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Perspective

A perspective on developing an AI-driven digital triage platform for chronic disease mental health: insights and potential from My-E-Health

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Abstract: Chronic illnesses, such as diabetes and chronic kidney disease (CKD), impose a substantial global burden, affecting hundreds of millions of people and straining healthcare systems. Managing these conditions involves not only physical challenges but also considerable psychosocial distress. Patients with complex treatment regimens—frequent medical appointments, dietary restrictions, and potential complications—often experience depression, anxiety, and reduced quality of life, all of which can impede treatment adherence and worsen clinical outcomes. Research, including meta-analyses in dialysis and diabetes populations, indicates that psychosocial interventions and integrated mental health support can improve quality of life, glycaemic control, and emotional well-being. Despite the clear value of mental health integration, current in-person care models face significant limitations. Scarcity of trained mental-health professionals, geographical barriers, financial constraints, and social stigma frequently preclude timely psychosocial support. Consequently, many patients with chronic conditions receive inadequate mental-health care, compromising overall treatment success. This perspective outlines how a digital mental-health triage solution—supported by platforms like My-E-Health—could leverage artificial intelligence (AI). By embedding routine assessments, such as the Empowerment for Participation (EFP) mini, into chronic-disease management, patients can be screened more frequently for emotional distress. AI algorithms would then stratify patients into low-, moderate-, or high-risk categories and deliver tailored interventions. Moderate-risk patients could receive AI-guided coaching and self-management tools, while high-risk patients would be promptly linked to clinicians for intensive therapy. This approach optimises resource allocation, directing professional attention to the most vulnerable patients. Integrating AI-driven digital platforms—

including telehealth portals and culturally sensitive, multilingual interfaces—may enable real-time monitoring, early intervention, and sustained patient engagement. Recent studies suggest that expanding telehealth options can reduce access barriers and stigma, encouraging patients to seek help. Further investigations—particularly longitudinal studies—are warranted to confirm sustained clinical benefits, cost-effectiveness, and scalability across diverse healthcare contexts. With continued improvements in AI-driven screening tools and patient-centred design, a well-implemented digital mental-health triage solution could make chronic disease care more holistic, sustainable, and effective.

Keywords: chronic disease; diabetes; chronic kidney disease; mental health; digital triage; artificial intelligence; telehealth; psychosocial care; risk stratification; My-E-Health; EFP mini

1. Introduction

1.1. Chronic illness burden and mental health

1.1.1. Global prevalence and increasing incidence of chronic conditions such as diabetes

Chronic illnesses, including diabetes and CKD, exert an escalating toll on global healthcare systems. Recent estimates indicate that CKD affects approximately 9.1% of the world's population—about 700 million individuals [1]. Concurrently, the International Diabetes Federation [2] projects that the number of people with diabetes will rise from 463 million in 2019 to 700 million by 2045. These trends reflect an ageing global population, lifestyle factors such as poor diet and physical inactivity, and persistent disparities in healthcare access and quality.

The physiological demands of managing these chronic conditions—ranging from constant blood glucose monitoring and insulin therapy for diabetes to repeated dialysis sessions for CKD—also impose a profound psychosocial burden. Patients frequently grapple with depression, anxiety, stress, and diminished quality of life. Michelsen's meta-analyses soon to be published, highlighted the significant prevalence of mental health symptoms among dialysis and diabetes populations [3]. In dialysis, psychosocial and holistic care approaches have improved quality of life and reduced depressive symptoms [4]. Similarly, in diabetes management, integrated mental health support has been associated with improved glycaemic control, lower psychosocial distress, and enhanced overall well-being [4,5].

The connection between chronic illnesses and mental health is bidirectional. Intensive treatment regimens—encompassing dietary constraints, frequent medical follow-ups, and the possibility of complications—fuel psychological distress. Depression and anxiety, in turn, can impede self-management behaviours and adherence, ultimately exacerbating disease severity [5]. Addressing mental health in the context of chronic illness is thus integral to patient-centred care, underscoring the urgency of interventions that simultaneously target psychosocial and clinical needs.

1.2. Bidirectional relationship between physical and mental health

The interplay between mental health and chronic diseases is multifaceted. Research consistently demonstrates that mental health disorders—such as depression—negatively affect treatment adherence, metabolic control, and overall patient well-being [6,7]. For example, depressed individuals with diabetes often experience worse glycaemic control, as reflected by elevated glycated haemoglobin (HbA1c) levels [7,8]. In dialysis, high levels of depression correlate with heightened morbidity and poorer management of the intensive dialysis schedule [6]. These findings emphasise the necessity of integrating psychological care into chronic disease management. By reducing mental health burdens, patients are more likely to adhere to medical advice and sustain better clinical outcomes.

The burden and expression of psychological distress in chronic illness vary with age, language, literacy, rurality, socioeconomic status, and culture. These differences shape help-seeking and adherence and inform design choices for digital triage (multilingual content, plain-language UX, low-bandwidth modes) and integrated psychosocial care in diabetes and CKD [2,5,6,9–11].

1.3. Limitations of current in-person mental health interventions

Although mental health support is vital for individuals with chronic diseases, several logistical, structural, and attitudinal barriers exist in traditional in-person care. A global shortage of mental health professionals with the requisite specialisation often leaves patients underserved [11–13]. Even where specialists exist, constraints such as time, insurance coverage, and high costs hinder comprehensive psychosocial care [14]. Geographic barriers further restrict access, particularly in remote or underserved communities. Stigma concerning mental health remains a formidable obstacle, deterring many patients from seeking timely assistance [15].

To address these challenges, several digital and telehealth models have emerged, providing a blend of asynchronous and synchronous mental health interventions. My-E-Health, see https://www.my-e-health.com for instance, offers a cloud-based platform that integrates video counselling, self-help modules, and continuous access to a “digital diary” for symptom tracking. It also provides an AI-assisted self-assessment module designed to flag early signs of distress and notify clinicians if risk scores surpass defined thresholds. Such telehealth solutions have become increasingly significant during the COVID-19 period and beyond [16,17], demonstrating their utility in circumventing geographic constraints, reducing wait times, and minimising stigma.

These virtual interventions often promote self-awareness, improve perception of mental health needs, and encourage proactive self-action. By embedding user-friendly design, multilingual resources, and flexible scheduling, platforms like My-E-Health can cater to diverse patient populations [18]. Nonetheless, many such platforms still rely heavily on human input from mental health professionals, underscoring the potential need for scalable AI-driven solutions to bridge the care gap, see Figure 1.

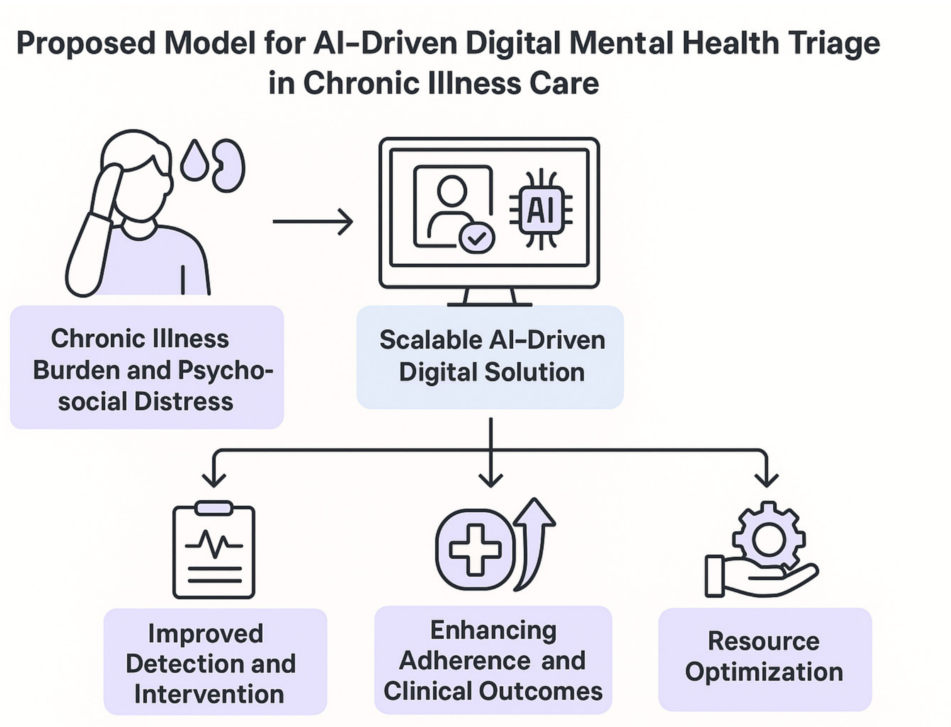

Figure 1. Model for AI-driven digital mental health triage.

2. The need for a scalable, digital solution

2.1. Linking limitations to AI-driven approaches

The increasing prevalence of chronic diseases, combined with logistical barriers to in-person mental health care, has intensified the spotlight on technology-driven models [16,17,19–21]. While platforms like My-E-Health demonstrate how digital tools can reduce structural barriers, a more robust AI component is critical to identifying at-risk patients earlier, personalising interventions in real time, and alleviating clinician workload. AI systems can support constant monitoring of psychological status, enhance patient engagement through tailored content, and triage high-risk cases to human professionals quickly. This enables patients to develop a deeper awareness of their emotional states, fosters self-efficacy, and allows for swift self-directed interventions [17]. By embedding validated psychometric tools—such as the Empowerment for Participation (EFP [4,18]) mini—an AI-driven system can heighten screening sensitivity and deliver scalable mental health support at lower cost.

2.2. Published evidence base for integrated psychosocial care

Published evidence in dialysis and diabetes shows that integrating psychosocial care improves quality of life, reduces depressive symptoms, and can improve glycaemic control [5,6,8,15]. These findings support making mental health care continuous and accessible alongside medical treatment—a goal for which digital triage solutions are well suited.

2.3. Significance of early triage and tailored interventions

Early identification of psychological distress can prevent progression from mild symptoms to severe mental health disorders. Chen et al. emphasised that timely screening and intervention can avert chronic deterioration in emotional well-being [16]. A digital triage model that integrates AI allows rapid stratification of patients into low-, moderate-, or high-risk levels, ensuring that clinical resources and interventions are efficiently allocated.

2.4. Algorithmic approach and explainability

Our first-line triage service uses regularised logistic regression and gradient-boosted trees trained on EFP-mini scores, temporal features (rolling trends and volatility), optional symptom-diary signals, and limited electronic health record (EHR) context via Fast Healthcare Interoperability Resources (FHIR [22]) APIs. Models are trained/validated on temporally split sets, calibrated with isotonic regression, and monitored post-deployment via the Area Under the Receiver Operating Characteristic (AUROC) or the Area Under the Precision-Recall Curve (AUPRC), Brier score, calibration curves, and decision-curve analysis. We expose global importances and local SHAP (SHapley Additive exPlanations)-style [23] rationales to clinicians to reduce automation bias and support auditability. Model versions, data slices, and performance are logged, with drift alarms for prevalence, feature, and performance shifts.

2.5. Feasibility and implementation

Deployment proceeds via a gated rollout: sandbox → single clinic → cluster, with Fast Healthcare Interoperability Resources (FHIR)-based EHR integration, a 4-hour clinician onboarding module, and explicit resource budgeting (~0.2 FTE clinician reviewer per 100 active patients). Low-bandwidth and device-agnostic modes address connectivity constraints; success criteria include median alert-to-action time ≤24 h and ≥80% screening completion by week 8. Change-management includes clinic champions, user training, and a rollback plan.

3. Objectives of the paper

(1) Justify digital mental health triage as a first-line approach for chronic illness; (2) demonstrate how AI-based tools can enable early detection, continuous monitoring, and appropriate referral pathways; (3) propose a stratified model in which moderate-risk patients receive AI-guided coaching and self-management tools, whereas high-risk patients receive timely clinician-directed intervention.

3.1. Design of the digital triage and treatment model

The digital triage model integrates with platforms such as My-E-Health to embed brief, validated assessments—the Empowerment for Participation (EFP) mini—into routine chronic-care touchpoints. Patients complete the EFP mini via mobile or laptop prior to or during scheduled visits (e.g., dialysis sessions, diabetes check-ups) and at home on a weekly–biweekly cadence, producing immediate well-being indices. An AI service ingests scores and trends to stratify risk (low, moderate, high) using pre-specified thresholds reviewed quarterly by a clinical governance group. Low-risk patients are nudged to self-guided modules (relaxation, CBT-based coping, psychoeducation) and periodic re-screening. Moderate-risk patients receive AI-guided coaching, structured self-management plans, and asynchronous clinician review within 72 hours. High-risk results trigger same-day alerts to assigned clinicians, with options for synchronous video consult or in-person escalation; any indications of suicidality or harm activate predefined safety protocols and emergency pathways. Clinicians can audit inputs and rationales (explanations based on the most influential features) and document actions. Data flow to electronic health records (EHRs) via standard APIs (e.g., FHIR) to support longitudinal monitoring, while privacy and security controls (role-based access, encryption in transit/at rest, audit logs) align with the General Data Protection Regulation (GDPR) [24]. The model's performance is tracked (screen-positive rate, referral-to-action time, adherence, repeat screening completion), and thresholds are iteratively calibrated to the clinical context, see Figure 2.

Thresholds and equity: Initial cut points are selected via ROC analysis and a safety-weighted Youden index [25] thresholds are then calibrated to local data and evaluated for parity of sensitivity/specificity and calibration across subgroups (e.g., age, sex, language). When gaps persist, we adjust thresholds and add targeted outreach to avoid inequitable under-triage. To reduce dependence on a single screener, moderate/high-risk flags trigger validated second-line instruments such as the Patient Depression Questionnaire 9 (PHQ-9 [26]) and General Anxiety Scale 7 (GAD-7 [27]) and clinician assessment.

3.2. Integration with existing chronic disease management protocols

To maximise impact, mental health screening is woven into standard care pathways. Examples include dialysis clinics—administer the EFP mini during scheduled sessions, prompting immediate digital intervention if distress is high and pair mental health assessments with regular glycaemic checks or telehealth consultations, allowing clinicians and patients to tackle emotional coping alongside medical measures. Linking triage results to the EHR fosters a more holistic approach. Additional staff training may be required to interpret AI outputs and maintain cultural competence [12].

3.3. Evaluating efficacy and usability

Effectiveness should be tested using mixed methods: randomised controlled trials (RCTs) comparing clinical and psychosocial outcomes (e.g., depression scores, HbA1c, adherence) between standard care and the digital triage pathway [28]; longitudinal follow-up to track sustainability and cost-effectiveness; and qualitative studies (interviews/focus groups) to gauge patient satisfaction, cultural relevance, user-friendliness, and digital literacy barriers, alongside clinician feedback to refine protocols.

Preliminary feasibility and user-feedback plan (for future work): We prespecify a pragmatic 8-week pilot in diabetes and CKD clinics ($n \approx 30$) to assess screening completion, median alert-to-action time for high-risk flags, PHQ-9/GAD-7 change among flagged patients, adherence to follow-ups, and usability (using interviews, or a System Usability Questionnaire Scale [29]). Findings will be reported separately; this perspective outlines the protocol to enhance transparency and reproducibility.

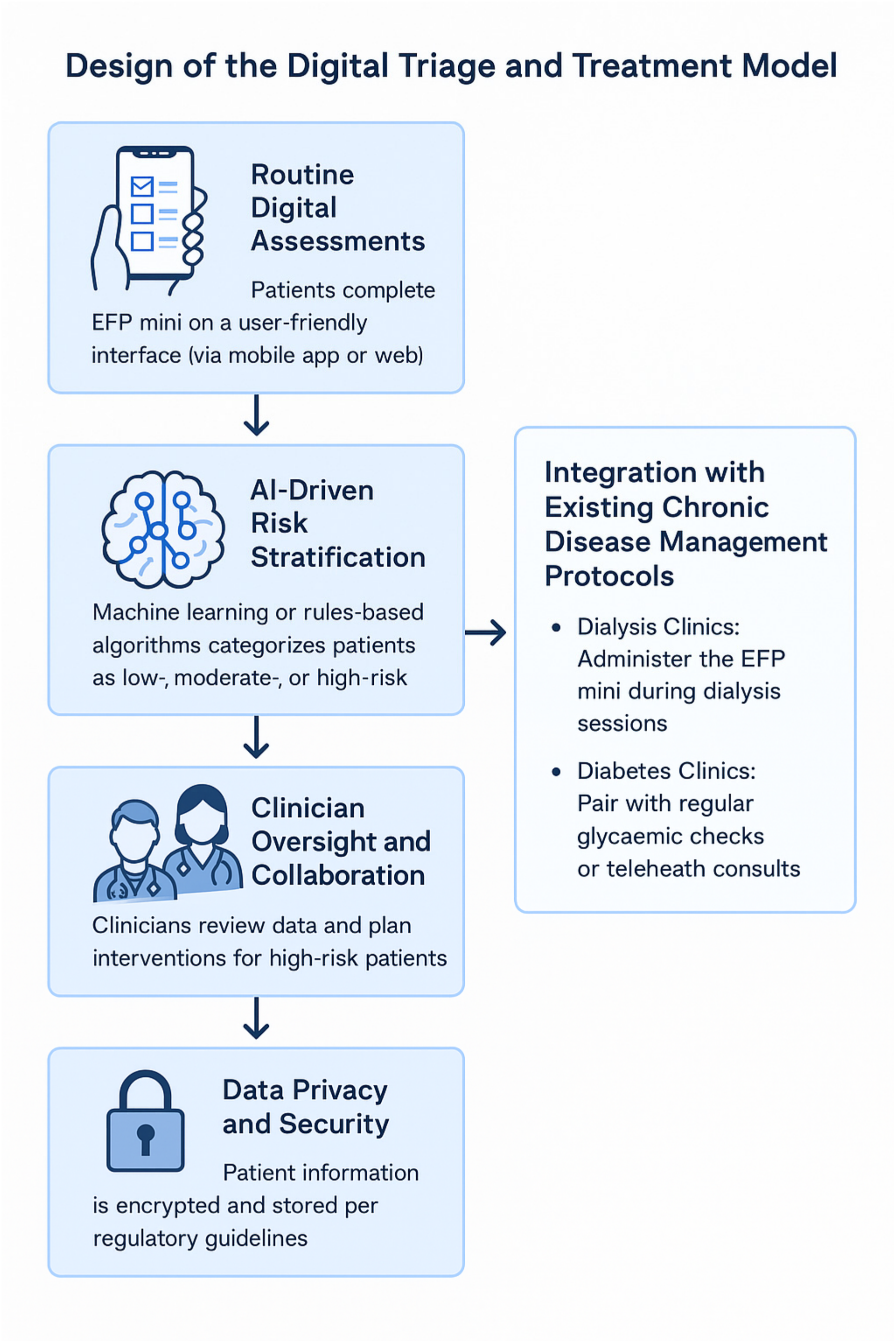

Figure 2. Model for AI-driven digital mental health support.

4. Anticipated results and benefits

4.1. Improved detection and intervention

A regular screening framework using the EFP mini can facilitate early detection of mild-to-moderate psychological distress. In dialysis and diabetes populations, this proactive identification may reduce the escalation of mental health symptoms [16,19]. Previous works include a scoping review of AI in mental health triage [30], a real-world evaluation of Limbic Access across 129400 patients [20], AI applications in chronic disease self-management, chatbot efficacy for chronic disease mental health, and a bibliometric analysis of AI in chronic disease care are considered essential today [17,31–33]. Michelsen's meta-analyses similarly suggest that timely psychosocial support in chronic disease contexts can substantially mitigate depressive and anxious symptomatology, thereby strengthening patient engagement [34].

4.2. Enhancing adherence and clinical outcomes

Improved mental health care is strongly correlated with better adherence to medical recommendations. For instance, in diabetes, alleviating depression and anxiety has been shown to stabilise glycaemic control, indicated by reduced HbA1c levels [7,8]. Dialysis patients receiving psychosocial interventions also demonstrate increased adherence to treatment schedules [18]. By minimising mental health barriers, the digital triage system fosters better self-management, ultimately reflecting enhanced clinical indicators and quality of life [12].

4.3. Resource optimisation

AI-driven triage optimises the allocation of scarce healthcare resources [14]. Specialists can dedicate more time to complex, high-risk cases, while moderate-risk patients benefit from structured AI-based coaching. This approach can reduce wait times for in-person mental health consultations and facilitate more efficient use of healthcare budgets. Over time, it may contribute to system-wide cost savings by decreasing the need for acute and emergency care arising from unaddressed mental health issues.

4.4. Potential risks and mitigations

Potential risks include false positives (anxiety, over-utilization) and false negatives (missed distress), as well as alert fatigue, automation bias, and inequitable performance across subgroups. We mitigate these risks through conservative thresholds with human review, rate-limited and batched alerting, routine fairness audits with subgroup calibration, and mandatory rationale display with clinician override to reduce automation bias.

5. Discussion

5.1. Interpreting the impact of an AI-driven first-line support model

Embedding AI-driven mental health assessments into routine dialysis sessions or diabetes check-ups offers potential synergy. Patients receive continuous support for psychosocial concerns alongside standard clinical evaluations, potentially improving outcomes such as adherence, glycaemic control, and overall quality of life [8]. The immediate availability of AI-guided interventions means patients can begin addressing emotional distress promptly, which may avert the development of more severe mental health conditions [16]. Adoption barriers—such as patient trust, clinician workload, and liability concerns—are addressed through co-design workshops, clinical champions, targeted training, and clear accountability lines.

5.2. Addressing potential barriers

Safe handling of sensitive health data is paramount. Platforms should implement robust encryption, role-based access, and auditable data flows, complying with the General Data Protection Regulation (GDPR) and local statutes. Because AI models can encode bias, training datasets must represent diverse populations; routine fairness audits, drift monitoring, and multidisciplinary oversight (clinicians, data scientists, ethicists) are required. Human-in-the-loop review and clear escalation pathways protect patient safety, while explanation features help clinicians understand triage rationales. To promote equitable uptake, the interface must be accessible for varying digital literacy levels (plain-language prompts, tutorial onboarding, device-agnostic design) and culturally adapted (multilingual content, sensitivity to norms). Dedicated user support and clinician training can mitigate scepticism and promote sustained engagement.

5.3. Broader applicability beyond diabetes and dialysis

Although diabetes and dialysis are emphasised here, the same principles could readily extend to other chronic conditions, such as heart failure, chronic obstructive pulmonary disease, or rheumatoid arthritis. AI-driven triage, coupled with digital psychosocial interventions, could help patients and clinicians in these contexts to reduce stress, enhance adherence, and improve clinical markers [14]. Additionally, global scalability can be facilitated through user-friendly interfaces, flexible telehealth modules, and multilingual content tailored to various healthcare systems.

5.4. Limitations and future directions

While initial data are promising, more robust evidence from longitudinal studies is needed to establish sustained benefits on clinical outcomes, mental well-being, and healthcare costs [20]. Randomised trials, followed by cost-effectiveness evaluations, will clarify the viability of large-scale implementations. AI-based risk stratification systems must continue to evolve to reduce false positives and negatives. Incorporating patient feedback, cultural norms, and regular updates to psychometric tools is key to maintaining accuracy, relevance, and patient-centredness. Qualitative research can inform iterative design improvements, ensuring that the technology is inclusive and intuitive [21]. Future research should also explore operational aspects, such as clinician training, telehealth infrastructure, and reimbursement frameworks.

Limitations of this manuscript: This is a perspective manuscript that proposes a conceptual model; it reports no original empirical data. As such, the generalisability of the EFP mini across cultures and clinical contexts, the suitability of our indicative thresholds, and the real-world feasibility of workflows remain to be established. We did not report algorithmic performance metrics, usability testing, or cost data for the full stack described. Future work should therefore include multi-site pilots with pre-registered outcomes, calibration of risk thresholds to local populations, process-safety evaluation, and health-economic analysis. These manuscript-level limitations are distinct from limitations already noted in the cited literature.

6. Conclusions

A digital mental health triage solution, supported by AI-driven coaching and strategic clinician oversight, shows promise for addressing the unmet psychosocial needs of patients with chronic illnesses such as diabetes and chronic kidney disease (CKD). Synthesised evidence from dialysis and diabetes literature suggests that early mental health support not only bolsters emotional resilience but also yields tangible improvements in adherence and clinical markers [18]. By incorporating routine screening, algorithmic risk stratification, and tailored interventions within standard chronic disease care, this model offers an accessible and patient-centred approach.

Next steps include multi-site pilots with pre-registered endpoints (screening completion, alert-to-action time, symptom change), subgroup calibration plans with fairness audits, a minimum safety/efficacy bar for scale-up, and prospective health-economic evaluation. A standing governance schedule (bias and drift audits, model updates, patient-reported outcomes) should oversee safe iteration from pilot to broader deployment.

7. Key messages/practical implications

Merging psychosocial support with routine chronic disease management can improve adherence and clinical markers such as glycated haemoglobin (HbA1c) in diabetes; an AI-driven triage layer that automates risk stratification helps ensure timely intervention for high-risk patients while optimising scarce specialist resources and reducing wait times; and privacy-preserving digital platforms can also lower access barriers and stigma by enabling private, culturally sensitive engagement. Although we focus on diabetes and CKD, the same triage principles can extend to other conditions, including chronic obstructive pulmonary disease (COPD) and heart failure. Finally, longitudinal and cost-effectiveness studies, structured user-experience feedback, and ongoing algorithm refinements are essential to confirm the broad applicability, safety, and equity of this model [35,36].

Author contributions

Both authors contributed equally.

Use of AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

Ethical and safety framework

Governance follows General Data Protection Regulation (GDPR) principles of data minimisation and purpose limitation; role-based access, encryption in transit/at rest, audit logs, and defined retention windows are enforced. We assess fairness (error-rate and calibration parity) across age, sex, language, and socioeconomic proxies, with corrective actions (recalibration and, where appropriate, subgroup-specific thresholds) reviewed by a multidisciplinary committee. Any self-harm indicators trigger immediate human review and emergency protocols; clinician override is mandatory for high-risk triage.

Conflict of interest

All authors declare that there are no competing interests.

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