

iALERTS: A Pragmatic Pilot Study of a Clinical Decision Support System for Long COVID Care

Krishna Mohan Surapaneni^{1*}, Manmohan Singhal², Ashish Joshi³

¹School of Pharmaceutical & Population Health Informatics, DIT University, Dehradun, Uttarakhand, India; Panimalar Medical College Hospital & Research Institute, Chennai, Tamil Nadu, India

²School of Pharmaceutical & Population Health Informatics, DIT University, Dehradun, Uttarakhand, India

³School of Public Health, The University of Memphis, Memphis, TN 38152, USA

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ABSTRACT

Background: Long COVID is a significant public health challenge due to its persistent multisystem symptoms. Few structured tools exist to support clinicians in identifying, stratifying, and managing patients at risk. This study reports the pilot implementation and evaluation of iALERTS, a clinical decision support system (CDSS) developed for real-time risk stratification and longitudinal management of Long COVID.

Methods: In this mixed-methods pragmatic pilot study, 148 healthcare providers underwent structured training and readiness testing. Real-world data from 120 patients with post-COVID symptoms were entered into iALERTS. Evaluation, guided by PRISM and Content-Context-Process frameworks, included descriptive statistics as well as qualitative interviews and observations to assess technical accuracy, clinical integration, and user acceptance.

Results: Data completeness exceeded 98%, with 100% concordance between system predictions and clinician judgment. Common symptoms were fatigue (72%), breathlessness (54%), brain fog (39%), headache (38%), and myalgia (36%). Providers reported high confidence in accuracy (mean = 4.3), positive workflow integration (mean = 4.0), and strong user acceptance (mean = 4.2).

Conclusion: iALERTS demonstrated feasibility, reliability, and strong endorsement in this pilot. Limitations include its single-center design and short duration. Further multi-site studies are needed to validate scalability and long-term utility.

Keywords: Long COVID, Clinical Decision Support System, Digital Health, Symptom Monitoring, Pilot Study, Mixed-Methods Evaluation, PRISM Framework, Content-Context-Process Framework

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***Correspondence:** Dr. Krishna Mohan Surapaneni (Email: krishnamohan.surapaneni@gmail.com)

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INTRODUCTION

The aftermath of COVID-19 has given rise to a complex and persistent health challenge, Long COVID, or post-acute sequelae of SARS-CoV-2 infection (PASC), defined as new, returning, or ongoing symptoms that persist ≥ 3 months after acute infection and last ≥ 2 months without an alternative diagnosis.¹ Characterized by a wide spectrum of fluctuating symptoms affecting multiple organ systems, Long COVID continues to strain both patients and healthcare systems, particularly in low- and middle-income countries where clinical follow-up is often fragmented.² In India, a recent community follow-up in Haryana reported that ~30-35% of recovered COVID patients experienced persistent multi-system symptoms 6 months later, aligning with global estimates.³ Another single-center cohort in Eastern India found a 29% prevalence of long COVID at one-year post-infection.⁴ These data underscore the significant and sustained burden in Indian settings, motivating the development of context-tailored tools like iALERTS.

To address this gap, we previously developed iALERTS (informatics Analytics for Long-term Evaluation and Repercussions Tracking of SARS-CoV-2 Infection), a digital platform that uses a logic-driven model to stratify patients based on self-reported symptoms, clinical indicators, and risk patterns.⁵ The initial study outlined the conceptual framework, design process, and internal testing of the Clinical Decision Support System (CDSS), establishing a foundation for risk stratification and symptom monitoring in post-COVID care.⁶

However, designing a digital health tool is only the first step. Successful implementation in real-world settings requires more than technical robustness; it demands meaningful integration into existing workflows, buy-in from clinical users, and adaptability to varied local contexts. CDSS tools, by nature, are sociotechnical systems. Their performance and impact are shaped not only by algorithms and data flows but also by how they interact with users, institutions, and daily clinical routines.^{7,8} Notably, some CDSS implementations have encountered challenges, for instance, external evaluations of the Epic Sepsis Model reported lower-than-expected predictive accuracy, underscoring the importance of thorough validation and alignment with clinical workflows for sustained trust and adoption.^{9,10}

Previous implementation studies have highlighted several key lessons. First, active involvement of clinicians during the design and deployment phase improves trust and long-term adoption.^{11,12} Second, embedding CDSS into existing electronic health records and minimizing workflow disruptions are critical for sustained use.^{13,14} Third, organizational support, including leadership endorsement and training, helps overcome resistance and enhances collective ownership.¹¹ Finally, iterative testing through pilot studies allows for refinement of system logic, alerts,

and user interfaces before wider rollout.^{15,16} These factors, when addressed together, can transform CDSS from a technical innovation into a practical and sustainable tool for healthcare delivery.

In this mixed-methods pragmatic pilot, we examine real-world deployment of the iALERTS CDSS, its usability, clinical integration, and user acceptance and test the hypothesis that iALERTS will achieve high data completeness ($\geq 95\%$), strong concordance with clinician judgment, and favorable provider ratings for confidence, workflow integration, and acceptance; additionally, we anticipate qualitative evidence (interviews/observations) of fit-with-workflows that explains adoption patterns. Limitations anticipated a priori include single-center scope and short duration, which may constrain generalizability and long-term inference.

METHODOLOGY

Study Design: This was a pragmatic pilot implementation and evaluation study of the iALERTS CDSS. The purpose was to assess not only the technical accuracy of the platform but also its feasibility, usability, and integration into everyday clinical practice. A mixed-methods approach was followed, combining system-generated quantitative data with qualitative insights gathered from healthcare providers through surveys, 20 semi-structured interviews, and 10 direct non-participant observations of outpatient consultations. Qualitative data were analyzed thematically using Braun and Clarke's six-step framework, with two independent coders; discrepancies were resolved by consensus, and inter-rater reliability (Cohen's kappa = 0.82) ensured coding consistency.

Setting and Participants: The study was conducted at Panimalar Medical College Hospital and Research Institute (PMCHRI), Chennai, India. iALERTS was deployed across all outpatient departments that managed post-COVID patients, ensuring that the evaluation reflected diverse workflows and clinical environments. Participants included physicians, nurses, hospital administration, allied health staff, and data entry officers. Random sampling was done and written informed consent was obtained from all participants. All were provided secure login credentials with role-based access. Patients were eligible if they had a confirmed history of SARS-CoV-2 infection (PCR or antigen positive), persistent or new symptoms lasting > 4 weeks after acute illness, and were attending post-COVID follow-up clinics. Exclusion criteria included patients < 18 years of age, those unable to provide consent, or those with alternative diagnoses explaining their symptoms. One hundred and twenty cases were consecutively enrolled during the pilot phase. Each case was processed by the system, and all categorizations aligned with clinician judgment, confirming accuracy during the pilot. The sample size (148 providers and 120 patients) was justified on feasibility grounds consistent with pilot

study guidance, aiming to capture diverse user roles and sufficient patient variability to assess early system performance.

Implementation Process: Implementation was carried out in a structured manner. A core team was established that included physicians, nurses, hospital administration, allied health staff, data entry officers, and IT lead to ensure technical readiness. Orientation sessions introduced the system and its goals, while training was delivered using the iALERTS Readiness Assurance Module.¹⁷ Training consisted of three 2-hour workshops conducted over two weeks, covering patient registration, dashboard use, risk alerts, and reporting. Each session included demonstrations, role-play exercises, and supervised practice. A readiness survey followed, consisting of fifteen knowledge items and ten confidence items rated on a five-point Likert scale, assessing user confidence, preparedness, navigation ability, and ethical awareness.

Once training was complete, iALERTS was deployed in all relevant outpatient clinics. Clinicians used the dashboard and alerts during consultations, while data officers ensured that demographic and clinical information was accurately recorded. Over one week, one hundred and twenty patient records were entered, and clinicians simultaneously validated the system's categorizations. Feedback was collected through short interviews and group discussions, which informed refinements to the dashboard display and data entry workflows.

Evaluation Framework: Evaluation was guided by the Practical, Robust Implementation and Sustainability Model (PRISM) and the Content-Context-Process (CCP) framework.^{18,19} PRISM constructs (organizational characteristics, intervention design, external environment, and implementation infrastructure) were explicitly mapped to questionnaire items (e.g., “ease of integration into workflow” for intervention design, “leadership support” for organizational setting). CCP elements were similarly operationalized: “content” corresponded to alert accuracy, dashboard usability, and readiness survey results; “context” to feasibility of cross-department adoption and administrative support; and “process” to training, observations, and interviews conducted.

Data Collection and Analysis: All quantitative analyses were performed using descriptive and inferential statistics. Metrics included the number of patients registered, completeness of data entry, frequency of logins, and dashboard use. These were expressed as counts and percentages. Responses from the Readiness Assurance Questionnaire were analyzed at both item and composite levels. Each of the twelve items was measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Item responses were summarized as means and standard deviations, while a composite readiness index was created by averaging item scores for each participant. Internal consistency of the scale was evaluated using Cronbach's alpha, with thresholds

above 0.7 considered acceptable. Comparisons of readiness scores across professional groups (clinicians, nurses, data officers) were conducted using one-way ANOVA, with Bonferroni-adjusted post-hoc tests applied where significant differences were observed. A p value of <0.05 was deemed to be significant. To evaluate system accuracy, risk categories generated by iALERTS were compared with clinician judgment. Concordance was calculated as a proportion, with all pilot cases showing complete agreement. In addition, correlations between domain scores (technical accuracy, clinical integration, user acceptance) were assessed using Pearson's r to explore interrelationships between perceptions of the system. Qualitative interview and observation transcripts were coded using NVivo software (version 14). Thematic analysis identified recurrent patterns across provider experiences, and triangulation with quantitative findings strengthened validity.

Ethical Considerations: Ethical approval was obtained from the Institutional Human Ethics Committee (PMCH&RI/IHEC/2021/60 dated: 13/08/2021; DITU/UREC/2022/04/10 dated: 12/05/2022). All staff participants provided informed consent. Patients also consented to their anonymized data being entered into iALERTS. Data were pseudonymized using unique study identifiers, with personal identifiers removed at the point of entry. Encrypted storage, role-based access, and audit trails safeguarded confidentiality, ensuring no re-identifiable information was available for analysis or reporting.

RESULTS

Participant Profile: A total of 148 healthcare providers participated in the pilot. The group included 60 clinicians, 50 nurses, 20 allied health professionals, 8 data officers and 10 IT professionals. The mean age of participants was 37.4 years $\pm$ 6.8, and their average duration of clinical or administrative experience was 9.1 years $\pm$ 4.3. Prior exposure to digital health platforms varied, with 60% reporting frequent use of electronic health records, while 25% described limited experience with structured digital tools.

During the one-week pilot period, 120 patients who attended outpatient departments were consecutively registered in iALERTS. The mean age of patients was 46.2 years $\pm$ 12.5 (range: 18-70 years); 60 (50.0%) were female and 60 (50.0%) male. BMI distribution included 66 (55.0%) in the optimum range, 38 (31.7%) overweight, 10 (8.3%) obese, and 6 (5.0%) underweight. Symptom duration was $\geq$ 28 days in 40 (33.3%), $\geq$ 8 weeks in 40 (33.3%), and $\geq$ 12 weeks in 40 (33.3%).

All patients reported cough (100%), fatigue (100%), headache (100%), dyspnea (100%), and myalgia (100%), while 90 (75.0%) reported hoarse voice. Hospitalization history showed 20 (16.7%) had ever

been hospitalized, and 12 (10.0%) required ICU admission. Vaccination status included 98 (81.7%) fully vaccinated, 10 (8.3%) partially vaccinated, and 12 (10.0%) unvaccinated. All patients had RT-PCR-confirmed SARS-CoV-2 infection. Comorbidities included hypertension in 18 (15.0%), diabetes in 16 (13.3%), heart disease in 8 (6.7%), asthma in 4 (3.3%), and hypothyroidism in 3 (2.5%). A total of 71 patients (59.2%) reported no comorbidities.

Knowledge-Based Questions (Q1-Q15): All 148 participants completed the 15-item knowledge test. Overall performance was strong, with a mean score of 13.4 ± 1.2 out of 15 corresponding to an accuracy of 89.3%. Table 1 summarizes the percentage of participants who answered each question correctly.

Confidence, Preparedness, and Adoption (Q16-Q25): The 10 Likert-scale items assessed user confidence in navigating iALERTS, preparedness to train

others, ability to interpret dashboards, and commitment to ethical use.

The mean confidence/adoption score was 4.27 ± 0.7 out of 5. Most participants rated themselves as “Very confident” or “Extremely confident” in dashboard navigation (81%) and data entry (78%). Ethical readiness was particularly high, with 95% of participants affirming they were fully prepared to ensure confidentiality and secure use of data.

When results were stratified by profession, both clinicians and nurses demonstrated the highest levels of knowledge and confidence, with clinicians achieving the strongest scores overall. Nurses performed only slightly lower, while allied health professionals, IT staff, and data officers also showed good levels of readiness. Differences across groups were statistically significant (ANOVA $p = 0.004$), particularly between clinicians and data officers.

Table 1: Knowledge-Based Assessment Results (n = 148 participants)

Q#	Knowledge Item (Statement)	Correct Responses (%)
1	Identifying the full form of iALERTS	136 (92.0%)
2	Understanding the primary function of iALERTS	141 (95.3%)
3	Recognizing symptom domains not covered in iALERTS	130 (87.8%)
4	Knowing required inputs during patient onboarding	133 (89.9%)
5	Awareness of ethical requirements when using iALERTS	145 (98.0%)
6	Knowing who can assign roles and manage users	126 (85.1%)
7	Identifying the tool used for quality-of-life assessment in iALERTS	137 (92.6%)
8	Recognizing the dashboard feature that tracks patients needing follow-up	132 (89.2%)
9	Awareness of the type of data integrated into iALERTS	135 (91.2%)
10	Knowledge of the framework guiding iALERTS implementation	129 (87.2%)
11	Knowledge of the external guideline informing the symptom list	124 (83.8%)
12	Awareness of password update requirements	118 (79.7%)
13	Identifying iALERTS risk categories	139 (93.9%)
14	Awareness of iALERTS' main security feature	133 (89.9%)
15	Knowing which professionals are eligible to access dashboards	127 (85.8%)

Table 2: Confidence and Adoption Assessment Results (n = 148)

Q#	Item (Statement)	Mean $\pm$ SD (1-5)	% High (≥ 4)
16	I am confident in navigating the iALERTS dashboard.	4.3 ± 0.6	81%
17	I feel prepared to train a new user in patient registration.	4.1 ± 0.7	76%
18	I can interpret risk alerts and dashboards for decision-making.	4.2 ± 0.6	79%
19	Using iALERTS fits smoothly into my outpatient workflow.	4.0 ± 0.7	72%
20	I believe iALERTS improves structured care for long COVID.	4.4 ± 0.5	85%
21	I am confident about maintaining confidentiality and ethical use.	4.7 ± 0.4	95%
22	I am comfortable entering quality-of-life data (EQ-5D-5L).	4.2 ± 0.6	78%
23	I trust the accuracy of alerts generated by iALERTS.	4.3 ± 0.5	83%
24	I am willing to recommend iALERTS to colleagues.	4.4 ± 0.6	86%
25	I am motivated to continue using iALERTS in future practice.	4.5 ± 0.5	88%

Table 3: Knowledge and Confidence by Profession

Profession	Knowledge (% Correct)	Confidence (Mean $\pm$ SD, 1-5)
Clinicians (n=60)	92%	4.4 ± 0.5
Nurses (n=50)	90%	4.3 ± 0.6
Allied health (n=20)	87%	4.2 ± 0.6
IT staff (n=10)	85%	4.1 ± 0.6
Data officers (n=08)	82%	3.9 ± 0.7
Overall (ANOVA)		0.004

Implementation & Testing: The iALERTS platform was implemented across all outpatient clinics within the hospital to ensure broad integration into routine clinical workflows. All users were provided secure logins and role-based access, with clinicians assigned to patient dashboards and data officers responsible for verifying demographic and symptom entries. Over the course of the pilot, 120 patient cases were registered, capturing demographic, clinical, and symptom data in real time. Clinicians actively engaged with the dashboard during consultations, us-

ing the automated alerts and visual summaries to guide decision-making.

The mean age of the cohort was 46.2 years $\pm$ 12.5. Gender distribution was equal, with 60 males (50.0%) and 60 females (50.0%). In terms of body mass index, the majority of participants were in the optimum range (n = 66), followed by those classified as overweight (n = 38), obese (n = 10), and underweight (n = 6). Symptom duration was evenly distributed across categories, with one-third of participants reporting symptoms lasting at least 28 days, one-third beyond 8 weeks, and one-third persisting beyond 12 weeks. Symptom prevalence was high, with cough, fatigue, headache, dyspnea, and myalgia reported in all patients. Hoarse voice was present in 75.0% of the cohort. Regarding severity, 20 patients (16.7%) required hospitalization during their illness, and 12 (10.0%) had ICU admissions.

Table 4: Summary of Patient Characteristics, Symptoms, and CDSS Predictions (n = 120)

Domain	Result N (%)
Demographics	
Age, mean (SD), range	46.2 years $\pm$ 12.5
Gender	
Female	60 (50.0%)
Male	60 (50.0%)
BMI categories	
Optimum	66(55%)
Overweight	38(31.7%)
Obese	10(8.3%)
Underweight	6(5%)
Symptom Duration	
$\geq$ 28 days	40 (33.3%)
$\geq$ 8 weeks	40 (33.3%)
$\geq$ 12 weeks	40 (33.3%)
Symptom Prevalence	
Cough	120 (100.0%)
Fatigue	120 (100.0%)
Headache	120 (100.0%)
Dyspnea	120 (100.0%)
Hoarse voice	90 (75.0%)
Myalgia	120 (100.0%)
Hospitalization	
Ever hospitalized	20 (16.7%)
ICU admission	12 (10.0%)
Vaccination	
Fully vaccinated	98 (81.7%)
Partially vaccinated	10 (8.3%)
Unvaccinated	12 (10.0%)
RT-PCR	
Comorbidities	
Confirmed positive	120 (100.0%)
Hypertension	18 (15.0%)
Diabetes	16 (13.3%)
Heart disease	8 (6.7%)
Asthma	4 (3.3%)
Hypothyroidism	3 (2.5%)
None reported	71 (59.2%)
CDSS Predictions	
Low risk	64 (53.3%)
Mild risk	16 (13.3%)
Moderate risk	20 (16.7%)
High risk	20 (16.7%)

Vaccination coverage was high, with 98 patients (81.7%) fully vaccinated, 10 (8.3%) partially vaccinated, and 12 (10.0%) unvaccinated. All patients had laboratory-confirmed SARS-CoV-2 infection. Comorbidities were reported by 40.8% of participants. The most frequent were hypertension (15.0%) and diabetes (13.3%), followed by heart disease (6.7%), asthma (3.3%), and hypothyroidism (2.5%). Notably, 71 patients (59.2%) had no comorbidities.

The CDSS-generated risk stratification classified 64 patients (53.3%) as low risk, 16 (13.3%) as mild risk, 20 (16.7%) as moderate risk, and 20 (16.7%) as high risk. The detailed illustration is given in Table 4.

Evaluation of CDSS: The evaluation questionnaire was structured into three domains: technical accuracy (6 items), clinical integration (7 items), and user acceptance and confidence (7 items). Each item was rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Of the 148 eligible participants, 142 returned complete responses (response rate = 95.9%). Six questionnaires had missing data in one or more items (<5% missing overall), which were excluded from domain mean calculations. Domain-specific scores were calculated as mean $\pm$ standard deviation (SD).

Technical Accuracy: Participants reported a high level of confidence in the technical performance of iALERTS. The system was consistently perceived to classify risk categories correctly (mean = 4.4 $\pm$ 0.6) and to produce alerts that aligned closely with clinicians' independent judgment (mean = 4.3 $\pm$ 0.7). Trust in the accuracy of outputs was strongly endorsed (mean = 4.2 $\pm$ 0.6), with recognition that data entry fields captured the full range of patient information (mean = 4.2 $\pm$ 0.7). Timeliness and reliability of outputs were rated very highly (mean = 4.4 $\pm$ 0.6). Overall, the technical accuracy domain achieved one of the strongest aggregate scores, with a domain mean of 4.3 $\pm$ 0.6. Figure 1 illustrates the distribution of responses across all six technical accuracy items. Technical accuracy was positively correlated with user acceptance ($r = 0.46$, $p < 0.01$), indicating that trust in system outputs reinforced willingness to adopt the platform.

Clinical Integration: Feedback on clinical integration highlighted positive uptake alongside areas for refinement. The CDSS was regarded as supportive of efficient resource use (mean = 4.2 $\pm$ 0.7) and helpful in standardizing care (mean = 4.1 $\pm$ 0.7). Alerts were clear and actionable (mean = 4.1 $\pm$ 0.8), and the system enhanced longitudinal management of long COVID patients (mean = 4.0 $\pm$ 0.8). Integration with existing practices scored slightly lower (mean = 3.9 $\pm$ 0.8), and participants expressed only moderate agreement that the system did not prolong consultation times (mean = 3.8 $\pm$ 0.9). Despite these concerns, the overall perception of integration was positive, with a domain mean of 4.0 $\pm$ 0.8. Figure 2 presents the item-level response patterns for clinical integration.

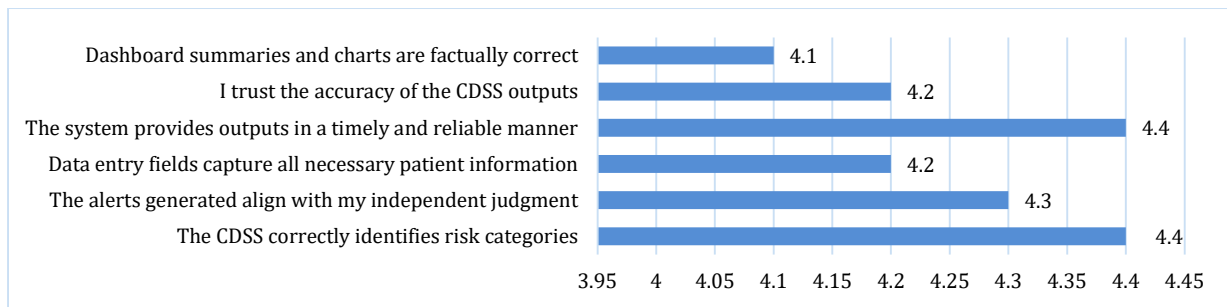


Figure 1: Section A. Technical Accuracy Evaluation

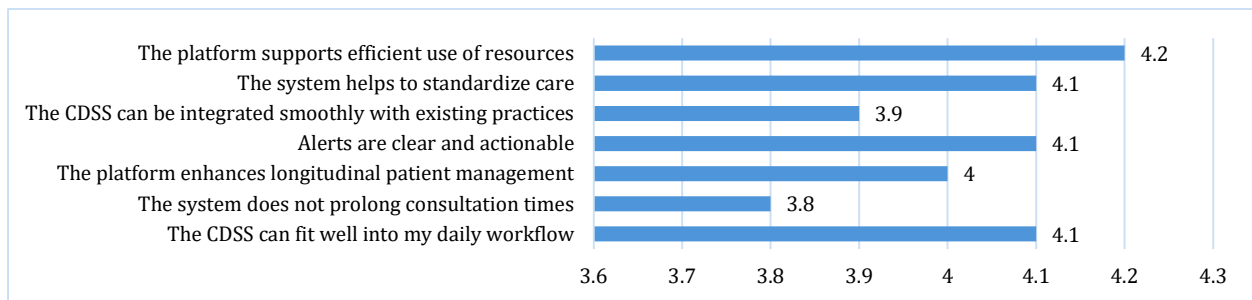


Figure 2: Section B. Clinical Integration Evaluation

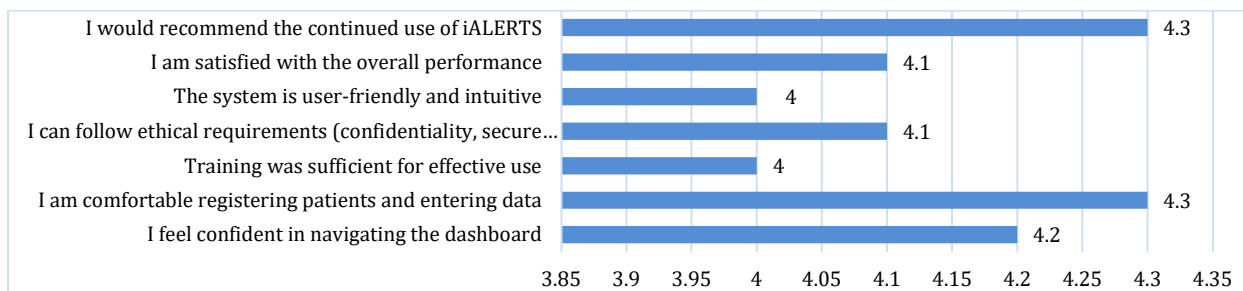


Figure 3: Section C. User Acceptance and Confidence Evaluation

Correlation analysis showed that clinical integration scores were strongly associated with both technical accuracy ($r = 0.52$, $p < 0.001$) and user acceptance ($r = 0.49$, $p < 0.001$), suggesting that ease of integration played a central role in shaping overall perceptions.

User Acceptance and Confidence: User acceptance scores confirmed strong endorsement of iALERTS across all professional groups. Providers felt confident navigating the dashboard (mean = 4.2 ± 0.7) and comfortable registering patients and entering data (mean = 4.3 ± 0.6). Training was considered adequate (mean = 4.0 ± 0.8), while ethical requirements such as data confidentiality and secure access were rated highly (mean = 4.1 ± 0.7). The system was judged user-friendly (mean = 4.0 ± 0.7), with overall satisfaction rated positively (mean = 4.1 ± 0.6). Importantly, willingness to recommend iALERTS for continued use scored among the highest items (mean = 4.3 ± 0.6). The overall domain mean was 4.2 ± 0.7 . Figure 3 depicts the distribution of responses for user acceptance and confidence. User acceptance correlated most strongly with clinical integration ($r = 0.55$, $p < 0.001$), reinforcing that staff endorsement was closely tied to how well the system fit into everyday routines.

Qualitative Results: Interviews highlighted that providers' first impressions of iALERTS were shaped by its usability. Some participants described the dashboard as intuitive after initial training, while others needed repeated exposure before feeling confident. A clinician explained, "At first the number of fields looked overwhelming, but once I understood the layout, it actually saved me time." Similarly, a nurse reflected, "It took me a day or two to get used to the icons, but after that I didn't need to keep asking for help." Observations during outpatient sessions confirmed that users navigated the dashboard more quickly after a few patient entries, suggesting that familiarity-built confidence.

Another strong theme was trust in the system's outputs. Clinicians repeatedly noted that the alerts and categorizations mirrored their own thinking, which encouraged them to rely on the tool. One nurse commented, "When it said moderate risk, I had already noted the same signs. That alignment gave me confidence." Another clinician remarked, "I didn't feel like I had to second-guess the system, it matched my judgment almost." This concordance was critical in fostering acceptance, with several providers describing iALERTS as "accurate" and "dependable."

However, participants also pointed out challenges in system use. Data officers and allied health staff were less confident in the beginning, especially when entering complex symptom histories. A data officer admitted, *"I felt slow compared to the doctors. I wasn't sure if I was doing it correctly until the trainer checked my entries."* Training sessions were widely acknowledged as helpful, with one participant adding, *"The workshop really made the difference. Before that, I was hesitant; after, I felt I could handle it."*

Technical readiness was another recurring theme. Internet connectivity and device availability influenced how smoothly the system could be used. In some clinics, limited access to dedicated terminals caused delays. As an IT staff member noted, *"Sometimes the internet lagged, and that made the page freeze. Once we switched to a stable connection, things worked fine."* Despite these barriers, most users agreed that the system itself was stable, with no major crashes or data loss reported during the pilot.

DISCUSSION

The pilot implementation of iALERTS provides an early view of how a decision support system can be embedded into routine outpatient care for long COVID. Our finding that fatigue was present in 100% of patients is consistent with international estimates of 70-80%, while breathlessness (100% in our sample) aligns with reports of 50-70% across global cohorts and cognitive complaints (39%) also fall within the 30-45% range documented.^{20,21} The alignment of our results with these wider patterns suggests that iALERTS has the sensitivity to reflect real-world clinical experience.

The ability of the platform to classify patients into distinct risk groups is particularly relevant. Previous research has demonstrated the heterogeneous trajectories of long COVID, with risk influenced by age, sex, comorbidities, vaccination status, and severity of the acute illness.²² By incorporating these predictors into a rule-based model, iALERTS provided stratification that matched closely with clinician judgment. This transparency and consistency are important because many digital tools struggle with trust when their underlying logic is unclear.^{23,24} In this pilot, the high concordance between system output and clinical evaluation supports confidence in its technical validity.

Unlike earlier digital tools that were designed mainly for acute COVID diagnosis or short-term hospital management, iALERTS was developed for longitudinal monitoring.^{25,26} The platform allowed repeated data entry, tracking of symptoms over time, and integration of comorbidities and vaccination history. This positions it closer to digital solutions for chronic disease management, where structured follow up and risk-based pathways are critical.²⁷ The ability to bring such an approach into the context of long

COVID fills a gap where routine care has often been fragmented and variable.

Adoption and usability were also encouraging. Prior work on clinical decision support has shown that systems are most effective when they fit naturally into workflow, provide patient-specific outputs, and are trusted by users.^{15,28-30} Our evaluation confirmed these principles. Mean domain scores reflected strong endorsement: technical accuracy (4.3 ± 0.6), clinical integration (4.0 ± 0.8), and user acceptance (4.2 ± 0.7). In particular, 95% of participants rated themselves highly confident (≥ 4) in maintaining confidentiality, and 88% expressed motivation to continue use. Engagement was not limited to physicians; nurses, allied health professionals, IT staff, and data officers all participated, which is critical for sustainability.

At the same time, it is important to recognize the contextual factors shaping these results. Studies of decision support consistently emphasize that performance depends on institutional readiness, local infrastructure, and user training.^{31,32} Our pilot was carried out in a supportive environment with structured onboarding and may not reflect conditions in less resourced settings. Reliance on patient self-reported outcomes introduces potential recall and reporting bias, particularly for symptoms such as fatigue and cognitive complaints. The single-center design and short duration also limit generalizability and prevent assessment of durability of adoption or long-term clinical outcomes. While accuracy and acceptance were strong, we did not measure long-term outcomes such as recovery, quality of life improvement, or healthcare utilization. These remain important areas for future work.

Thus, the findings indicate that iALERTS can be integrated into outpatient practice with technical reliability and high levels of user trust. The system captured the complexity of long COVID, provided meaningful stratification, and standardized elements of care that are often variable. While broader validation is needed, the pilot suggests that digital platforms such as iALERTS have genuine potential to enhance post-COVID care and could serve as a model for applying decision support to other complex post-viral conditions.

STRENGTHS

The pilot implementation of iALERTS was marked by clear evidence of reliability and acceptance. The system consistently produced predictions that were in complete agreement with independent clinical judgment, which demonstrates the robustness of its decision model and reassures users about its accuracy. Integration into all outpatient clinics gave the opportunity to test the platform in a wide range of workflows and with a diverse patient population, strengthening confidence that the tool can function in real practice rather than under controlled condi-

tions. Domain-level means: technical accuracy (4.3), clinical integration (4.0), and user acceptance (4.2) quantify this endorsement. The readiness assessment showed that providers across roles were able to use the system after a short training session, and this adaptability is essential for long term adoption. The use of PRISM and the Content Context Process model added rigor to the evaluation, ensuring that the study captured not only technical performance but also contextual relevance, user trust, and sustainability.

LIMITATIONS

The study was limited to one institution, which reduces the extent to which findings can be applied to other settings. The short pilot period did not allow examination of longer-term outcomes such as recovery trajectories, relapse, or sustained system use. Reliance on self-reported symptom data introduces the possibility of recall bias and subjective misclassification, particularly for fatigue, sleep quality, and cognitive impairment. The single-center, short-duration design also means findings may not generalize to settings with different patient profiles or infrastructure. Some users noted minor disruption in consultation time, pointing to the need for further refinement of the dashboard. In addition, reliance on patient reported outcomes introduces the possibility of recall bias and may affect the accuracy of risk classification.

FUTURE DIRECTIONS

Expansion into multiple centers will be important to confirm generalizability. Longer follow-up studies should assess measurable patient outcomes such as recovery trajectories, functional status, and quality of life using validated instruments like EQ-5D-5L or PROMIS scales. Health system outcomes, including healthcare utilization, referral rates, and adherence to follow-up protocols, should also be tracked. Technical refinements may improve integration with electronic health records, reducing duplication and streamlining workflows. The addition of adaptive learning functions has the potential to improve predictions as more data are collected.

CONCLUSION

The pilot implementation of iALERTS demonstrated that a clinical decision support system tailored for long COVID can be embedded into outpatient practice with high user acceptance. By integrating patient-reported and clinical data into an accessible dashboard, the system enabled reliable symptom tracking and risk stratification, giving providers actionable insights. While findings are promising, they remain preliminary given the single-center scope and short duration. Future multi-center trials with longer follow-up are needed to validate scalability, assess

patient outcomes using standardized measures, and determine the platform's broader health system impact.

iALERTS readiness assurance module:

<https://doi.org/10.6084/m9.figshare.30069550>

iALERTS PLATFORM: <https://lca.projects.fhhs.ac.in>

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This article was prepared without the use of generative AI tools for content creation, analysis, or data generation. All findings and interpretations are based solely on the authors' independent work and expertise.

REFERENCES

1. Koc HC, Xiao J, Liu W, Li Y, Chen G. Long COVID and its management. *Int J Biol Sci.* 2022;18(12):4768-4780. DOI: <https://doi.org/10.7150/ijbs.75056> PMID:35874958
2. Zeraatkar D, Ling M, Kirsh S, et al. Interventions for the management of long covid (post-covid condition): living systematic review. *BMJ.* 2024;387:e081318. DOI: <https://doi.org/10.1136/bmj-2024-081318> PMID:39603702
3. Chaudhry D, Khandelwal S, Bahadur C, et al. Prevalence of long COVID symptoms in Haryana, India: a cross-sectional follow-up study. *Lancet Reg Health Southeast Asia.* 2024;25:100395. DOI: <https://doi.org/10.1016/j.lansea.2024.100395>
4. J VK, Koshy JM, S D, et al. Prevalence and predictors of long COVID at 1 year in a cohort of hospitalized patients: A multi-centric qualitative and quantitative study. *PLoS One.* 2025;20(4):e0320643. DOI: <https://doi.org/10.1371/journal.pone.0320643> PMID:40215236 PMCID:PMC11990506
5. Surapaneni KM, Singhal M, Joshi A. Design, development and implementation of iALERTS (informatics analytics for long-term evaluation and repercussions tracking of SARS-CoV-2 infection): A research protocol. *J Clin Diagn Res.* 2025; 19(2): LK01-LK07. DOI: <https://doi.org/10.7860/JCDR/2025/72559.20601>
6. Surapaneni KM, Singhal M, Joshi A. Decision-making logic model for risk stratification using iALERTS (Informatics Analytics for Long-Term Evaluation and Repercussions Tracking Of SARS-Cov-2 Infection). *Natl J Community Med.* 2025; 16(9): 867-878. DOI: <https://doi.org/10.55489/njcm.160920255736>
7. Kilsdonk E, Peute LW, Jaspers MW. Factors influencing implementation success of guideline-based clinical decision support systems: a systematic review and gaps analysis. *Int J Med In-*

- form. 2017;98:56-64. DOI: <https://doi.org/10.1016/j.ijmedinf.2016.12.001> PMID:28034413
8. Abell B, Naicker S, Rodwell D, et al. Identifying barriers and facilitators to successful implementation of computerized clinical decision support systems in hospitals: a NASSS framework-informed scoping review. *Implement Sci.* 2023;18(1):32. DOI: <https://doi.org/10.1186/s13012-023-01287-y>
9. Wong, A., Otlles, E., Donnelly, J. P., Krumm, A., McCullough, J., DeTroyer-Coolley, O., Pestruie, J et al. External Validation of a Widely Implemented Proprietary Sepsis Prediction Model in Hospitalized Patients. *JAMA internal medicine.* 2021;181(8): 1065-1070. DOI: <https://doi.org/10.1001/jamainternmed.2021.2626> Erratum in: *JAMA Intern Med.* 2021 Aug 1; 181(8):1144. DOI: <https://doi.org/10.1001/jamainternmed.2021.3907>. PMID:34152373 PMCID:PMC8218233
10. Ostermayer DG, Braunheim B, Mehta AM, Ward J, Andrabi S, Sirajuddin AM. External validation of the Epic sepsis predictive model in 2 county emergency departments. *JAMIA Open.* 2024 Nov 13;7(4):ooae133. DOI: <https://doi.org/10.1093/jamiaopen/ooae133> PMID:39545248 PMCID:PMC11560849
11. Fathauer L, Meek J. Initial implementation and evaluation of a Hepatitis C treatment clinical decision support system (CDSS). *Appl Clin Inform.* 2012;3(3):337-348. DOI: <https://doi.org/10.4338/ACI-2012-04-RA-0012> PMID:23646082
12. Liberati EG, Ruggiero F, Galuppo L, et al. What hinders the uptake of computerized decision support systems in hospitals? A qualitative study and framework for implementation. *Implement Sci.* 2017;12(1):113. DOI: <https://doi.org/10.1186/s13012-017-0644-2> PMID:28915822 PMCID:PMC5602839
13. Trivedi MH, Daly EJ, Kern JK, et al. Barriers to implementation of a computerized decision support system for depression: an observational report on lessons learned in "real world" clinical settings. *BMC Med Inform Decis Mak.* 2009;9:6. DOI: <https://doi.org/10.1186/1472-6947-9-6> PMID:19159458
14. Damoiseaux-Volman BA, van der Velde N, Ruige SG, Romijn JA, Abu-Hanna A, Medlock S. Effect of interventions with a clinical decision support system for hospitalized older patients: systematic review mapping implementation and design factors. *JMIR Medical Informatics.* 2021;9(7):e28023. DOI: <https://doi.org/10.2196/28023> PMID:34269682 PMCID:PMC8325084
15. Castillo RS, Kelemen A. Considerations for a successful clinical decision support system. *Comput Inform Nurs.* 2013; 31(7):319-326. DOI: <https://doi.org/10.1097/NXN.0b013e3182997a9c> PMID:23774450
16. Osheroff JA, Teich J, Levick D, et al. Improving outcomes with clinical decision support: an implementer's guide. 2nd ed. Chicago: HIMSS Publishing; 2012.
17. Surapaneni KM. iALERTS readiness assurance module. figshare; 2025. DOI: <https://doi.org/10.6084/m9.figshare.30069550>
18. Trinkley KE, Kahn MG, Bennett TD, et al. Integrating the Practical Robust Implementation and Sustainability Model with best practices in clinical decision support design: implementation science approach. *J Med Internet Res.* 2020;22(10):e19676. DOI: <https://doi.org/10.2196/19676> PMID:33118943 PMCID:PMC7661234
19. Laka M, Carter D, Merlin T. Evaluating clinical decision support software (CDSS): challenges for robust evidence generation. *Int J Technol Assess Health Care.* 2024;40(1):e16. DOI: <https://doi.org/10.1017/S0266462324000059>
20. Crook H, Raza S, Nowell J, et al. Long covid-mechanisms, risk factors, and management. *BMJ.* 2021;374:n1648. DOI: <https://doi.org/10.1136/bmj.n1648> PMID:34312178
21. Davis HE, McCorkell L, Vogel JM, et al. Long COVID: major findings, mechanisms and recommendations. *Nat Rev Microbiol.* 2023;21(3):133-146. DOI: <https://doi.org/10.1038/s41579-022-00846-2> PMID:36639608 PMCID:PMC9839201
22. Fuller T, Mamani RF, Santos HF, et al. Sex, vaccination status, and comorbidities influence long COVID persistence. *J Infect Public Health.* 2024;17(11):102562. DOI: <https://doi.org/10.1016/j.jiph.2024.102562> PMID:39418956
23. Jones C, Thornton J, Wyatt JC. Enhancing trust in clinical decision support systems: a framework for developers. *BMJ Health Care Inform.* 2021;28(1):e100247. DOI: <https://doi.org/10.1136/bmjhci-2020-100247> PMID:34088721
24. Richardson JE, Middleton B, Platt JE, et al. Building and maintaining trust in clinical decision support: recommendations from the Patient-Centered CDS Learning Network. *Learn Health Syst.* 2020;4(2):e10208. DOI: <https://doi.org/10.1002/lrh2.10208> PMID:32313835 PMCID:PMC7156865
25. Subramanian M, Shanmuga Vadivel K, Hatamleh WA, et al. The role of contemporary digital tools and technologies in Covid-19 crisis: an exploratory analysis. *Expert Syst.* 2022; 39(6):e12834. DOI: <https://doi.org/10.1111/exsy.12834> PMID:34898797 PMCID:PMC8646626
26. Phillips J, Babcock RA, Orbinski J. The digital response to COVID-19: exploring the use of digital technology for information collection, dissemination and social control in a global pandemic. *J Bus Contin Emer Plan.* 2021;14(4):333-353. DOI: <https://doi.org/10.69554/QLQR5882> PMID:33962702
27. Larsen LB, Sondergaard J, Thomsen JL, et al. Step-wise approach to prevention of chronic diseases in the Danish primary care sector with the use of a personal digital health profile and targeted follow-up-an assessment of attendance. *BMC Public Health.* 2019;19(1):1092. DOI: <https://doi.org/10.1186/s12889-019-7419-4> PMID:31409343
28. Castaneda C, Nalley K, Mannion C, et al. Clinical decision support systems for improving diagnostic accuracy and achieving precision medicine. *J Clin Bioinforma.* 2015;5:4. DOI: <https://doi.org/10.1186/s13336-015-0019-3> PMID:25834725 PMCID:PMC4381462
29. Sim LL, Ban KH, Tan TW, et al. Development of a clinical decision support system for diabetes care: a pilot study. *PLoS One.* 2017;12(2):e0173021. DOI: <https://doi.org/10.1371/journal.pone.0173021> PMID:28235017 PMCID:PMC5325565
30. Fitriyani NL, Syafrudin M, Alfian G, et al. HDPM: an effective heart disease prediction model for a clinical decision support system. *IEEE Access.* 2020;8:133034-133050. DOI: <https://doi.org/10.1109/ACCESS.2020.3010511>
31. Newton N, Bamgboje-Ayodele A, Forsyth R, et al. Opportunities and challenges associated with the pilot implementation of clinical decision support systems in a rural hospital: a qualitative study. *Appl Clin Inform.* 2025;16(4):777-788. DOI: <https://doi.org/10.1055/a-2581-6236> PMID:40216403
32. Misro A, Mehta A, Whittington P, et al. From concept to reality: examining India's clinical decision support system (CDSS) challenges & opportunities. *medRxiv* 2023.04.02.23288046 [preprint]. DOI: <https://doi.org/10.1101/2023.04.02.23288046>