Digital Pathways to Recovery: Developing and Testing an AI-Supported Rehabilitation Tool in Low-Resource Settings

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ABSTRACT

Background

Psychosocial rehabilitation for homeless persons with severe mental illness (SMI) in low- and middle-income countries is frequently constrained by staff shortages, high turnover, and reliance on uniform, non-individualized care. This paper reports the development and validation of PRAGATI Care (Psychosocial Rehabilitation with AI-Guided Assistance for Therapeutic Interventions), a web-based, artificial intelligence (AI)-augmented care-planning tool designed for residential rehabilitation centres in Kerala, India.

Methods

Following an adapted design-and-development framework (Rothman 1994), PRAGATI Care was engineered through iterative prompt development across ten versions, integrating standardized assessments (WHODAS 2.0, SOFS, WHOQoL-BREF) with OpenAI's GPT-4.1 via a one-shot, chain-of-thought prompting strategy, refined through consultation with clinical practitioners and expert review ($n = 4$). The prototype was piloted across three non-governmental rehabilitation centres among 59 residents with SMI, generating individualized care plans within a human-in-the-loop, closed-loop workflow. Evaluation assessed test–retest consistency, blinded expert-rated quality relative to human-authored plans, clinical similarity, and utility reported by field investigators.

Results

Expert review demonstrated the relevance and comprehensiveness of the tool's modules and prompt logic, with 19 of 22 rated components achieving mean scores of 4.00 or higher on a 5-point scale. AI-generated plans demonstrated high test–retest consistency (overall similarity $M = 4.00$) and quality ratings statistically equivalent to human-authored plans ($M = 3.88$ vs. 3.82; $p = .755$, Cohen's $d = 0.08$), with similarity ranging from partial to close ($M = 3.60$). Field investigators reported the utility of the tool for standardizing documentation and supporting continuity of care, alongside implementation barriers including unreliable connectivity, technical learning curves, and occasional contextually inappropriate recommendations that were corrected through mandatory human review.

Conclusion

This study suggests the potential of AI-supported care planning to augment, rather than replace, human clinical judgment in psychosocial rehabilitation care planning. By combining clinical insight with scalable technology, it provides a cost-effective and adaptable framework for enhancing rehabilitation services in resource-limited settings.

Keywords: artificial intelligence; psychosocial rehabilitation; severe mental illness; homelessness; care planning; low-resource settings

INTRODUCTION

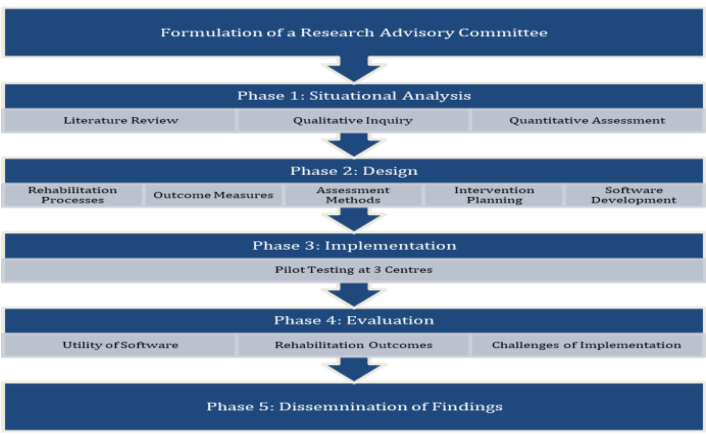
Homelessness among persons with severe mental illness (SMI) constitutes a persistent public health concern, often compounded in low- and middle-income countries (LMICs) by resource constrained mental health systems and a heavy reliance on non-governmental organizations for long-term residential care (Ali & Gajendragad, 2025; Fowler et al., 2019; Gowda et al., 2017; Kalyanasundaram et al., 2023; Kwobah et al., 2021; Singh et al., 2018). In Kerala, India, such organizations have historically filled critical service gaps, providing shelter, basic psychiatric treatment, and custodial support to persons with SMI who lack pathways to family or community reintegration (Anish, 2013; Radhakrishnan & Abraham, 2017).

In psychosocial rehabilitation frameworks, the focus is often on functional recovery, extending beyond symptom stabilization to address deficiencies in community living, interpersonal, and occupational domains (Farkas et al., 2007; Periyasamy & Jangam, 2024; Rosa & Lima, 2019). However, in resource-limited, caregiving is primarily focused on addressing immediate physical and clinical needs, while psychosocial rehabilitation takes a backseat (Meghrajani et al., 2023; Philip et al., 2024). In contexts where manpower is scarce, digital tools and artificial intelligence (AI) have been proposed as scalable complements, rather than substitutes, for human expertise for screening, monitoring, and, more recently, generative decision-support for treatment and care planning (Olawade et al., 2024; Wang et al., 2023).

AI applications in mental health have found use mostly in detection and diagnosis, using electronic health records where available, imaging, and leveraging electronic health records, imaging, and digital biomarkers (Graham et al., 2019; Shatte et al., 2019). There have also been recent applications into therapeutic support, including AI chatbots and decision-support systems to address psychological distress and improve treatment adherence (Cruz-Gonzalez et al., 2025; Olawade et al., 2024). The integration of AI specifically into rehabilitation care planning, a labour-intensive task dependent on trained personnel, remains underexplored, particularly within LMIC institutional settings where multidisciplinary teams are rarely available (Philip et al., 2024). Large language models (LLMs) present a distinct opportunity in this regard. Unlike rule-based systems, generative LLMs can synthesize heterogeneous clinical and contextual data into structured, individualized outputs through carefully engineered prompts (Sahoo et al., 2023; Wei et al., 2022).

The present work is part of the Digital Pathways to Recovery project, which adopted a phased design -and-development approach based on Rothman and Thomas's (1994) framework. Figure 1 illustrates the phases. In Phase 1, a situational analysis, which included a bibliometric analysis, a scoping review, and mixed-methods fieldwork across twenty rehabilitation centres and 544 residents in Kerala, established the empirical basis for tool development: institutional care was found to prioritize symptom management and basic self-care over individualized psychosocial intervention, with residents recording markedly lower community living and interpersonal functioning relative to physical health domains, and symptom stabilization emerging as a prerequisite for functional gains. These insights directly informed the design logic of PRAGATI Care (Psychosocial Rehabilitation with AI-Guided Assistance for Therapeutic Interventions), a web-based, AI-augmented application intended to generate individualized rehabilitation care plans.

Figure 1 Phases of Digital Pathways to Recovery Project



This paper reports on the design and technical development of PRAGATI Care, its real-world pilot deployment across three residential rehabilitation centres, and its formal evaluation for reliability, quality, and utility.

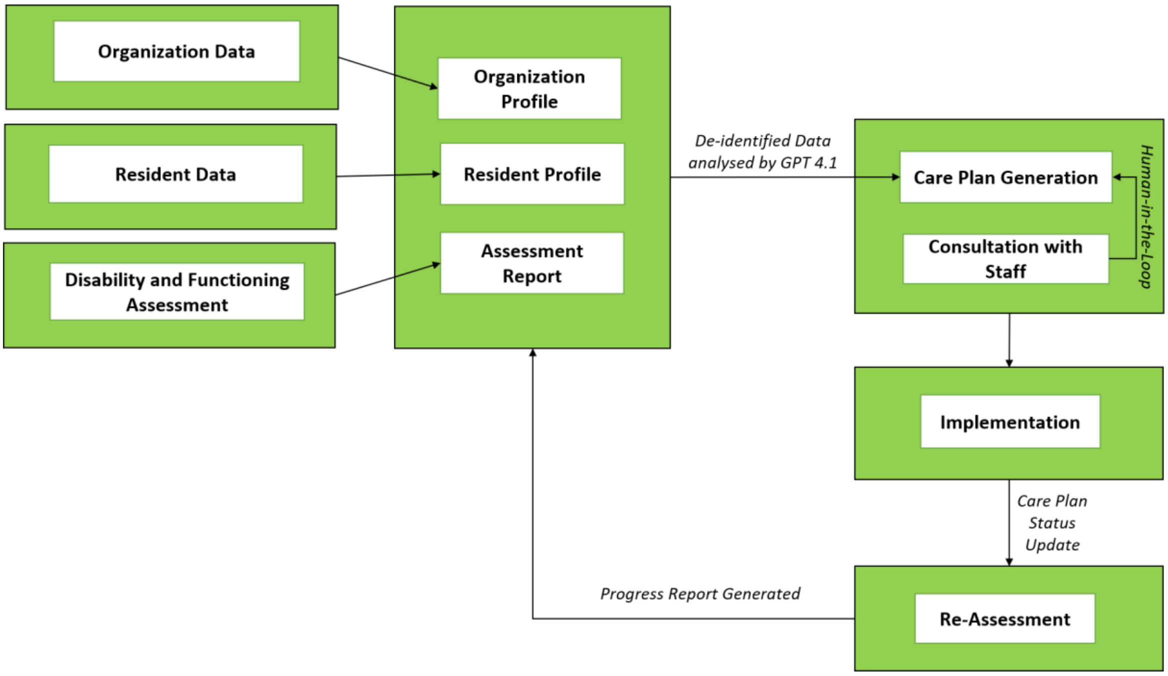
MATERIALS AND METHODS

This study adapted Rothman and Thomas's (1994) design-and-development model, comprising a situational analysis, design and development of the intervention, pilot implementation, and evaluation. Ethical approval was obtained from the Rajagiri Institutional Research Ethics Committee (Ref: RCSS/IEC/018/2025), with institutional consent secured from all participating organizations and individual informed consent, or caregiver assent where applicable, obtained from residents.

Design and Development

PRAGATI Care was conceptualized as AI-enhanced care planning tool in settings with resource constraints. The process flow is based on a closed-loop model, as shown in Figure 2, that integrates continuous assessment, AI-assisted care-plan generation, human oversight and editing, implementation tracking, periodic re-assessment, and automated revision of care plans. This model was designed to be dynamic, evidence-informed, and responsive to changes in residents' clinical and functional status over time.

Figure 2 PRAGATI Care System: A Closed-Loop Care Plan Generation Model



Technical Architecture

PRAGATI Care is hosted on a Hostinger Virtual Private Server (VPS). The source code is stored and managed in a private GitHub repository accessible only to approved team members through multi-factor authentication and role-based permissions.

The application uses a MySQL database that is not exposed to the public internet and is accessible solely by the application itself. User authentication requires strong passwords, with password recovery performed via one-time passcode (OTP) sent to the registered email address. Role-based access control (RBAC) is implemented with three user levels (central administrator, organisation administrator, and staff).

When care plans are generated, de-identified clinical data (assessment responses, symptoms, medication details, and organisational services) are transmitted via encrypted HTTPS to OpenAI's GPT-4.1 model through its API. No personal identifiers are sent, and no permission has been granted for OpenAI to use the submitted data for model training.

These measures were implemented to protect resident confidentiality and ensure alignment with the Mental Healthcare Act, 2017 and the Digital Personal Data Protection Act, 2023.

Core Modules

Three data-capture modules were developed: an Organization Module recording institutional services, staffing, and resident distribution; a Resident Module capturing details of admission, family and support, background, clinical observations, diagnosis, medication, rehabilitation history, strengths and readiness for change; and an Assessment Module digitizing three standardized instruments. They were: the WHO Disability Assessment Schedule 2.0 (WHODAS 2.0) (Üstün et al., 2010), the Social Occupational Functioning Scale (SOFS) (Saraswat et al., 2006), and the WHO Quality of Life-BREF (WHOQoL-BREF) (World Health Organization, 2004). WHODAS 2.0 was selected over the Global Assessment of Functioning scale for its structured, ICF-aligned, proxy-ratable design suited to LMIC settings (Habtamu et al., 2017; Koopmans et al., 2020).

De-identified outputs from these modules were transmitted to GPT-4.1 to generate structured care plans in the fourth module, which staff could review and edit through a mandatory human-editing interface, with reasons for all edits recorded for accountability. A fifth module tracked implementation progress and challenges, feeding this information back into subsequent AI-assisted plan revisions. At follow-up, updated clinical observations and repeated standardized assessments were entered. The new data, together with the previous care-plan status report, were sent to GPT-4.1 to produce a progress report and a revised care plan, restarting the closed-loop cycle.

AI Prompt Development

The AI prompt was developed through an iterative prompt engineering across ten versions, combining one-shot and chain-of-thought (CoT) prompting strategies (Wei et al., 2022) to strengthen the model's reasoning and consistency. The prompt established the model's role and context and structured its output through six decision rules governing, in sequence: a prioritization hierarchy for needs identification (safety, psychiatric stabilization, then functional and social domains); goal formulation; resource-matched, strengths-based intervention planning; mandatory rationale for each intervention, intended to promote explainability; and a standardized output format.

Successive versions transitioned from tabular to structured JSON output, introduced explicit prioritization logic, incorporated feedback loops using prior care-plan and implementation-status data, and refined language for clarity. Early iterations were tested using synthetic resident datasets, with outputs subsequently reviewed by the research team and, from the sixth version onward, by four independent experts.

Expert Review on Relevance and Comprehensiveness of AI-authored Care Plans

Four mental health professionals (two psychiatrists and two psychiatric social workers) reviewed the data-collection modules, prompt guidelines, and two AI-generated care plans based on dummy resident profiles, rating twenty-two components on a five-point Likert scale with accompanying open-ended feedback.

Pilot Implementation

PRAGATI Care was piloted across three NGO-run rehabilitation centres registered under the Kerala Federation of Care of Mentally Disabled (KFCMID), located in three districts of Kerala. Sixty residents (twenty per centre) meeting inclusion criteria (age 18 years or above; primary diagnosis of schizophrenia, bipolar disorder, or psychosis not otherwise specified; minimum three months of continuous residence) were randomly selected; one participant was excluded following hospitalization for a medical emergency, yielding a final sample of 59.

Trained field investigators (n = 3) completed the Organization Module for each centre before entering individual resident data and administering the three standardized assessments digitally. PRAGATI Care generated an initial AI-authored care plan for each resident, which was reviewed and formally endorsed by the centre's caregiving team. Following a thirty-day implementation period, staff recorded implementation progress and barriers, repeated the standardized assessments, and PRAGATI Care generated a revised, progress-informed care plan, completing one cycle of the closed-loop model.

Evaluation: Instruments

Three evaluation instruments were developed by the research team: a seven-item Care Plan Quality Check Rubric (identification of needs, clarity of goals, appropriateness of interventions, potential effectiveness, rationale, overall relevance, and overall quality); a five-item Care Plann Similarity Check Rubric (needs, goals, interventions, rationale, and overall similarity); and an eleven-item Feedback Interview Guide administered as a group conference with field investigators.

Test–retest consistency was assessed by re-entering identical baseline data for six residents (two per centre) after a four-week interval and comparing the resulting plan pairs using the Care Plan Similarity Check Rubric. Quality was assessed by comparing three AI-authored plans against three human-authored plans, developed by the research team using identical input data and the prompt's structural logic, for the same residents; all six plans were anonymized and independently rated by five experts using the Care Plan Quality Check Rubric. The same three AI–human plan pairs were additionally rated for clinical similarity using the Similarity Check Rubric. Utility and implementation barriers were explored through a single group interview with the three field investigators assigned to the NGOs for implementation.

Data Analysis

Analysis was carried out using IBM SPSS Statistics Version 25. Internal consistency of both rubrics was assessed via Cronbach's alpha, and inter-rater reliability was calculated using the intraclass correlation coefficient (ICC) under a two-way mixed-effects, consistency model. A paired-samples t-test compared mean quality ratings between AI-authored and human-authored plans, with Cohen's d as the effect-size estimate. Descriptive statistics summarized test–retest similarity and AI–human comparison scores. Qualitative feedback from field investigators was compiled and summarized descriptively under each guide domain.

Ethical Considerations

All resident data were de-identified prior to transmission to the AI model, with role-based access control restricting visibility according to function. A human-in-the-loop approach was mandatory throughout the workflow: AI-generated plans required review, endorsement, and, where necessary, modification by centre staff prior to implementation, with all edits and their rationale logged for accountability. No experimental or untested technology was introduced to bypass or replace existing clinical decision-making; an established, commercially available LLM was used solely to augment, not substitute, professional judgment.

RESULTS

Prototype and AI Prompt Development

The final prototype for the web-application, hosted on a Hostinger VPS with role-based access control, data anonymization for research users, and encrypted transmission of de-identified resident data to OpenAI GPT-4.1, consisted of five modules carrying out three major tasks: data capture, AI-assisted care plan generation, and status update. The modules and their functions are described in Table 1.

Table1 Core Modules of PRAGATI Care

Module	Description	Purpose
Organization Data Module	Collects and records organizational details, staffing overview and resident distribution statistics. It also records the services and facilities available at the centre.	To provide the AI with relevant data to generate interventions mapped to the services offered at the centre to ensure feasibility.

Resident Data Module	Captures the qualitative and background data covering Basic Details, Admission Requirements, Family & Support, Background & Social, Clinical Observations, Diagnosis & Health, Medication Details, and Strengths & Aspirations.	To generate a comprehensive resident profile for the AI to identify needs, readiness for change, and determine appropriate interventions.
Assessment Module	Digitizes and automates scoring for three standardized instruments: WHODAS 2.0, SOFS, and WHOQoL-BRE. It also displays domains and total scores, displaying areas of impairment.	To generate assessment scores and identify areas of impairment in functioning for care plan generation and progress tracking for subsequent revisions to care plans as needed.
Care Plan Generation Module	Generates a structured care plan based on de-identified client data that prioritizes needs across six domains and aligns specific goals and interventions with the available institutional services; a mandatory human-editing interface allows staff to modify the AI-authored plans prior to implementation.	To generate AI-assisted rehabilitation care plan reviewed by human personnel for addressing identified needs.
Status Update Module	Captures implementation progress including consistency of the intervention delivery; records challenges faced during implementation, resident-related, resource-related, intervention-related, or others.	To facilitate the continuity of the care cycle by enabling staff to track plan implementation and gather relevant feedback data.

The AI prompt for care plan established the context and role of the AI, mandating it to act as an “AI Assistant for a mental health rehabilitation centre in Kerala, specializing in providing care for homeless individuals with mental illness.” The model was also directed to adopt a professional, empathetic, and contextually informed clinical suitable for the target setting.

The decision logic of the AI was governed by a set of six rules with specific instructions for the implementation of each rule.

Relevance and Comprehensiveness of AI-authored Care Plans

Expert (N=4) review of relevance and comprehensiveness of the AI-authored care plans (N=3) was favourable: nineteen of twenty-two rated components achieved mean scores of 4.00 or higher on a five-point scale (Table 2), including the AI prompt’s contextual framing, its instructions for needs identification, and its instructions for need prioritization. Two components of the Resident Module, Admission Requirements and History of Rehabilitation, received comparatively lower, though still favourable, ratings; qualitative feedback proposed minor field additions, most of which were incorporated prior to pilot implementation.

Table 2 Expert Ratings (N = 4) on Relevance and Comprehensiveness of AI-authored Care Plans (Selected Items)

Item	**Mean**	**SD**
Relevance of Services and Facilities	4.50	0.58

Comprehensiveness of the Assessment Module	4.50	0.58
AI Prompt – Context	4.50	0.58
AI Prompt – Instructions for Needs Identification	4.75	0.50
AI Prompt – Instructions for Need Prioritization	4.50	0.58
AI Prompt – Instructions for Goal Setting	4.50	0.58
AI Prompt – Instructions for Intervention Planning	4.50	0.58
Overall Relevance of Data Collected	4.25	0.50
Overall Comprehensiveness of Care Plans	4.00	0.00
Admission Requirements (Resident Module)	3.75	0.50
History of Rehabilitation (Resident Module)	3.50	0.58

Pilot Deployment

PRAGATI Care generated care plans for the participants (N=59) across the three pilot centres (mean age 50.85 years, SD = 11.44; 47.5% women; primary diagnoses of schizophrenia [52.5%], bipolar affective disorder [35.6%], and psychosis not otherwise specified [11.9%]). Table 3 summarizes the characteristics of the three participating centres, which varied considerably in scale and composition. Although no technical modifications were made, every AI-authored care plan was discussed and reviewed with the respective caregiving team at the rehabilitation centre. This process served two purposes: accountability and vetting.

Table 3 Characteristics of Pilot Sites

Centre	Bed Capacity	Total Residents	Male	Female
C1 (Kottayam)	75	62	46	16
C2 (Kannur)	90	82	0	82
C3 (Wayanad)	300	342	234	108

Note. C2 is an all-female facility; C3 is a substantially larger institution. Figures reflect resident counts at the time of recruitment.

The implementation phase was limited to a 30-day period for the residents. Given this short duration, the primary goal of this phase was not to achieve definitive outcomes, but rather to assess the feasibility of implementation.

Pilot Implementation: Evaluation

<u>Test-Retest Consistency</u>

Across three pairs of care plans generated for similarity check, overall similarity was rated as a close match (M = 4.00, SD = 0.00), with interventions showing consistency (M = 4.00, SD = 0.00) and needs showing the greatest, though still moderate, variability (M = 3.50, SD = 0.55), attributable to minor differences in prioritization order rather than substantive differences in content.

<u>Quality Check: AI-Authored versus Human-Authored Plans</u>

Both the Care Plan Quality Check Rubric (Cronbach's $\alpha = .91$ overall; .93 for AI-authored plans; .88 for human-authored plans) and the Care Plan Similarity Check Rubric ($\alpha = .81$) showed strong internal consistency. Inter-rater reliability for quality ratings was low at the level of individual raters (ICC single measures = .13) but improved when averaged across the five reviewers (ICC average measures = .43, 95% CI [−.87, .91]); inter-rater reliability for similarity ratings was considerably stronger (ICC single measures = .46; ICC average measures = .81, $p < .001$). A paired-samples t-test found no significant difference in overall quality between AI-authored (M = 3.88, SD = 0.67) and human-authored plans (M = 3.82, SD = 0.58), $t(14) = 0.32$, $p = .755$, with a negligible effect size (Cohen's d = 0.08), as summarized in Table 4.

Table 4 Summary of Quality Check Results

Domain	Metric	Value
Test–retest consistency (n = 6 pairs)	Overall similarity, M (SD)	4.00 (0.00)
Quality: AI vs. human (n = 6 plans, 5 raters)	AI-authored, M (SD)	3.88 (0.67)
	Human-authored, M (SD)	3.82 (0.58)
	t(14), p, Cohen's d	0.32, .755, 0.08
AI–human similarity (n = 3 pairs, 5 raters)	Overall similarity, M (SD)	3.60 (0.51)
	Rationale (highest), M (SD)	3.73 (0.70)
	Interventions (lowest), M (SD)	3.33 (0.72)

Similarity Check between AI- and Human-Authored Plans

Blinded comparison of three AI–human plan pairs indicated partial-to-close similarity overall (M = 3.60, SD = 0.51), with rationale showing the closest alignment (M = 3.73, SD = 0.70) and interventions the weakest (M = 3.33, SD = 0.72). This pattern suggests that while the AI's underlying clinical reasoning broadly paralleled human judgment, specific intervention recommendations showed differences.

Utility and Implementation Feedback

The field investigators (N=3) noted the issue of chronic understaffing and reliance on custodial routines, within which PRAGATI Care was perceived to offer structure for individualized planning otherwise unavailable given the absence of multidisciplinary teams. One of them pointed out how the centre often operated on a "survival mode" where the priority is simply completing the day-to-day tasks.

Perceived benefits included predictive utility, support for continuity of care amid incomplete legacy records, and standardization of documentation. Investigators found the interface broadly usable following an initial learning curve, though confidence in technical aspects varied across users. Implementation was constrained by unreliable internet connectivity, the time required to build rapport with residents and staff, and the need to schedule data collection around existing institutional routines.

Staff response, as reported by the field investigators, to AI-generated plans was mixed: some staff expressed willingness to implement recommended interventions, while others, particularly amid existing workload pressures, perceived the plans as an added administrative task rather than a time- and labour-saving tool. Investigators further identified instances of contextually inappropriate recommendations, such as physical exercise suggested for residents with documented mobility limitations or advanced age, despite this information being available in the resident profile. These instances were consistently identified and adapted during mandatory human review prior to implementation. Recommendations for improvement included auto-save functionality to mitigate connectivity-related data loss, integration of general health indicators, streamlined navigation, in-app guidance for less technically confident users, and dedicated staff support during initial rollout.

DISCUSSION

This study aimed to demonstrate the feasibility of developing and deploying a generative-AI-augmented care-planning tool for psychosocial rehabilitation within a low-resource, LMIC institutional setting. Three findings merit close discussion. First, expert validation and quantitative evaluation converge in indicating that carefully engineered prompting, combining one-shot and chain-of-thought reasoning, and an explicit clinical prioritization hierarchy, can produce care plans judged comparable in quality to those authored by trained professionals ($d = 0.08$), consistent with emerging evidence on LLM applications in structured clinical documentation tasks (Cruz-Gonzalez et al., 2025; Olawade et al., 2024). Second, test–retest consistency was high for interventions and overall similarity, suggesting that, given stable input data, PRAGATI Care produces reproducible strategic recommendations, an important property for a decision-support tool intended for routine institutional use.

Third, the evaluation pointed to reproducible failure modes of general-purpose LLMs in this domain: occasional contextually inappropriate recommendations that did not adequately weight variables such as advanced age or physical comorbidity against functional impairment. This pattern is consistent with documented limitations in LLMs' handling of complex, multi-attribute prompts, wherein models may over-weight dominant patterns at the expense of secondary but clinically decisive constraints (Liu et al., 2023), compounded by the absence of domain-specific fine-tuning on psychiatric rehabilitation data (Johnson et al., 2023; Suenghataiphorn et al., 2025). But these errors were consistently identified and corrected through the mandatory human-in-the-loop review built into the workflow, rather than encouraging unchecked into implementation. This finding supports a broader position advanced in the literature: that generative AI in psychosocial rehabilitation is best conceptualized as a decision-support mechanism augmenting, rather than substituting, clinical and caregiving judgment (Wang et al., 2023).

The API-based deployment model, transmitting only de-identified data to a cloud-hosted LLM rather than requiring local computational infrastructure, makes the scalability of this approach for NGOs with limited technical capacity a possibility (Kwobah et al., 2021; Philip et al., 2024). The feedback on implementation from the field officers revealed barriers extending beyond the technical performance of the AI itself. Connectivity constraints, variable staff digital literacy, and, the perception of AI-generated plans as an additional administrative burden amid existing workload pressures, point to an implementation gap in digital health adoption. Technical validity alone is insufficient for sustained adoption; institutional readiness, dedicated onboarding support, and integration into existing workflows are equally consequential to scaling up.

LIMITATIONS

The limitations also warrant consideration. The evaluation of consistency, quality, and clinical similarity relied on small purposive subsamples (three to six plan pairs), reflecting the resource constraints of a pilot phase but limiting the precision and generalizability of inter-rater reliability estimates, several of which yielded wide confidence intervals. The thirty-day implementation window did not allow for testing longer-term effects of AI-assisted care planning on resident functioning and quality of life. This remains to be established through extended, multi-site trials. The pilot was also confined to three centres within a single Indian state, limiting generalizability to institutions with differing organizational structures or resource profiles.

Finally, PRAGATI Care's reliance on a general-purpose, proprietary LLM means its outputs are contingent on a model that needs to be fine-tuned on psychiatric rehabilitation data and is independent of the version-dependent behavioural shifts characteristic of rapidly evolving generative AI systems. These limitations point toward concrete directions for future development: domain-specific fine-tuning using anonymized, expert-vetted care plans generated through this and subsequent pilots; explicit prompt-level constraint-checking for variables such as age, mobility, and comorbidity prior to intervention recommendation; longitudinal, multi-site evaluation of resident outcomes; and continued attention to institutional change management alongside technical refinement.

CONCLUSION

This study suggests that a carefully engineered, human-in-the-loop generative-AI tool can generate psychosocial rehabilitation care plans comparable in quality to those authored by human professionals The tool's value lies not in replacing clinical judgment but in structuring and standardizing individualized care planning where multidisciplinary expertise is scarce, but with sustained human oversight. Scaling this model will require continued technical refinement, including domain-specific fine-tuning, alongside institutional and policy-level investment in digital readiness, positioning AI-augmented care planning as a feasible, though not self-sufficient, pathway toward more individualized psychosocial rehabilitation in low-resource settings.

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