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A Cloud-Based Artificial Intelligence Framework for Risk Assessment in Post-Transplant Patient Management

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KEYWORDS:

Artificial Intelligence (AI), Cloud Based Intelligent, Decision Support Knowledge Based System (DSKBS), COVID-19.

ABSTRACT:

The COVID-19 pandemic exposed serious weaknesses in the delivery of routine healthcare services, particularly for patients who depend on continuous medical supervision, such as kidney transplant recipients. During periods of lockdown and restricted movement, many patients were unable to visit hospitals for regular follow-ups, laboratory tests, or specialist consultations. This situation was especially challenging in public healthcare institutions, where limited medical staff must serve a very large patient population. As a result, many transplant patients were left without timely medical advice, increasing the risk of undetected complications and treatment delays.

Even in the years following the pandemic, several of these challenges have not been fully resolved. Public hospitals continue to face heavy patient loads, access to specialists remains limited, and regular in-person monitoring is still difficult for many patients. The gap between urban and rural healthcare services further complicates long-term disease management, making remote and technology-supported care an important requirement rather than a convenience. For transplant recipients, who need lifelong monitoring and strict medication adherence, the lack of consistent follow-up can have serious consequences for graft survival and overall health.

To respond to these persistent challenges, this paper presents a cloud-based, artificial intelligence–enabled framework for risk assessment and decision support in post-transplant patient management. The proposed system integrates cloud computing infrastructure, machine learning models, and a clinical knowledge base to analyze patient-reported symptoms and health data. Based on this analysis, the platform classifies patient risk levels and provides appropriate guidance, such as follow-up recommendations or medication-related advice. A simple and accessible web interface allows patients to receive clinical support without the need for frequent hospital visits, thereby reducing both travel burden and exposure to crowded healthcare environments.

To evaluate the practical usefulness of the system, a user survey was conducted with 100 kidney transplant recipients. The majority of participants reported that the platform was easy to use, helpful for routine health monitoring, and suitable for long-term adoption. Users particularly valued the ability to receive timely guidance and reassurance without waiting for in-person appointments. The findings suggest that such an AI-driven cloud platform can play an important role in improving continuity of care, enhancing patient engagement, and supporting early identification of potential health issues.

Overall, this study demonstrates that intelligent, cloud-based healthcare systems can address ongoing gaps in post-transplant care delivery. By combining remote accessibility with automated risk assessment, the proposed framework offers a practical solution for strengthening patient support in both post-pandemic and resource-constrained healthcare settings.

1. Introduction

Digital health technologies played a central role in strengthening India’s response to the COVID-19 crisis by ensuring uninterrupted access to essential healthcare information and services [1]. A key objective of modern healthcare applications is to enable continuous supervision of patients through tele-monitoring. Tele-monitoring, widely used in information technology, allows healthcare providers to assess patient conditions remotely across diverse and geographically dispersed locations [7].

With the integration of cloud computing and artificial intelligence, digital medical systems have become more efficient, scalable, and capable of handling complex tasks such as secure data storage, real-time processing, and remote accessibility at significantly reduced operational costs [8]. As IoT-based medical devices increasingly interact with critical patient data, reliable and seamless communication becomes vital, particularly for individuals residing in remote or underserved areas where access to specialized care is limited [1,9].

During the COVID-19 pandemic, strict social-distancing norms and restricted hospital access made remote medical supervision essential for vulnerable groups such as kidney-transplant recipients [10]. These patients require regular monitoring to detect infections early, manage complications, and maintain stable post-transplant outcomes [2]. Consequently, healthcare systems must incorporate advanced AI-driven approaches, including machine learning, to support timely and accurate clinical decision-making [11].

This paper introduces an AI-Powered Cloud Platform for Risk Prediction and Support in Post-Transplant Patient Care developed to assist kidney-transplant patients through automated risk assessment and personalized clinical guidance. The framework includes a web-based intelligent application that provides recommendations for medications, diagnostic tests, and follow-up actions without requiring physical hospital visits. By combining machine-learning models, rule-based reasoning, and cloud infrastructure, the proposed system offers efficient, accessible, and reliable remote healthcare support [12].

2. Problems Faced by Patients

The COVID-19 pandemic caused severe disruptions in routine clinical care, particularly for kidney-transplant patients who require continuous monitoring and timely medical intervention [10]. With outpatient departments (OPDs) closed or operating at limited capacity, many patients were unable to consult nephrologists for essential follow-ups. This challenge was magnified for individuals living far from tertiary care hospitals [13]. The following cases illustrate common problems experienced by transplant recipients during the lockdown period.

2.1 Case I: Elevated Haemoglobin (Hb) Post-Transplant

One kidney-transplant patient recorded a haemoglobin level of 17.2 g/dL, significantly above the normal post-transplant range of 10–14 g/dL [14]. Although specialist consultation at AIIMS was required, the patient residing in Jammu & Kashmir was unable to travel to Delhi because of lockdown restrictions. Under normal circumstances, a nephrologist might advise medications such as Etofylline or Theophylline, along with procedures like phlebotomy. An AI-enabled decision support system can bridge this gap by providing preliminary guidance irrespective of geographical barriers [15].

2.2 Case II: Increased Creatinine After Transplantation

Another patient reported a sudden rise in creatinine levels and feared possible graft dysfunction. Later evaluation revealed that the increase was associated with a stomach infection [2]. Since transplant patients cannot take antibiotics or analgesics without medical supervision, the inability to physically visit an OPD caused significant distress. An intelligent decision-support system could help by identifying low-risk conditions and suggesting safe initial measures such as probiotics or mild antibiotics until professional consultation becomes accessible [16].

2.3 Case III: Hyperkalemia (High Potassium) Post-Transplant

A patient from Safdarjung Hospital experienced elevated potassium levels but was unable to consult a doctor due to COVID-19-related OPD restrictions. Standard treatment options include sodium bicarbonate (Nodosis) and sodium polystyrene sulfonate, both of which help reduce serum potassium levels [17]. The proposed intelligent system can offer timely recommendations in such situations, enabling patients to initiate appropriate actions and prevent complications.

3.0 S/W Tools and Techniques for Proposed System:

3.1 Decision Support System (DSS)

The proposed web-based Decision Support System (DSS) is designed to assist patients, clinicians, and healthcare institutions in identifying and monitoring risk factors associated with kidney-transplant care [18]. The DSS is evaluated using historical medical reports from transplant patients and expert feedback from senior nephrologists [2].

By integrating AI-driven analysis with patient data, the system supports remote medical guidance an essential requirement for low-income and rural populations where

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access to specialized care is limited [13]. The relevance of such a system became more evident during public health emergencies like COVID-19, when physical hospital visits were restricted and vulnerable patients required continuous supervision [10]. The DSS enhances remote accessibility, ensures continuity of care, and strengthens decision-making by providing timely, data-driven risk evaluations.

3.2 Artificial Intelligence–Based Machine Learning Model

Artificial intelligence and machine learning augment clinical workflows by supporting tasks ranging from administrative processing to diagnostic assistance and patient monitoring [11]. While AI does not replace medical professionals, it enhances efficiency and supports informed decision-making [19].

In the proposed system, patient laboratory data and clinical inputs form the dataset for evaluating the ML-based subsystem. A 10-fold cross-validation approach is used to assess the stability and accuracy of predictive models [20]. This method partitions the dataset into multiple training and testing sets to minimize bias and improve reliability.

The machine-learning model uses self-improving algorithms capable of identifying optimal treatment patterns and minimizing unnecessary dosage repetitions, thereby reducing the likelihood of complications in transplant patients [2,21].

3.3 Knowledge-Based System (KBS)

The Knowledge-Based System is developed to generate clinically sound recommendations for immunosuppressive drugs such as Tacrolimus, along with other medications routinely prescribed to kidney-transplant patients [2]. A structured model is built to classify medication levels, interpret blood-level variations, and suggest adjustments based on aggregated clinical data and expert consultations.

These medical rules are encoded using Arden Syntax, a standardized language for representing and sharing medical knowledge [22]. Once deployed, the KBS integrates with hospital information systems to deliver automated, context-aware recommendations.

Development of the KBS involves extensive interaction with nephrologists from major government hospitals, many of whom have more than two decades of clinical experience. Historical patient data, documented treatment patterns, and clinical insights are incorporated to ensure completeness, reliability, and clinical relevance [23].

3.4 Cloud Computing Framework

Cloud computing forms a foundational component of the proposed system by enabling secure data storage, real-time access, and scalable processing capabilities. The growing adoption of cloud infrastructure across sectors has made it a natural choice for modern healthcare solutions.

In this system, cloud technology supports centralized electronic health records (EHR), enabling instant access to patient histories without reliance on physical documentation. Cloud platforms also facilitate safe record-sharing, automated back-end operations, and rapid deployment of telehealth applications.

Fig.1 illustrates how hospitals connect to cloud-based services including IaaS, PaaS, and SaaS to efficiently manage patient data within an e-health ecosystem.

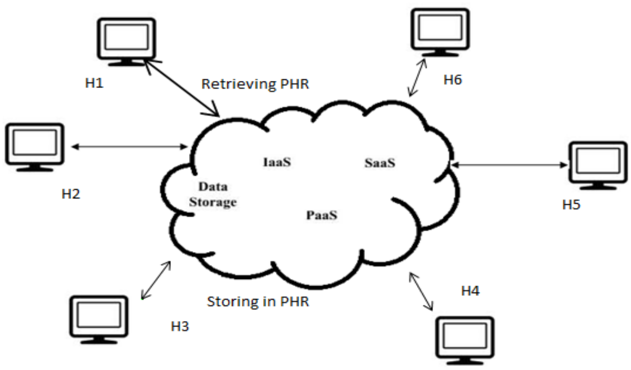

Fig.1. Hospitals connected with Cloud

4.0 Materials and Methods for Purposed System

We primarily collected the test reports of 50 patients and provided them a questionnaire to fill by which they can easily tell the current health problems they are facing. After compiling the report data, we consulted some senior nephrologists and created some high-risk and low-risk factors. This task will be guided by medical guidelines, specifically, the KDIGO guideline [4], the national institute for health and care excellence guideline [5], and the KDOQI guideline [6].

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Based on the different patients' reports and problems, the risk analysis system categorizes the high-risk and low-risk patients.

The following Table.1 gives example results of Risk Analysis Module:

UHID	DM	U	Creat	Na	K	Hb	TLC	PLT Ct.	History	Risk
2675	True	23	1.7	149	6.3	14.7	4500	190	Low	High
2198	False	32	1.2	140	6.0	13.2	5300	245	Low	Low
1145	False	27	1.0	140	4.9	14.9	6000	195	Low	Low
1087	True	40	1.3	141	5.2	15.0	4700	150	Low	Low
2111	False	30	0.9	144	4.5	16.5	5300	230	Low	Low
1348	False	24	1.1	143	3.9	14.6	8700	175	Low	Low
1132	True	38	2.1	152	5.2	14.0	6200	210	High	High
2123	False	97	1.8	145	5.0	15.1	5100	240	Low	High
2000	False	34	0.8	141	4.6	13.5	9000	210	Low	Low

Table.1. Risk Analysis Module Results

Above Fields description:

UHID: - Patients ID in Hospital.

DM: - Diabetes mellitus

U: - Urea level

Creat: - Creatinine

Na: - Sodium

K: - Potassium

Hb: - Haemoglobin

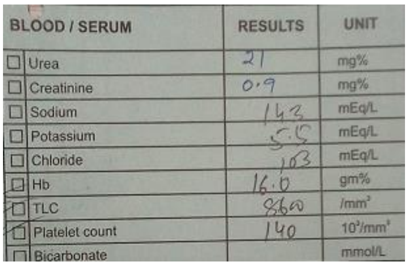
TLC: - Total leucocyte count

PLT Ct.:- platelet count

History: - Patients previous risk history

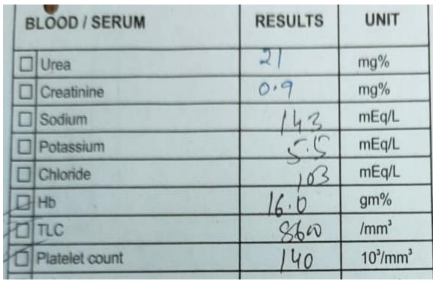
Risk:- Current Risk analysis

4.1 Below figures shows some patient reports for analysis and finding Risk Factor



BLOOD / SERUM	RESULTS	UNIT
Urea	21	mg%
Creatinine	0.9	mg%
Sodium	143	mEq/L
Potassium	5.5	mEq/L
Chloride	103	mEq/L
Hb	16.0	gm%
TLC	8600	/mm³
Platelet count	140	10³/mm³
Bicarbonate		mmol/L

Fig 2: Sample Report of a patient for analysis



BLOOD / SERUM	RESULTS	UNIT
Urea	21	mg%
Creatinine	0.9	mg%
Sodium	143	mEq/L
Potassium	5.5	mEq/L
Chloride	103	mEq/L
Hb	16.0	gm%
TLC	8600	/mm³
Platelet count	140	10³/mm³

Fig 3: Sample Report of another patient for analysis

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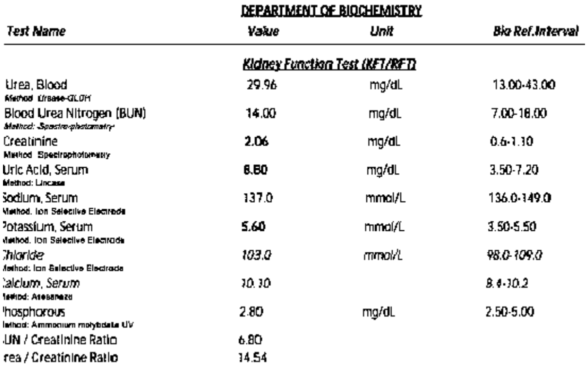
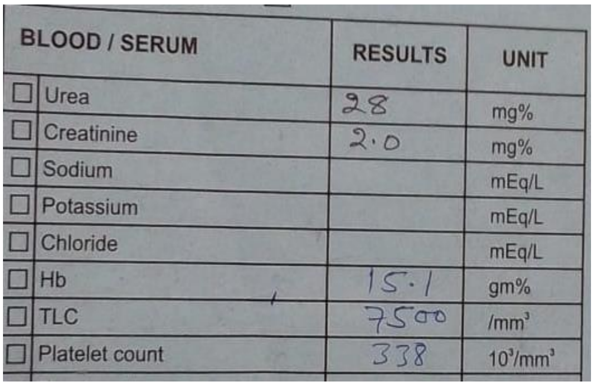


DEPARTMENT OF BIOCHEMISTRY

Test Name	Value	Unit	Bio Ref.Interval
	Kidney Function Test (KFT/RFT)		
Urea, Blood Method Urease-GLDH	29.96	mg/dL	13.00-43.00
Blood Urea Nitrogen (BUN) Method: Spectro-photometry	14.00	mg/dL	7.00-18.00
Creatinine Method Spectrophotometry	2.06	mg/dL	0.6-1.10
Uric Acid, Serum Method: Uricase	8.80	mg/dL	3.50-7.20
Sodium, Serum Method. Ion Selective Electrode	137.0	mmol/L	136.0-149.0
otassium, Serum ethod. Ion Selective Electrode	5.60	mmol/L	3.50-5.50
hloride ethod: Ion Selective Electrode	103.0	mmol/L	98.0-109.0
alcium, Serum ethod: Arsenazo	10.10		8.4-10.2
hosphorous ethod: Ammonium molybdate UV	2.80	mg/dL	2.50-5.00
UN / Creatinine Ratio	6.80		
rea / Creatinine Ratio	14.54		

Fig 4: Sample Report of another patient for analysis



BLOOD / SERUM	RESULTS	UNIT
☐ Urea	28	mg%
☐ Creatinine	2.0	mg%
☐ Sodium		mEq/L
☐ Potassium		mEq/L
☐ Chloride		mEq/L
☐ Hb	15.1	gm%
☐ TLC	7500	/mm³
☐ Platelet count	338	10³/mm³

Fig 5: Sample Report of another patient for analysis

The data collected by these reports and the advice given by the nephrologists to these patients our knowledge base prototype is prepared and the Risk Analysis module calculates the risk factor with the help of that knowledge base.

5.0 Proposed System Methodology Schema

Fig. 6 shows the architecture for the proposed methodology to design CBIDKBS for identifying and monitoring CKD in Brazilian communities. Two entities interact with the proposed system: Patient, and Hospital. This type of architecture is advisable because countries such as India usually lacking of precarious health care in remote areas, e.g., hard-to-reach and rural settings [13]. Below Fig.6 shows the architecture of the proposed system

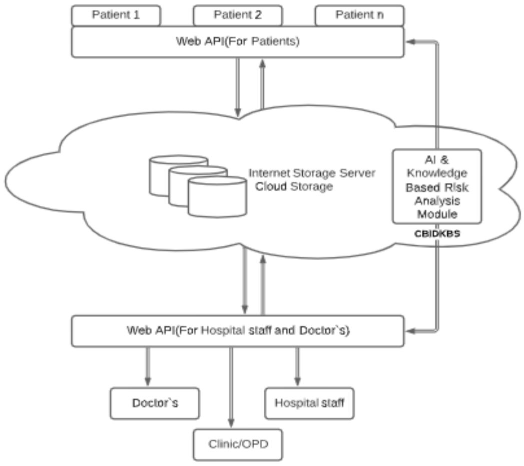


Fig.6. Architectural Schema for the proposed system.

5.1 System for Patients

The system must contain previous health records data (PHR) and risk evaluation functionalities. The risk evaluation of the transplanted patients under observation will be derived on the basis of machine learning technique and knowledge base analysis [11].

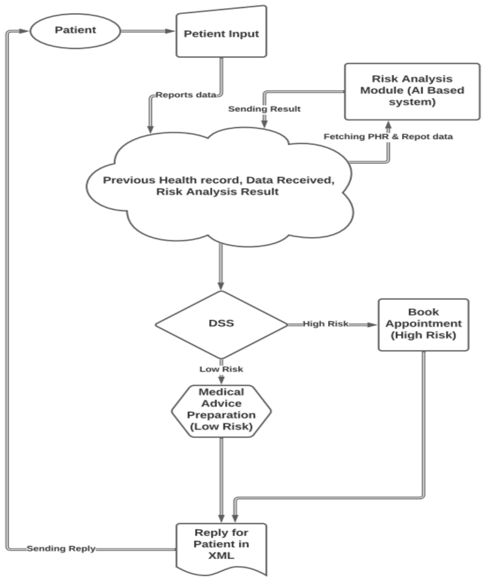


Fig.7. Flow Chart Patient Module

Patients residing in distant and hard-to-reach areas can work on it using different gadgets, such as desktop PCs, smart-phones, and tablets. The knowledge-based risk evaluation is used to address indeterminate patient health issues; absence of specialist doctors related to distant and hard-to-reach areas in underdeveloped nations like India

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[7]. Fig.8 shows the sample online input form to be filled by the patients.

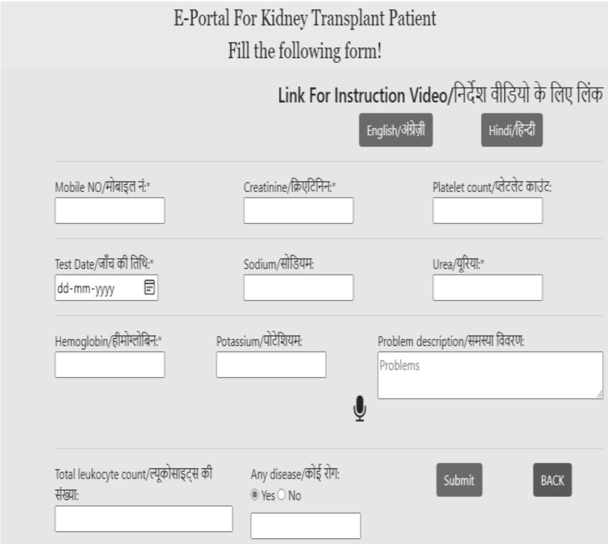


Fig.8. Patients Online Form

After submitting the input by the patient, the intelligent system evaluates the patient's test results and problems he/she is facing. Then it sends clinical feedback as an XML to the patient. In the high-risk case, will book an online or physical appointment for the patient, and a message is forwarded to the patient's mobile number. In the case of low risk, the AI system will guide the patient's medical advice using a knowledge base and machine learning technology [2].

6.0 New system adoption survey and result

During the pandemic situation patients are not able to visit the hospitals physically. OPDs of the hospitals are not open for a long time because of that every patient specially suffering with chronic diseases are in great trouble [10]. So, we want to know our proposed system will help them in this scenario or not and will they actually use it or not.

6.1 Questionnaire

For this purpose, we conducted a survey on the group of 137 patients (out of which only 100 responded) to find out, is the proposed web-based system is worthy for them and will they actually use it as shown in Fig 9. For analysis we used chi-square test to understand impact of proposed system on the patients.

The questions in the survey are:

Q1. Is this intelligent system useful for patients?

Q2. Will they use it?

Below diagram show the actual questionnaires provided to the patients.

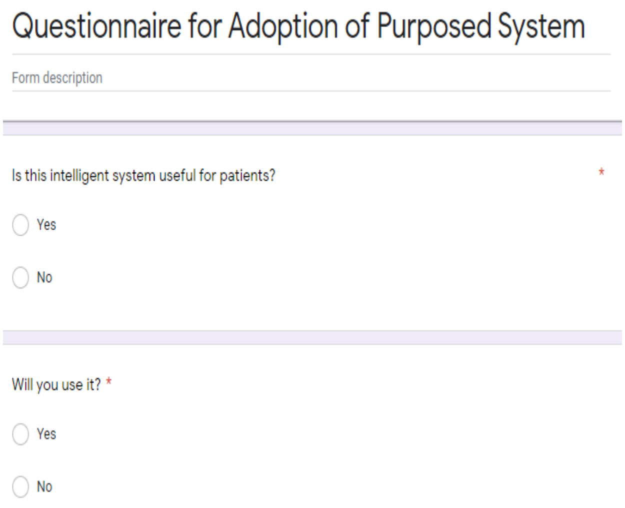


Fig: 9 Questionnaires for patient's

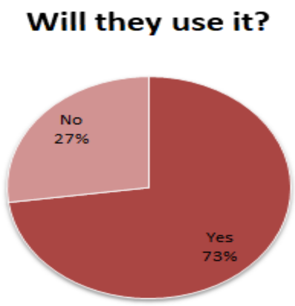
Below table shows the results of above questionnaires.

		Question:2		
		Yes	No	
Question:1	Yes	51	19	70
	No	10	20	30
Total		61	39	100

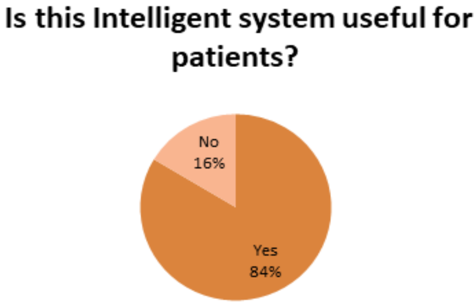
Table 9 Result summary table of the survey

6.2 Survey Evaluation Results:

To evaluate our proposed systems usability, we conducted this survey. And for analysing the results we used chi-square test. Fig 10 Chi-square is a statistical hypothesis test also named x2. It is used to determine the difference between the observed and expected frequencies from a crosstab. Yates gives the correction for this test also known as Yates's chi-squared test. It focuses to correct the error caused by taking the discrete probabilities. Evaluation results are shown below:



Question 2 result



Question 1 result

Fig 10. Result of Questionnaire for Adoption of Purposed System

Chi-square with Yates correction:

Chi squared equals 12.178 with 1 degree of freedom.

The two-tailed P value equals 0.0005

The association between rows (Question 1) and columns (Question 2) is considered to be extremely statistically significant.

From the above we conclude that, our hypothesis is accepted and according to patients surveyed, the AI based Web portal is worthy and can be used.

7.0 Must Have Considerations for the Proposed System

A real-Time application encounters a high traffic volume that's why it demands efficient use of resources. Some important considerations for designing this intelligent system are:

- The web-based application should be lightweight so that anyone can open the app on any device with minimum bandwidth.
- It must be Multi-lingual so that any person can operate it efficiently [7].
- It must have examples of all the tasks to perform so nobody will be stuck on running it.
- It must be scalable [8].
- Navigation structure must be simple and short.
- It includes real-time monitoring and support of the cloud, so all the patient's previous history is visible easily [24].
- Provides Iterative Development.
- Content must be in organised and structured manner.

8.0 Conclusion and Future Scope

The proposed model is an effort towards the integration of cloud and AI technique in the health delivery procedure [8,11]. The intelligent cloud and web-based system proposed in this paper help patients, doctors, and hospitals. With the help of the proposed approach, hospitals can easily monitor the patient's risk factors [18]. We will evaluate the Knowledge-Based System using a transplanted patient's dataset and interviews with some experienced nephrologists [2,23]. In this paper we only focused on the patient's module and its working. We are working on the Doctors and Hospitals module to complete new system. Furthermore, we can expand this system for other patients (AKD, CKD) and other departments (Cardio, Cancer, Neuro,) as well as we can include new services also. The proposed approach will surely help remote medical advice and tracking of patients having severe diseases. Considering epidemics that preclude physical presence in the hospitals, this concept is even more relevant [10].

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