ORIGINAL RESEARCH ARTICLE

Decision-Making Logic Model for Risk Stratification Using iALERTS (Informatics Analytics for Long-Term Evaluation and Repercussions Tracking of SARS-Cov-2 Infection)

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ABSTRACT

Background: Long COVID presents a significant public health challenge with its wide-ranging and persistent symptoms. However, there remains a lack of structured tools to identify, stratify, and manage individuals at risk of Long COVID. This study aims to develop the decision-making logic model for risk stratification using iALERTS platform.

Methods: This is a mixed-methods, quasi-experimental study. Data were collected from 684 adults with confirmed COVID-19 who were at least 12 weeks post-recovery. A validated survey captured sociodemographic data, clinical history, anthropometry, vaccination status, and a comprehensive symptom profile. A rule-based decision-making logic model was embedded within iALERTS, incorporating ten key factors to generate individualized risk assessments.

Results: Fatigue (80.8%), cough (83.3%), cognitive dysfunction (68.3%) and myalgia (74.3 %) were the most common persistent symptoms. High-risk groups included females, older adults, individuals with obesity, unvaccinated participants, and those hospitalized or admitted to ICU during acute infection. The logic model enabled automated risk stratification into low, moderate, or high categories, guiding clinical recommendations for monitoring, referrals, and rehabilitation.

Conclusion: The iALERTS platform offers a novel informatics-driven solution for risk stratification and management of Long COVID. Its decision logic integrates validated clinical and demographic predictors with real-time symptom data.

Keywords: Long COVID, Post-Acute Sequelae of SARS-CoV-2, Clinical Decision Support System, Risk Stratification, Digital Health, Symptom Monitoring, Post-COVID Management

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INTRODUCTION

The global COVID-19 pandemic has not only caused acute illness on an unprecedented scale but has also led to the emergence of Long COVID, a complex, multisystem condition with an unpredictable clinical course.[1,2] Formally referred to as Post-Acute Sequelae of SARS-CoV-2 Infection (PASC), Long COVID affects millions worldwide and manifests through persistent symptoms such as fatigue, breathlessness, cognitive dysfunction, chest pain, and psychological disturbances that may last for weeks or months after the initial infection.[3,4]

As health systems adapt to manage these long-term consequences, digital health technologies are increasingly recognized for their potential to enhance patient care. Among these, Clinical Decision Support Systems (CDSS) have proven effective in improving diagnostic accuracy, reducing variability in care, and optimizing clinical workflows by integrating patient data with current evidence-based guidelines.[5-7]

The application of CDSS to Long COVID holds substantial promise. Clinicians require tools that enable real-time symptom integration, longitudinal symptom tracking, and risk stratification to personalize care for this heterogeneous condition.[8] Additionally, CDSS can facilitate public health surveillance by monitoring trends, outcomes, and healthcare resource utilization related to post-COVID conditions.

However, current CDSS frameworks are not equipped to address these needs. Most are focused on acute COVID-19 management or generalized chronic disease support, lacking the capacity for longitudinal tracking, real-time symptom integration, or condition-specific logic models necessary for managing Long COVID.[9,10] This gap underscores the need for a specialized informatics solution that reflects the complexity and evolving nature of Long COVID.

In response, we developed **iALERTS** (Informatics Analytics for Long-term Evaluation and Repercussions Tracking of SARS-CoV-2 Infection), a novel clinical decision support platform. iALERTS addresses key gaps in existing CDSS by integrating patient-reported outcomes, structured clinical data, and predictive analytics to support early identification, individualized risk stratification, and longitudinal care management of Long COVID. This paper presents the conceptual framework, design methodology, and logic model underpinning iALERTS, offering a new approach to decision support in post-COVID care.

METHODOLOGY

Study Design: This mixed-methods, quasi-experimental study combined retrospective analysis and prospective data collection to design, develop, and evaluate an informatics-driven Clinical Decision Support System (CDSS) for Long COVID, named iALERTS. The study aimed to develop a predictive tool to facilitate early identification, risk stratification, and longitudinal tracking of patients with post-acute sequelae of SARS-CoV-2 infection.

The study was conducted in four phases:

Phase 1 (June–December 2023; 7 months): Development and validation of a predictive survey instrument.
Phase 2 (January –December 2024; 12 months): Design and development of the iALERTS software.
Phase 3 (January -August 2025, 8 months): Pilot implementation of the platform in a clinical setting.
Phase 4 (September-December 2025, 4 months): Evaluation of functionality, usability, and clinical relevance.

Phase 1: Development and Validation of the Predictive Survey Instrument

Study Setting: The study was carried out at Panimalar Medical College Hospital and Research Institute (PMCHRI), a tertiary care hospital in Chennai, India, which served as a designated COVID-19 treatment center during the pandemic. The hospital's diverse patient population, extensive electronic health record system, and ongoing post-COVID outpatient follow-ups provided a robust environment for both retrospective analysis and prospective recruitment.

Study Population & Sampling: Participants included adults aged 18 years or older with laboratory-confirmed SARS-CoV-2 infection (RT-PCR) who had clinically recovered. A total of 684 participants were recruited through convenience sampling, based on their availability and willingness to participate during post-COVID follow-up visits. Patients were eligible regardless of whether their acute infection was managed on an inpatient or outpatient basis.

Eligibility criteria

Patients aged 18 years or above, having confirmed SARS-CoV-2 infection documented in medical records, minimum of 12 weeks post-recovery from acute infection and ability and willingness to provide informed consent were included in the study.

Case without laboratory-confirmation of COVID-19 infection, unreachable after three contact attempts, having cognitive impairment or severe mental illness interfering with participation or not giving or withdrawing consent at any point during the study was excluded from the study.

Instrument Development: A comprehensive survey instrument was developed based on guidelines from the World Health Organization, the Indian Council of Medical Research, and the National Institute for Health and Care Excellence. Literature on Long COVID and expert clinical input shaped the tool, which consisted of six domains:

1. **Sociodemographic Information:** Age, gender, education, occupation, household income, and living environment.

2. **Anthropometric and Lifestyle Factors:** Self-reported weight, height, waist-hip ratio, smoking status, alcohol consumption, and dietary habits.
3. **Clinical Profile of Acute COVID-19:** Date of diagnosis, hospitalization history, ICU admission, oxygen therapy, and vaccination status.
4. **Post-COVID Symptom Inventory:** A checklist of over sixty symptoms categorized into respiratory, neurological, gastrointestinal, psychological, and systemic groups. Duration and severity of each symptom were recorded.
5. **Quality of Life Assessment:** EuroQol EQ-5D-5L scale with visual analogue scoring.[11]
6. **Functional Status:** Post-COVID Functional Status (PCFS) scale evaluating residual functional limitations[12]

Validation Process: The tool underwent pilot testing for clarity and relevance, followed by psychometric validation. Internal consistency was high, with a Cronbach's alpha of 0.89. Expert review ensured content validity, and iterative modifications were made based on pilot feedback.

Data Collection: Data were collected in three formats: 1) **In-person interviews** at outpatient clinics, 2) **Telephone-based surveys** for remote participants, and 3) **Secure web-based forms** for self-administration in English or Tamil

A role-based online data portal was developed with three access levels: 1) **Super Admin:** Full access to data and system management, 2) **Admin:** Operational oversight without access to raw patient data, and 3) **Operator:** Data entry access only for conducting surveys

Data security measures included encrypted storage, anonymization, and audit trails for all user activities. Missing data were handled using listwise deletion for incomplete records during statistical analysis, ensuring that only complete cases were included in hypothesis testing and model development.

Phase 2: Design and Development of iALERTS Software

System Architecture:
iALERTS (https://lca.projects.fhts.ac.in) was developed using a modular architecture composed of the following components:

- **Knowledge Base:** Encapsulates clinical guidelines, risk thresholds, symptom definitions, and management pathways for Long COVID, updated from global and national health agencies and peer-reviewed literature.
- **Inference Engine:** Applies rule-based logic to patient data, generating risk stratification, diagnostic alerts, and care recommendations based on symptom patterns and clinical history. The inference engiis a decision-making component that applies predefined clinical rules to patient data in order to generate individualized risk scores and care recommendations.
- **Data Input Layer:** Seamlessly integrates inputs from electronic health records, survey data, and patient-reported outcomes.
- **Communication Interface:** Presents actionable insights via color-coded dashboards, risk scores, alerts, and tailored recommendations to clinicians.
- **Continuous Monitoring and Feedback Loop:** Tracks patient data over time, dynamically updating risk assessments and recommendations based on changes in clinical status.

Technological Framework

- **Backend:** PHP 8.2, MariaDB 10.3, SMAART Framework, hosted on AlmaLinux with Apache web server.
- **Frontend:** HTML5, CSS3, JavaScript, jQuery, Aione Framework, and Google Charts for dynamic visualization.
- **Security:** HTTPS with SSL encryption, role-based authentication via WordPress, SQL injection protection, regular backups, and server-side encryption.

The iALERTS platform was custom-built specifically for this project to address the unique clinical and informatics needs of Long COVID risk stratification. It was not adapted from any existing CDSS or public health platform.

Performance and Data Integrity: Performance optimization included caching, compression of assets, and use of a Content Delivery Network for faster load times. Data validation routines were integrated at both frontend and backend levels to prevent incomplete or erroneous submissions.

Data Analysis: Data were analyzed using IBM SPSS version 26. Descriptive statistics summarized demographic profiles, symptom prevalence, and functional scores. Chi-square tests were used to assess associations between categorical variables such as vaccination status and Long COVID symptoms. Independent t-tests and ANOVA evaluated differences in quality-of-life scores and functional outcomes. A p-value below 0.05 was considered statistically significant.

System Requirements

Server: Processor: 2-core minimum (4-core recommended), RAM: 4 GB or higher, Storage: 10 GB SSD minimum, OS: AlmaLinux 8 or CentOS 7, Web Server: Apache 2.4+ with PHP 8.0+, Database: MariaDB 10.3+, and SSL enabled for secure communication

Client: Compatible with Chrome, Firefox, Edge, and Safari, JavaScript enabled, and Stable internet connection

External Validation: Recognizing the limitations of a single-center design, efforts are underway to validate the iALERTS decision logic in an independent cohort drawn from multiple clinical sites. This next step is essential to assess the generalizability and predictive consistency of the model across diverse healthcare settings and population groups. The external validation will allow for recalibration of thresholds if needed and provide a more robust foundation for widespread clinical adoption.

Ethical Approval:
Approval was secured from the Institutional Human Ethics Committees of both PMCHRI (PMCH&RI/IHEC/2021/60 dated: 13/08/ 2021) and DIT University (DITU/UREC/ 2022/04/10 dated: 12/05/2022). Given the hybrid approach to data collection, ethical procedures were adapted to fit both in-person and remote formats. For telephone-based participation, informed consent was obtained verbally and documented following ethics committee guidance. In the web-based surveys, consent was integrated electronically, requiring participants to acknowledge their understanding before proceeding in alignment with the principles of the Declaration of Helsinki.

RESULTS

Sociodemographic Profile: The majority of participants were aged between 25 and 54 years (53.3%), followed by 21.8 % in the 55 to 64 years group and 16.2 % aged 65 years or above. Males comprised 62.7 % of the cohort. Most participants were married (94 %) and predominantly Hindu (69.2%).

Educational attainment was diverse, with 44.7 % holding professional qualifications. Residence was evenly split between urban (46.5 %) and rural (46.5 %) settings, with a small subset from slum areas (2.8 %). Occupations ranged widely, with elementary workers (27.6%) being the largest group. (Table 1)

Anthropometric and Lifestyle Profile: The mean BMI was 25.36 (SD = 4.62), with 56.7 percent of participants in the normal range, 31.2 percent overweight, and 8.8 percent obese class I (Table 2) with lifestyle habits as shown in Table 3.

Functional Status and Quality of Life: A significant portion reported functional limitations. About 52.4 %could not perform certain daily activities, while 74.6 % were able to live independently. Pain, fatigue, anxiety, and depression were major factors affecting quality of life. (Table 4)

COVID-19 Clinical Profile: Most infections occurred during the second wave (January–June 2021). RT-PCR confirmation was reported by 96.6 % Hospitalization was required in 14.9 % of cases, and ICU admission in 2.8 percent. A high vaccination rate was observed with 77.6 % having received two doses. (Table 5)

Table 1: Sociodemographic Characteristics

Variable	Cases (n=684) (%)
Age (years)	
18–24	38 (5.6)
25–54	365 (53.3)
55–64	149 (21.8)
65+	111 (16.2)
Sex	
Male	429 (62.7)
Female	233 (34.1)
Marital Status	
Married	643 (94.0)
Others	41 (6.0)
Religion	
Hindu	473 (69.2)
Muslim	163 (23.8)
Others	48 (7.0)
Education	
Professional	306 (44.7)
High school	154 (22.5)
Middle	122 (17.8)
Primary	91 (13.3)
Residence	
Urban	318 (46.5)
Rural	318 (46.5)
Slum	19 (2.8)
Occupation	
Elementary	189 (27.6)
Technician	121 (17.7)
Clerical	89 (13.0)
Professional	59 (8.6)
Others	Others (33.1)

Table 2: BMI Distribution

BMI Category	Cases (%)
Underweight	20 (3.1)
Normal	369 (56.7)
Overweight	203 (31.2)
Obese Class I	57 (8.8)

Table 3: Lifestyle Habits

Variable	Cases (%)
Smoking	
Never	553 (80.8)
Past	71 (10.4)
Current	42 (6.1)
Alcohol	
Never	545 (79.6)
Past	80 (11.7)
Current	39 (5.7)
Diet	
Non-vegetarian	616 (90.1)
Vegetarian	33 (4.8)

Table 4: Functional Limitations (N = 684)

Functional Domain	Yes (%)	No (%)
Able to live alone without assistance	511(74.6)	157(22.9)
Inability to perform certain tasks	359(52.4)	313(45.7)
Persistent symptoms (pain, fatigue, mood)	448(65.4)	223(32.6)
Need to avoid/spread tasks over time	402(58.7)	272(39.7)

Table 5: COVID-19 Clinical History (N = 684)

Variable	Categories	Cases (%)
Infection Period	Jan–Jun 2021 / Jul–Dec 2020	412 (60.2) / 234 (34.2)
RT-PCR Positive	Yes	661 (96.6)
Hospitalized	Yes	102 (14.9)
ICU Admission	Yes	19 (2.8)
Vaccination (Two doses)	Yes	531 (77.6)

Post-COVID Symptom Profile

Cardio-pulmonary Symptoms: Cardiorespiratory symptoms were widespread among participants, with fatigue emerging as the most dominant complaint. Dyspnoea, both at rest and on exertion, along with chest-related symptoms such as pain, tightness, and palpitations, were reported frequently, indicating lingering cardiopulmonary dysfunction following SARS-CoV-2 infection.

Naso-oropharyngeal and Gastrointestinal Symptoms: A substantial burden of upper respiratory, auditory, and gastrointestinal symptoms persisted well beyond the acute infection. Cough, altered taste, and loss of smell were among the most frequently reported. Gastrointestinal issues such as diarrhoea, nausea, and abdominal discomfort were also notable.

Musculoskeletal Symptoms: Pain in muscles and joints was highly prevalent, reflecting a significant impact on physical mobility and quality of life in the post-COVID period.

Neuropsychological Symptoms: Neurological and psychological complaints formed a major component of the symptom burden. Brain fog, memory loss, sleep disturbances, and mood changes were frequently reported, with a concerning proportion experiencing anxiety, depression, and even thoughts of self-harm.

Systemic and Miscellaneous Symptoms: Generalized weakness, pain, headaches, and dermatological issues were common. Additionally, less frequently discussed symptoms like bladder dysfunction and hot flushes were present in a notable fraction. The symptoms response rate and statistical analysis are shown in Table 5 & 6.

Of the 684 participants, BMI data were available for 672 individuals (98.2%), vaccination status for 676 (98.8%), and hospitalization history for 682 (99%). Post-COVID symptom inventory responses were complete for 662 participants (96.7%). Quality of life data using EQ-5D-5L were available for 659 participants (96.3 %), and PCFS scores were recorded for 660 participants (96.4%). Missing data entries were excluded using listwise deletion during statistical analysis.

Decision-Making Logic Model for Long COVID Risk Stratification: In developing the iALERTS platform, a structured risk stratification logic model was incorporated to predict the likelihood of Long COVID based on validated demographic, clinical, and symptomatic factors (Figure 1, 2 & 3).

Table 5: Symptomatology of cases included in the study

Symptom	Present (%)	Absent (%)
Cardio-pulmonary Symptoms		
Fatigue	553(80.8)	123(18.0)
Shortness of breath (dyspnoea)	456(66.7)	207(30.3)
Shortness of breath at rest	292(42.7)	379(55.4)
Shortness of breath with exertion	469(68.6)	204(29.8)
Chest pain	351(51.3)	325(47.5)
Palpitations	372(54.4)	307(44.9)
Chest tightness	382(55.8)	296(43.3)
Wheezing	304(44.4)	375(54.8)
Naso-oropharyngeal and GI Symptoms		
Loss of smell (anosmia)	408(59.6)	265(38.7)
Altered taste (dysgeusia)	480(70.2)	194(28.4)
Sore throat	455(66.5)	217(31.7)
Cough	570(83.3)	104(15.2)
Tinnitus	362(52.9)	305(44.6)
Sputum production	476(69.6)	200(29.2)
Hoarse voice / voice change	302(44.1)	377(55.1)
Aphonia	267(39.0)	408(59.6)
Rhinitis / rhinorrhoea	387(56.6)	295(43.1)
Sneezing	335(49.0)	349(51.0)
Chronic sinusitis	234(34.2)	449(65.6)
Ear pain	282(41.2)	400(58.5)
Hearing loss	298(43.6)	379(55.4)
Diarrhoea	326(47.7)	356(52.0)
Nausea	318(46.5)	365(53.3)
Loss of appetite	428(62.6)	246(35.9)
Abdominal pain	332(48.5)	350(51.2)
Weight loss / anorexia	347(50.7)	335(49.0)
Vomiting	270(39.5)	408(59.6)
Gastritis	299(43.7)	373(54.5)
Musculoskeletal Symptoms		
Joint pain (arthralgia)	481(70.3)	200(29.2)
Muscle pain (myalgia)	508(74.3)	173(25.3)
Neuropsychological Symptoms		
Memory loss (amnesia)	432(63.2)	249(36.4)
Difficulty thinking / brain fog / cognitive impairment	467(68.3)	216(31.6)
Sleep disorders such as insomnia	408(59.6)	273(39.9)
Visual disturbances	278(40.6)	404(59.1)
Anxiety and depression	382(55.8)	296(43.3)
Depression	367(53.6)	311(45.5)
Mood change	383(56.0)	300(43.9)
Thoughts of self-harm or suicide	123(18.0)	557(81.4)
Neuralgia / neuropathy / tingling / paresthesia	377(55.1)	303(44.3)
Tremors	205(30.0)	474(69.3)
Seizures	104(15.2)	575(84.0)
Miscellaneous Symptoms		
Fever or chills	419(61.2)	263(38.5)
Headache	438(64.0)	246(35.9)
Dizziness or vertigo	377(55.1)	303(44.3)
Skin rash/itching/cutaneous signs	248(36.3)	436(63.7)
Significant hair loss	388(56.7)	292(42.7)
Red eyes or eye irritation	278(40.6)	404(59.1)
Asthenia / general weakness	490(71.6)	190(27.8)
Unspecified pain or body ache	515(75.3)	169(24.7)
Bladder incontinence	146(21.3)	534(78.1)
Hot flushes	210(30.7)	472(69.0)
Sweats	292(42.7)	388(56.7)
Sicca syndrome (dry eyes / dry mouth)	267(39.0)	413(60.4)
Ulcers	198(28.9)	478(69.9)

Table 6: Statistical Significance Summary by Symptom Category

Symptom Category	Gender p-value	Age Group p-value	BMI Category p-value
Cardiopulmonary	0.004	0.026	0.001
Naso-oropharyngeal and GI	0.034	0.048	0.018
Musculoskeletal	0.012	0.039	0.006
Neuropsychological	0.003	0.007	0.020
Miscellaneous	0.001	0.015	0.004

This model was grounded in evidence from international predictive models and cohort analyses, including those published in *eBioMedicine* and *PubMed*, and further refined through expert consultations to ensure contextual relevance to the Indian population.

The decision-making logic model was developed through a thoughtful and layered process that combined evidence, clinical experience, and patient data. The team began with a detailed review of published literature to identify variables that are consistently associated with Long COVID, drawing on guidelines, cohort studies, and systematic reviews. This was followed by statistical analysis of data from 684 participants to identify factors that were significantly linked to ongoing symptoms and reduced functional status. Ten variables were selected based on both statistical strength and clinical relevance. These included age, gender, body mass index, hospitalization or intensive care admission, symptom burden during the first week of infection, duration of symptom persistence, current symptom profile, vaccination status, and the presence of comorbidities. A panel of medical and public health experts reviewed the findings to ensure they were applicable in the local clinical context. Weights were assigned using a combination of methods, regression results were used for variables with strong statistical support, while expert opinion guided the weighting of variables like symptom frequency and vaccination status This decision logic powered the inference engine of iALERTS, enabling automatic classification of patients into Low, Moderate, or High-risk tiers for developing or sustaining Long COVID.

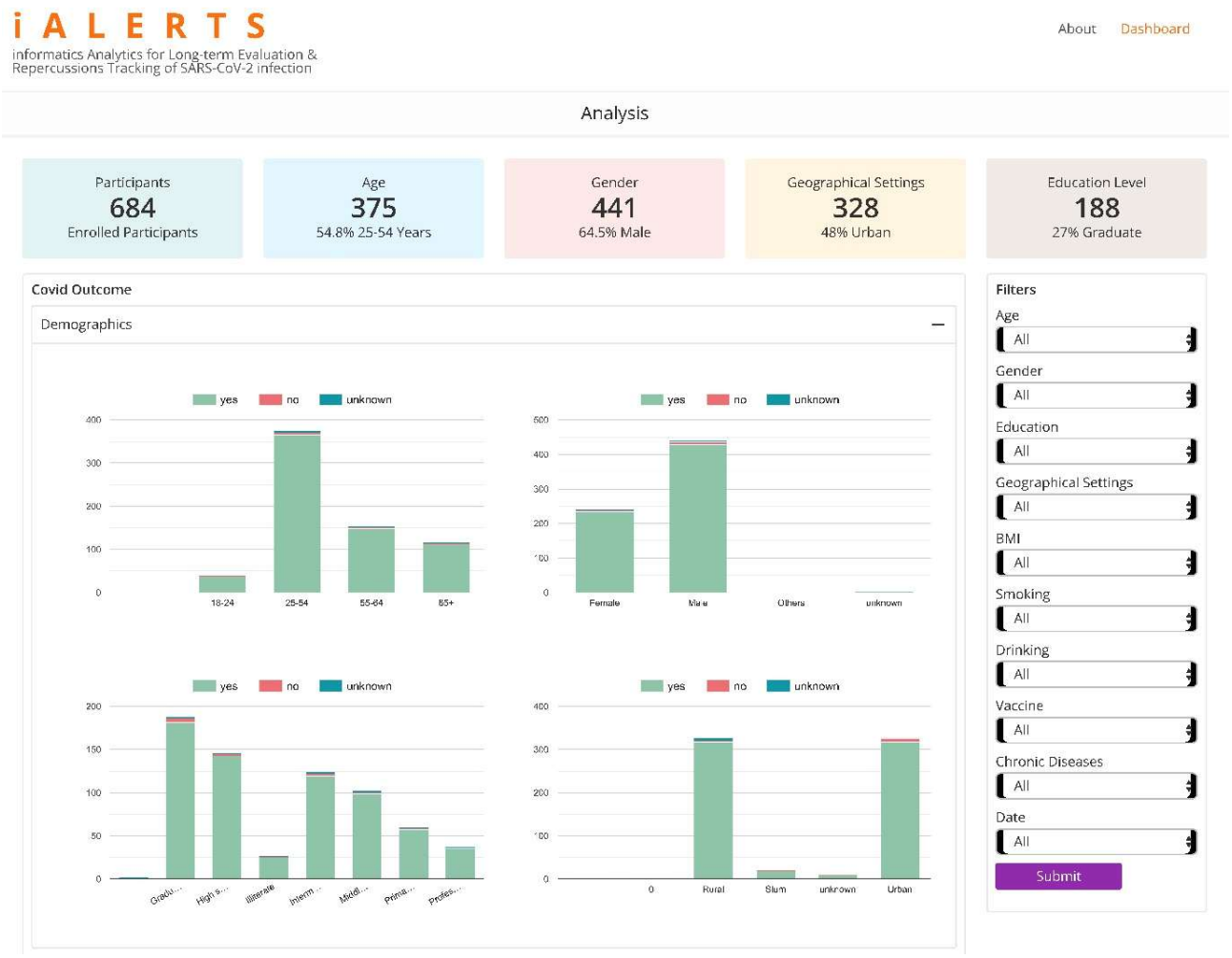

Figure 1: **Decision-Making Logic Model for Long COVID Risk Stratification – 1**

Figure 2: **Decision-Making Logic Model for Long COVID Risk Stratification - 2**

Figure 3: **Decision-Making Logic Model for Long COVID Risk Stratification - 3**

Demographic Factors: Age was a primary determinant, with risk increasing progressively from Low in individuals aged 18 to 49 years, to Moderate in those aged 50 to 69 years, and High in individuals over 70 years. Gender played a significant role, with female participants classified as High risk, reflecting consistent findings of greater symptom persistence in females.

Anthropometric Risk: Body Mass Index (BMI) was directly proportional to risk. Individuals with Class II obesity (BMI 35 to 39.9) were classified as High risk, while Class I obesity (BMI 30 to 34.9) corresponded to Moderate risk, and overweight (BMI 25 to 29.9) reflected Mild risk. Participants with normal BMI (18.5 to 24.9) were designated Least risk, and those underweight (<18.5) were classified as None, consistent with a negligible contribution to Long COVID risk from low BMI.

Acute Illness Severity Indicators: A history of significant symptom burden during the first week of COVID-19 infection was a strong predictor, assigning a high-risk classification. Similarly, individuals with hospital admissions or ICU admissions during their acute COVID-19 illness were also categorized as High risk, reflecting the impact of disease severity on long-term sequelae.

Symptom Duration: Risk was stratified based on symptom persistence thresholds. Participants with symptoms lasting 28 days were assigned Low risk, those persisting for 8 weeks were considered Mild risk, and those persisting for 12 weeks or more were classified as High risk, consistent with established definitions of Long COVID.

Symptom Burden at Assessment: The model integrated real-time symptom reporting, with higher risk attributed to the presence and frequency of key symptoms:

High risk: Cough, fatigue, intermittent headaches,
Mild risk: Dyspnoea, and
Low risk: Hoarse voice, myalgia.

Frequency ranging from "Not at all" to "All the time" further adjusted risk within each symptom category.

Vaccination Status: Vaccination was incorporated as a protective factor. Individuals who were unvaccinated were assigned High risk, those partially vaccinated were classified as Mild, while fully vaccinated participants were classified as Low risk, consistent with global literature demonstrating mitigation of Long COVID risk through vaccination.The figure 1 presents the analytical dashboard of the iALERTS platform, highlighting demographic breakdown and COVID-19 outcome data for 684 participants. The upper summary tiles display key aggregated metrics including total enrolled participants, predominant age group (25–54 years), gender distribution (64.5% male), urban-rural residence (48% urban), and education level (27% graduates). Below, bar charts visualize COVID-19 outcome status (yes/no/unknown) across demographic categories age, gender, occupation, and geographical settings. The interactive filters on the right allow real-time stratification by age, gender, education, BMI, smoking and alcohol status, vaccination, comorbidities, and time. These functionalities support granular subgroup analysis for clinicians and researchers, enabling identification of vulnerable populations and informing risk-based follow-up planning in Long COVID care.

The figure 2 displays hospital outcome distributions among participants across four key clinical domains. The upper left chart illustrates the proportion of individuals with persistent post-COVID symptoms based on hospitalization status, showing markedly higher prevalence among hospitalized participants. The upper right chart depicts ICU admission, with individuals not requiring ICU care reporting a higher burden of lingering symptoms. The lower left graph categorizes symptom persistence by vaccination status, indicating that participants who were unvaccinated had a greater frequency of Long COVID-related symptoms compared to those with one or two doses. The lower right chart maps symptom outcomes against infection timeline across different waves of the pandemic, emphasizing differences in post-acute sequelae based on timing of infection. These charts enable clinicians and researchers to correlate hospitalization variables with Long COVID outcomes and validate risk components used in the iALERTS decision logic.

The figure 3 illustrates the distribution of persistent post-COVID symptoms in relation to key health behavior indicators. The top left chart stratifies responses by body mass index (BMI) category, showing symptom prevalence across normal weight, overweight, and obese groups, highlighting BMI as a graded risk factor in the iALERTS model. The top right and bottom left graphs show associations between past and current smoking and alcohol consumption respectively, with the majority of persistent symptom cases clustering among non-smokers and non-drinkers, reflecting the demographic composition of the cohort. The bottom right chart represents chronic disease status, comparing symptom persistence among participants with self-reported comorbidities versus those without. These visualizations reinforce the behavioral and clinical dimensions integrated into iALERTS for individualized risk prediction and longitudinal monitoring of Long COVID.

Pre-existing Comorbidities: Participants with any of the following chronic conditions were assigned High risk: asthma, diabetes, hypertension, cardiovascular disease, or chronic kidney disease. Those without such conditions were considered Low risk for this factor.

Confirmed COVID-19 Diagnosis: Only participants with laboratory confirmation via RT-PCR, antigen testing, or a clinically documented diagnosis of COVID-19 were evaluated through this decision model.

Example of Risk Stratification Using iALERTS

To illustrate the application of the iALERTS decision-making logic model, consider the following patient scenario:

A 58-year-old female presents for follow-up 14 weeks after recovery from laboratory-confirmed SARS-CoV-2 infection. Her clinical profile includes:	Based on the **iALERTS logic model**:
• **Age:** 58 years • **Gender:** Female • **BMI:** 32.4 kg/m^2 (Class I obesity) • **Hospitalization:** Required admission for oxygen therapy during acute illness • **ICU Admission:** Not required • **Symptom Burden During First Week:** High (fatigue, cough, fever, dyspnea) • **Current Symptoms:** Persistent fatigue, brain fog, and myalgia • **Symptom Duration:** >12 weeks • **Vaccination Status:** Not vaccinated • **Comorbidities:** Type 2 diabetes and hypertension • **Occupation:** Elementary worker in a high-exposure environment • **Residence:** Urban slum area	• **Age** (50–69 years): Moderate risk • **Gender** (female): High risk • **BMI** (32.4): Moderate risk • **Hospitalization + high early symptom burden:** High risk • **Symptom duration >12 weeks with disabling symptoms:** High risk • **Unvaccinated status:** High risk • **Multiple comorbidities:** High risk • **Socioeconomic and occupational vulnerability:** High contextual risk
Final Stratification: High Risk Clinical Implication: Immediate referral for multidisciplinary rehabilitation, cognitive evaluation, and structured follow-up through post-COVID care pathways.	

DISCUSSION

The findings of this study provide important insights into the evolving clinical profile and risk stratification of Long COVID within an Indian tertiary care context. The prevalence of persistent symptoms observed in this cohort was remarkably high, with fatigue, dyspnea, cognitive impairment, musculoskeletal pain, and mood disturbances emerging as the most commonly reported issues. These results are consistent with patterns documented globally. The longitudinal cohort study conducted reported that more than half of individuals continued to experience fatigue and sleep-related disturbances even one year after discharge.[13] Similarly, data from another study identified fatigue and brain fog as among the most persistent and disabling features of Long COVID, findings that mirror those seen in this population.[14]

Cognitive dysfunction, memory loss, and psychological distress were particularly prominent in this cohort. These neuropsychological sequelae align with the findings of the international patient-led study which described cognitive impairment as one of the most disabling features of Long COVID, often affecting individuals' ability to function in professional and personal domains.[15] Functional impairment was widespread, with a substantial proportion of participants reporting difficulty performing routine tasks and a sustained inability to return to their pre-COVID levels of productivity. These observations are in keeping with the UK Office for National Statistics reports, which similarly highlight that a significant proportion of individuals with Long COVID remain functionally limited for many months after acute infection.[16]

Gender-based disparities were particularly notable. Female participants exhibited a higher burden of persistent symptoms, a finding that has been consistently reported in the ZOE study and by the UK Office for National Statistics.[17] Existing evidence suggests that this gender-based vulnerability may be multifactorial, encompassing biological factors such as sex-based immune differences, hormonal influences, and possibly psychosocial stressors or caregiving responsibilities that intersect with health outcomes.[18] In parallel, the relationship between elevated BMI and the likelihood of persistent post-COVID symptoms observed in this study is well-supported by previous research. The large-scale cohort analysis and meta-analyses have similarly demonstrated that obesity is associated with a heightened risk of developing long-term sequelae, likely mediated by chronic systemic inflammation and metabolic dysfunction.[19,20]

Vaccination status emerged as a powerful protective factor against the development of Long COVID, reinforcing findings from other studies which showed that fully vaccinated individuals have a significantly reduced risk of developing persistent symptoms.[21] This observation strengthens the growing consensus that vaccination not only mitigates the severity of acute infection but also reduces the likelihood of prolonged post-viral complications.

The decision-making logic model embedded within the iALERTS platform represents a novel and clinically meaningful contribution to the management of

Long COVID. Each component of the model was designed in alignment with established literature while being adapted to the specific needs of the Indian healthcare context. The age-based risk stratification closely parallels international findings, particularly those from the UK Office for National Statistics, which consistently demonstrate that older age groups are at higher risk of persistent symptoms. Gender, similarly weighted in the model, reflects epidemiological patterns identifying female sex as a consistent risk factor for symptom persistence.

The incorporation of BMI as a graded risk factor rather than a binary threshold strengthens the predictive power of the model. This approach is consistent with contemporary understanding that the relationship between obesity and Long COVID risk is incremental rather than absolute. The inclusion of clinical severity markers such as hospitalization, ICU admission, and early symptom burden further enhances the model's clinical validity, reflecting well-established associations reported in global cohort studies.[22,23]

The time-based thresholds applied to symptom duration, 28 days, eight weeks, and twelve weeks are grounded in the current definitions proposed by the World Health Organization and NICE, allowing the model to differentiate between post-viral recovery and chronic post-acute sequelae.[24] Furthermore, the weighting of symptom-specific risk, wherein symptoms such as fatigue, cough, and headaches are treated as high-risk indicators, is firmly supported by previous longitudinal studies, which identified these symptoms as particularly predictive of long-term disability.[25,26]

The inclusion of vaccination status as a dynamic risk modifier is another strength of the model, reflecting the protective effect documented in recent observational studies. Similarly, the presence of comorbidities including diabetes, hypertension, cardiovascular disease, asthma, and chronic kidney disease appropriately elevates risk within the model, in line with long-established predictors of both acute COVID severity and post-acute sequelae.[27]

Importantly, this model incorporates contextual variables often excluded from conventional CDSS developed in high-income settings.[28,29] By accounting for occupation, socioeconomic status, and area of residence, iALERTS adapts to the realities of healthcare delivery in low- and middle-income countries, where environmental exposures, healthcare accessibility, and digital infrastructure vary widely.

However, the generalizability of these findings remains limited by the single-center design. Genetic, environmental, and sociocultural determinants in this Indian cohort may differ substantially from those in other regions, potentially affecting symptom reporting, risk perception, and healthcare-seeking behaviors. Multi-center validation involving diverse demographic and geographic populations will be essential to establish the broader applicability and robustness of the iALERTS model.

In contrast to conventional CDSS platforms used in chronic disease management such as for diabetes or heart failure which primarily focus on static thresholds and laboratory value iALERTS integrates evolving symptomatology, layered risk factors, and contextual determinants into its logic model.[30,31] This represents a shift toward more adaptive, patient-centered decision support in post-viral syndromes.

Nonetheless, the scalability of iALERTS will hinge on several factors. Key barriers include infrastructural costs associated with digital integration, the need for clinician training on the use of the platform, and variability in electronic health record systems across institutions. Potential solutions include modular integration with existing hospital information systems, creation of mobile app-based interfaces for use in low-resource settings, and incorporation of training modules into routine continuing medical education programs.

This study not only affirms the clinical validity of the iALERTS platform but also highlights it as a scalable tool for enhancing risk-based management of Long COVID. By combining global evidence with local realities, iALERTS positions itself as a contextualized decision-support innovation with potential for transformative impact in primary and secondary care.

Limitations

This study is limited by its single-center design, which may restrict generalizability to wider populations. Although the cohort was diverse, reliance on self-reported symptoms introduces potential recall and reporting bias. Moreover, the absence of longitudinal follow-up limits our ability to capture the dynamic progression, resolution, or relapse of symptoms, which are known to fluctuate in Long COVID. The decision-making logic, while based on strong evidence, is constructed on a rule-based framework that may not capture complex interactions between risk factors. Additionally, the current model has not yet undergone external validation in different clinical settings, and the cross-sectional nature of much of the data limits the ability to track symptom progression over time.

Conclusion

The iALERTS platform offers a timely and clinically grounded approach to addressing one of the most complex challenges of the post-pandemic era; managing Long COVID. By enabling early risk identification, structured follow-up, and symptom-based triage, iALERTS has the potential to reduce unnecessary hospital visits, optimize specialist referrals, and improve overall resource allocation in strained healthcare systems. Its integration of demographic,

clinical, and patient-reported data provides a scalable framework for proactive care that aligns with evolving public health priorities. As a next step, pilot implementation is planned across three outpatient clinics that manage post-COVID follow-up, targeting a diverse sample of at least 200 patients. Evaluation metrics will include system usability, clinician acceptance, accuracy of risk categorization, and impact on patient care decisions. These findings will inform further refinement of the decision logic and support its potential adoption into broader clinical and telemedicine workflows. Scaling iALERTS beyond the pilot phase will require not only technical expansion but also partnerships that support training, interoperability, and equitable access across healthcare settings.

iALERTS platform: https://lca.projects.fhts.ac.in

Author's contribution: KMS was responsible for the conceptualization, software development, resource provision, and funding acquisition for the project. The methodology, validation, formal analysis, and investigation were collaboratively carried out by **KMS**, **SM**, and **JA**. Data curation was handled by **A.J**. and **KMS**. The original draft of the manuscript was prepared by **KMS**, **SM**, and **JA**, who also contributed to the review and editing process. Visualization tasks were jointly performed by **KMS**, **SM**, and **JA**. **SM** and **JA** provided supervision and were also involved in project administration. All authors have read and agreed to the published version of the manuscript.

Availability of Data: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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