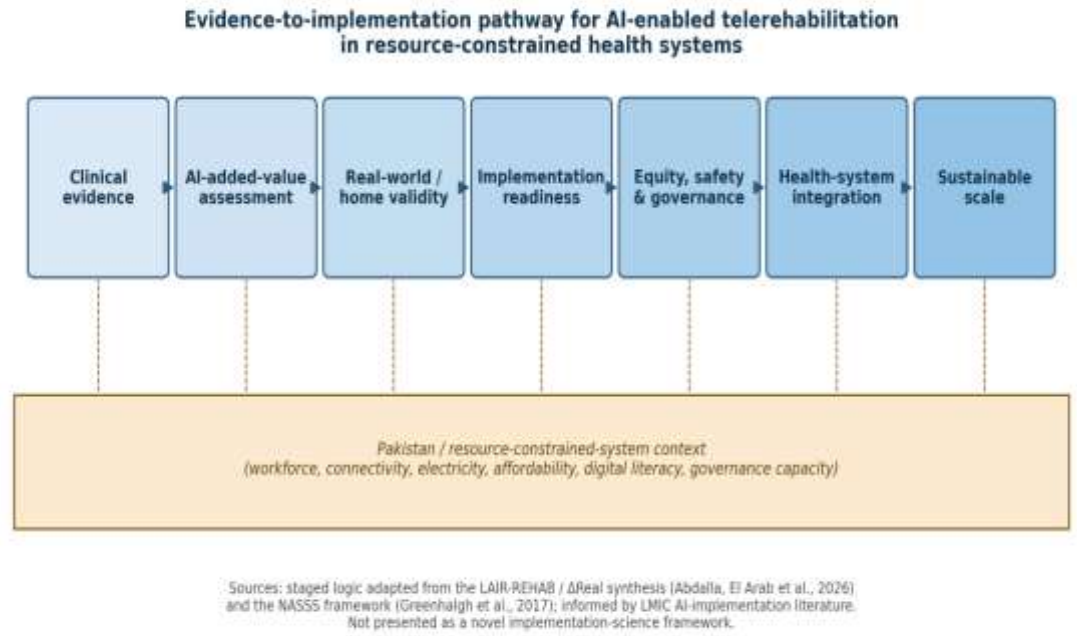

Figure 1. Evidence-to-implementation pathway for AI-enabled telerehabilitation in resource-constrained health systems. The pathway is not presented as a novel implementation-science framework; it synthesises staged logic adapted from the LAIR-REHAB/ΔReal synthesis [6] and the NASSS framework [1], informed by LMIC AI-implementation literature [16-18]. Resource-constraint factors are depicted as a cross-cutting band influencing every stage rather than as a discrete final stage.

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