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'Routine' versus 'Smart Phone Application Based – Intense' follow up of patients with acute coronary syndrome undergoing percutaneous coronary intervention: Impact on clinical outcomes and patient satisfaction

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ABSTRACT

Background: Acute coronary syndrome (ACS) refers to the spectrum of clinical presentation of coronary artery disease (CAD). As a routine practice at our institute, following PCI, ACS patients are called for the first follow up after two weeks. This period of two weeks can be full of anxieties, concerns and medical issues. In this study, we planned to assess the feasibility/acceptability of smart phone application (app) based system for patient follow-up and its comparison to routine practice among patients with ACS who have undergone a PCI.

Methods: A randomized controlled trial (RCT) was conducted over a period of one year from January to December 2017. After the PCI was deemed successful, patients were recruited and enrolled based on the understanding of basic English language and operation of a smart phone. Those who consented to be part of study were then randomly allocated either the conventional follow up group or the intense follow up (routine + smart phone app based follow up) group. First co- primary outcome was composite of clinical outcomes (mortality, myocardial infarction, stroke, target vessel revascularisation, heart failure admission and emergency visit). Second co- primary outcome was patient satisfaction. The overall patient satisfaction was assessed by the patients using a five-point patient satisfaction survey instrument containing five questions with 5 marks each, in which higher scores meant more satisfaction. Secondary outcome was controlled hypertension in hypertensive patients. It was defined as systolic BP less than 130 and diastolic BP less than 80 mmHg.

Results: A cohort of 228 patients (109 in intense app-based arm; 119 in routine follow up arm) were analyzed. The result showed significant improvement in blood pressure control in hypertensive population in intense app based follow up group (76.2%) when compared to routine follow up group (45%) with p value 0.0062. The satisfaction score was significantly higher in the intense app based follow up (20.7 ± 1.29) as compared to routine follow up (16.5 ± 2.68); p value 0.0001. In the intense app based follow up 72.5% patient felt it was excellent tool (score 21–25) while 27.5% categorized it as good (score 16–20). While the routine follows up was perceived as good by most (91.6%) of the patients. Only 4.2% graded it as excellent and an equal number (4.2%) graded it as a poor way of follow up.

Conclusions: App based system shows higher satisfaction rate and comparable clinical outcome when compared to traditional hospital based follow up protocol alone. It has a high acceptance rate and thus this system should be explored further to optimize long term patient care.

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Patient Satisfaction Questionnaire:

1. I am fully satisfied with the medical care I have been receiving.
   Strongly Agree (5) Agree (4) Uncertain (3) Disagree (2) Strongly Disagree (1)

2. I think my doctor's Hospital has everything needed to provide complete care.
   Strongly Agree (5) Agree (4) Uncertain (3) Disagree (2) Strongly Disagree (1)

3. My doctor and their team treat me in very friendly and courteous manner.
   Strongly Agree (5) Agree (4) Uncertain (3) Disagree (2) Strongly Disagree (1)

4. My doctors are careful to check everything when treating and examining me.
   Strongly Agree (5) Agree (4) Uncertain (3) Disagree (2) Strongly Disagree (1)

5. I am satisfied with the follow-up care after discharge.
   Strongly Agree (5) Agree (4) Uncertain (3) Disagree (2) Strongly Disagree (1)

Fig. 1. Patient Satisfaction Questionnaire.

1. Introduction

Acute coronary syndrome (ACS) refers to the spectrum of clinical presentation of coronary artery disease (CAD) that includes unstable angina (UA), ST segment elevation myocardial infarction (STEMI) and non ST segment elevation myocardial (NSTEMI) [1]. Reported as the 'deadliest disease' globally, CAD is a major health concern, with a huge economic burden. In India, CAD is a major contributor to mortality not only among the aged population but also among the young adults, and unfortunately, the trend is on rise in India. In 2001–2003 CAD accounted for 17% of total deaths and 26% adult deaths, which increased to 23% of total and 32% of adult deaths in 2010–2013 [2].

Percutaneous Coronary Intervention (PCI), whenever available is the treatment of choice for ACS [3]. Despite the good outcome following a timely PCI, the rates of long-term morbidity in terms of recurrence are substantial. In India as well as in other developing nations the need for implementation of secondary prevention strategies is huge [4]. Following PCI, titration of Guideline directed medical therapy (GDMT) as recommended by the American college of cardiology (ACC), European society of cardiology (ESC), for secondary prevention like aspirin, statin, and anti-hypertensive agents in a tailored way is the most crucial step to prevent long-term sequel and recurrences.

As a routine practice at our institute, following PCI, ACS patients are called for the first follow up after two weeks, wherein their cardiac status is assessed and drugs are titrated. For obvious reasons this two weeks period for the patient who has experienced an ACS, and has undergone an invasive procedure for the same, can be full of anxieties, concerns and medical issues.

We hypothesized that a smart phone application (app) based system, wherein the patient is able to communicate with his/her health care providers, in addition to the routine follow up protocols might have a positive impact in clinical outcome and patient satisfaction among patients with ACS who have undergone a PCI.

2. Material & methods

This randomized controlled trial (RCT) took place at a University Hospital of North India, over a span of one year (January – December 2017). The institutional ethical committee approved the study protocol. The sample size was calculated on the basis of patient enrolment data of year 2016. A total of 1980 patient underwent PCI for an ACS. As sample was to be collected from a consultant's OPD. So, of six days OPD one nit was estimated to have approx. 330 per year. Keeping a drop of 30% in enrolment with a type I error rate (alpha) of 5% and a type II error rate (beta) of 20%, sample size of 231 was calculated. After the PCI was deemed successful, patients were recruited and enrolled based on the understanding of basic English language and operation of a smart phone. Written informed consent was obtained after 24–48 h following the procedure, once the patient was clinically stable and fit for discharge. Those who consented to be part of study were then randomly allocated either the conventional follow up group or the intense follow up (routine + smart phone app based follow up) group. Simple randomization was done with computer generated numbers.

All participants were called to the hospital for the routine protocol of follow up after two and subsequently four weeks following the index procedure. However, in the intense app based follow up arm patients received additional benefit of direct communication with their health care providers as and when required during this duration. To facilitate this communication at the time of discharge for this group of participants the app (HealthRADAR by Evolko) was installed in the smart phone of the patient and all medical information and health related data was fed in the app by one of the investigators. With the help of this app the patients were able to clarify their doubts and discuss their minor problems directly with their health care providers by means of a message. The provider could then at his/her ease and time see the query and instruct changes in management plan online. For symptoms and events which were either equivocal in nature or deemed serious necessitating direct supervision of a physician, patient was advised to contact nearby health facility or report back to the hospital. We hypothesized that this system not only decreases anxiety of the patient but also reduces unnecessary patient visits to the hospital and saves doctor's precious time during the outpatient hours.

HealthRADAR by Evolko Systems Inc. California, USA - HealthRADAR is a smart phone based solution which allows doctors to review self-monitoring updates of the long-term care patients and interact with them via chat. The Artificial Intelligence (AI) algorithms of HealthRADAR prompts the patient to interactively enter BP, Pulse, pertinent symptoms etc. on their smart phones. The system asks further questions based on the response of the patient. HealthRADAR analyzes the data and sends the clinical summary to the specialist. The doctor reviews the details for an early warning, chat with the patient, and alters the treatment (if needed) before the next regular visit. It saves precious time of

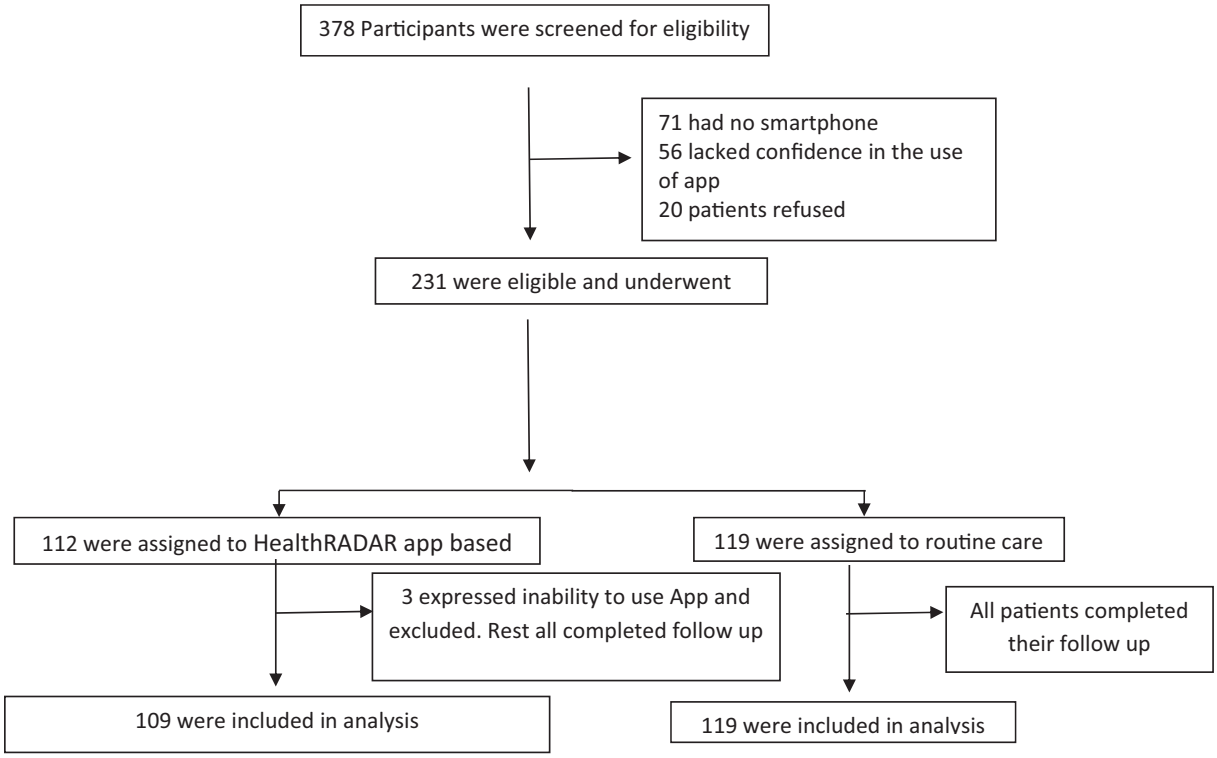

Fig. 2. Flow chart of sample enrolment in the study.

Table 1
Comparison of Baseline Characteristics in Routine vs. Intense app. Based Follow up of Post Intervention ACS Patients.

Characteristics		Intense (n = 109)	Routine (n = 119)	P-value
Age (years)	Mean ± SD	54.3 ± 11.3	54.2 ± 10.2	0.973^{NS}
Age group (years), n (%)	20 – 29	3 (2.8)	1 (0.8)	0.780^{NS}
	30 – 39	6 (5.5)	5 (4.2)	
	40 – 49	27 (24.8)	31 (26.1)	
	50 – 59	31 (28.4)	37 (31.1)	
	60 – 69	36 (33.0)	35 (29.4)	
	70 – 79	6 (5.5)	10 (8.4)	
Sex, n (%)	Male	88 (80.7)	102 (85.7)	0.313^{NS}
	Female	21 (19.3)	17 (14.3)	
Diagnosis, n (%)	STEMI	57 (52.8)	65 (54.6)	0.784^{NS}
	NSTEMI	40 (37.0)	45 (37.8)	
	USA	11 (10.2)	9 (7.6)	
Risk factors, n(%)	Diabetes	36 (33.0)	30 (25.2)	0.194^{NS}
	Hypertension	42 (38.5)	40 (33.6)	0.364^{NS}
	Smoking	54 (49.5)	64 (53.8)	0.522^{NS}
Ejection Fraction (%)	Mean ± SD	51.2 ± 7.5	46.4 ± 4.6	0.001***
Treatment at Discharge	Aspirin	107(98.1)	116(97.5)	0.724^{NS}
	Clopidogrel/Prasugrel/ Ticagrelor	104(95.4)	114(95.8)	0.887^{NS}
	Statin	108(99.1)	116(97.5)	0.359^{NS}
	Beta blockers	64(58.71)	71(59.66)	0.359^{NS}
	ACE I/ARB	56(51.3)	64(53.78)	0.716^{NS}

the specialists while the patient saves money and gets timely expert advice. The detailed representation of the app is given in Fig. 4.

Statistical Analysis: After the completion of study descriptive statistics were used to summarize demographic and clinical variables of the target population. Data collected via the application were utilized to show trends and frequency distributions of questions related to patient's recovery at the end of two consecutive hospital follow up 4 weeks apart, first being 2 weeks after the procedure. First co– primary outcome was composite of clinical outcomes (mortality, myocardial infarction, stroke, target vessel revascularisation, heart failure admission and emergency visit). Second co– primary outcome was patient satisfaction. Secondary outcome was controlled hypertension in hypertensive patients. Statistical analysis was done using GraphPad Prism 6. P value ≤ 0.05 was considered to be statistically significant. Patient satisfaction in both groups was scored and compared based on a small five-point patient satisfaction survey instrument (Fig. 1).

3. Results

A total of 378 patients underwent PCI for ACS over a period of 1 year (Jan 2017 to Dec 2017) at the recruiting unit. Of total 305 were male and 73 were females. Mean age of the study population (n = 228) was 54.24+/-10.7, male 190 (83.3%) female 38 (16.7%).

Table 2
Comparison of Short Term Clinical Outcomes at Thirty days in Routine vs. Intense app. Based Follow up of Post Intervention ACS Patients.

Outcome	Intense (n = 109)	Routine (n = 119)	P-value
1. Primary outcome: A. Composite of clinical outcomes (mortality, myocardial infarction, stroke, target vessel revascularization, heart failure admission and emergency visit)	14 (12.8)	18 (15)	0.620^{NS}
B. Patient Satisfaction Score	16.569	13.269	less than0.001***
2. Secondary outcome: Controlled blood pressure/Total Hypertensive, n (%)	32/42 (76.2)	18/40 (45.0)	0.0062***

231 patients with a diagnosis of ACS were randomized in the study. The details of sample enrolment is given in Fig. 2. Out of them 112 were randomly assigned the intense smart phone app based follow up arm (that included routine hospital based follow up plus smart phone app based communication with the health care provider), while 119 were selected for the routine hospital based follow up arm. Three patients from the intense follow up arm demonstrated their inability to use the app effectively and thus were removed from the study. Therefore, the cohort for final analysis included 228 patients (109 in intense app based arm; 119 in routine follow up arm). Completion rate of the smart phone app in the study was 97.3% Fig. 2.

The demographics or better clinical characterstics of patients belonging to the two arms were tabulated and were found to be statistically comparable except for the ejection fraction (Table 1). Mean ejection fraction in the intense app based follow up arm-at the time of presentation (51.2 ± 7.5%), was significantly higher as compared to the routine follow up arm (46.4 ± 4.6%) (Table 1).

On comparing the short-term clinical outcome (first co primary outcome); a composite of clinical outcomes (mortality, myocardial infarction, stroke, target vessel revascularization, heart failure admission and emergency visit) at 30 days - follow up was found to be statistically non significant. Incidence of composite outcome was 12.8%(14 out of 109 patients) in routine follow up ; 15%(18 out of 119 patients) in intense app based follow up; p value 0.620. The only significant difference in the two groups was found in the proportion of patients with controlled blood pressure (intense app based follow up 76.2%(32 out of 42 hypertensive); routine follow up 45%(18 out of 40 hypertensive); p value 0.0062) (Table 2). The mean time of patient contact to consultant through app was through 1.2 times per patients while three patient were referred to visit hospital for urgent evaluation.

The overall patient satisfaction (second co primary outcome) as subjectively reported by the patients in a five point scoring system in which higher scores meant more satisfaction, was significantly higher in the intense app based follow up (20.7 ± 1.29) as compared to routine follow up (16.5 ± 2.68); p value 0.0001. In the intense app based follow up 72.5% patient felt it was excellent tool (score 21–25) while 27.5% categorized it as good (score 16–20). Conversly the routine follow-up was perceived as fairly good by most (91.6%) of the patients. Only 4.2% graded it as excellent and an equal number (4.2%) graded it as a poor way of follow up (Fig .3).

4. Discussion

This study demonstrates the high completion rate (97.3%) and satisfaction rate (72.5% - excellent) of an intense smart phone app based follow up system combined with the routine follow up protocol among patients who underwent PCI for ACS.

Owing to the improvement of medical technology and better understanding of natural history and disease progression, mortality from ACS has declined substantially [5]. Yet the estimates are

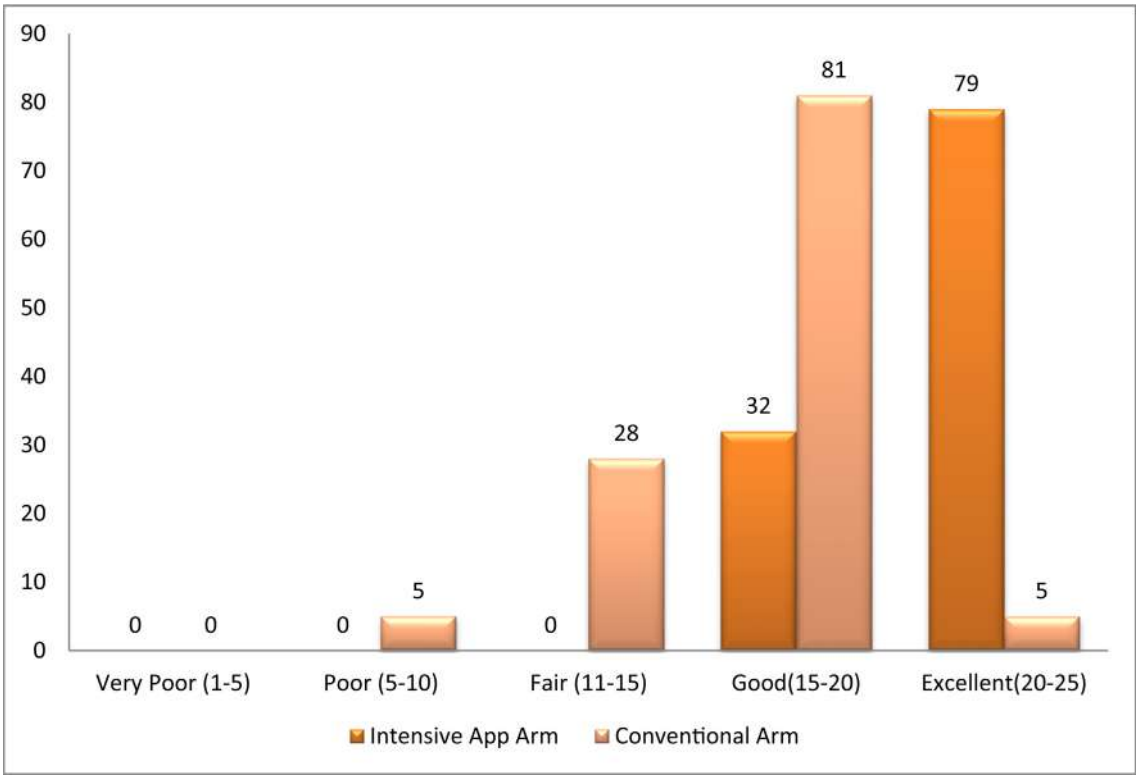

Fig. 3. Patient Satisfaction Score among Intense Follow-up and Routine Follow-up.

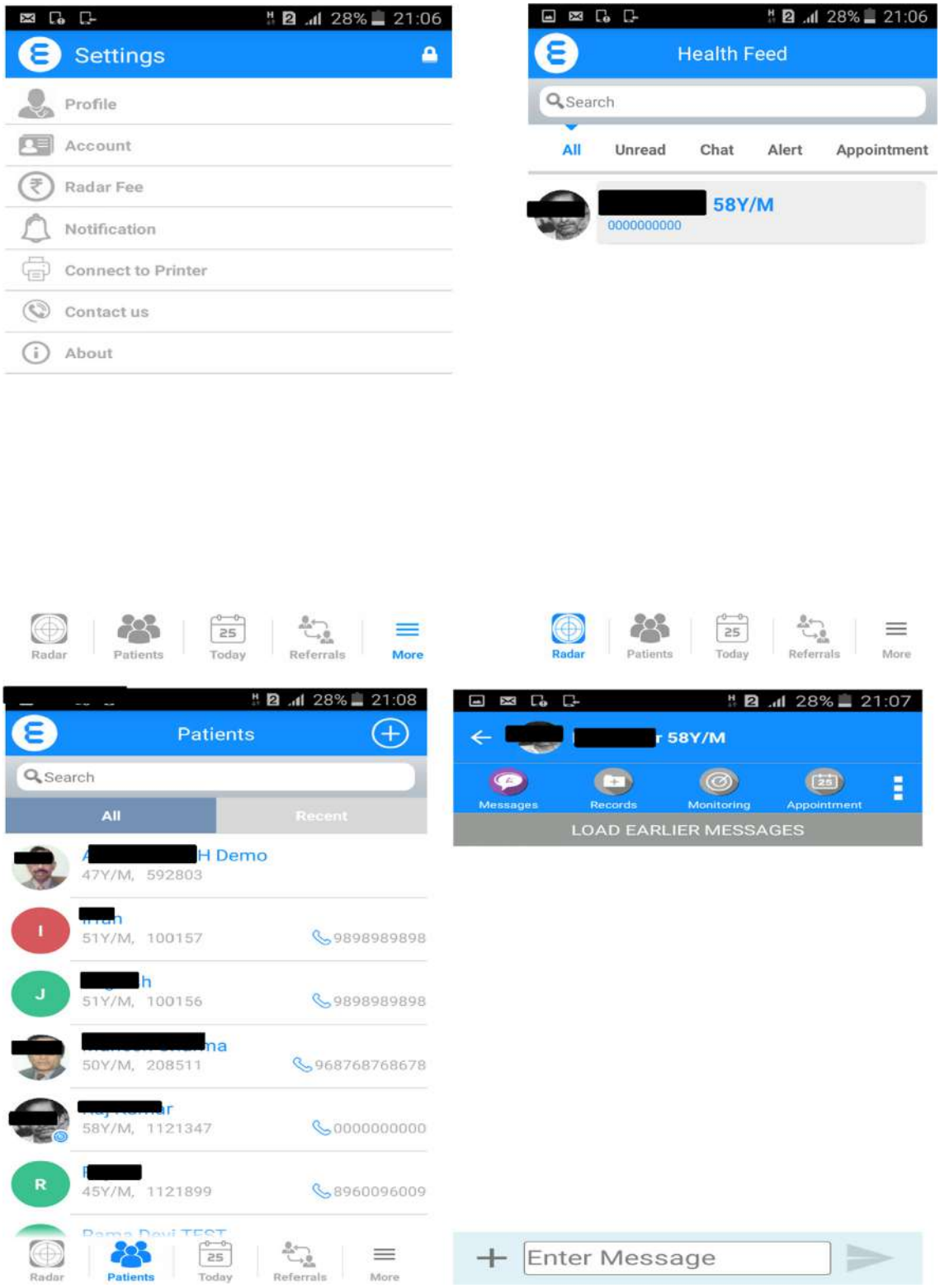

Fig. 4. Preview of smartphone application to be used in the study.

that 40% of the patients who experience ACS will die within 5 years with the risk of death being 5 to 6 times higher in individuals who experience a recurrent event [6–8]. Thus, ACS being an entity with a significant mortality rate require a close follow up. Even when the acute event has been taken care of with the best possible therapies, follow up of patients for secondary prevention and early diagnosis of recurrence or related events is of the utmost importance. Encouragingly in RCTs following an ACS event, with structured treatment regimens and frequent follow-up protocols, the compliance rate is high and recurrent event rate is low [9].

Despite improvements in management and survival after primary ACS hospitalization, early readmissions remain common, posing significant clinical and financial impact. Though readmissions within 30 days after discharge for an ACS are common, it is

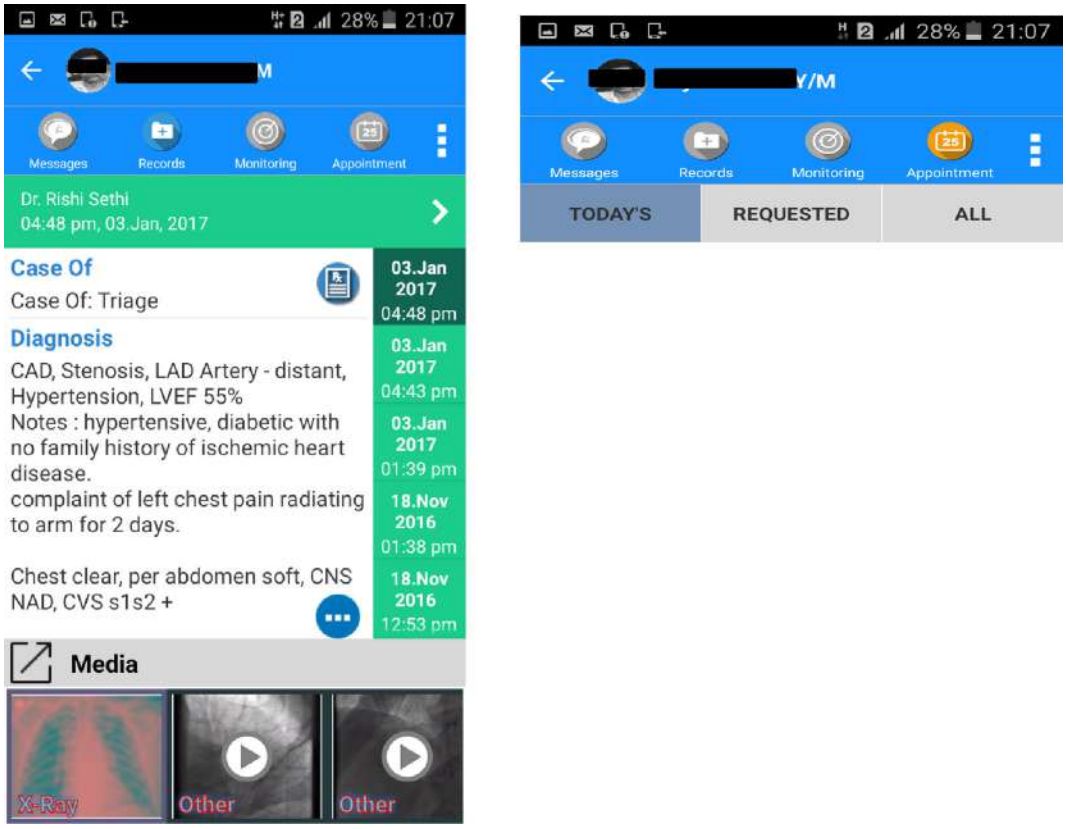

Fig. 4 (*continued*)

realized that these readmissions are rather heterogeneous in nature and that many readmissions are unrelated to the index ACS event and complication associated with it [10].

We are living in an era of rapid technological revolution and medical field is also trying to explore its potential in various arenas; may it be creating health awareness among the masses, triaging patients in the hospital or providing home based follow up. The adult population of twenty first century is an extremely important group which is tech-comfortable. Owing to the sound understanding and growing friendliness of the present population to the technological advancements, smart phone based apps in medical field can be a boon for this generation for regular use as well as for designing and development of apps for future generations [11,12].

As far as cardiovascular health is concerned, there are apps available to target preventive strategies for cardiovascular diseases (CVD), to access cardiac rehabilitation and to facilitate behavioral changes [13–15]. To the best of our knowledge, the present study is the first RCT to utilize an app-based technology in following up patients with ACS who have undergone PCI procedure.

Smart phone App based follow up of patients has a theoretical potential to reduce the direct and indirect (loss of work related) cost of hospital visits for the patients [16,17]. On other hand, this system will also avoid unnecessary cluttering of outpatient departments for trivial reason, thus optimizing health care providers' time. This pilot study is an effort to analyze the short- term clinical outcome of patients treated for ACS with or without a smart phone app, while both arms undergoing routine protocol based hospital follow up. We also tried to compare the overall rate of satisfaction between the two groups.

Previously a RCT of around 700 patients of coronary heart disease in Australia has shown the benefit of mobile phone text messaging service compared with usual care by showing improvement in LDL-C level in blood pressure, BMI, and smoking status [18].

Meta analysis involving 16 RCTs found that mobile telephone text messaging increased adherence to taking medications among middle-aged patients with chronic disease. Although most trials were of short duration and used seft reported outcome measures [19].

Not many studies in literature have attempted to evaluate the efficacy of health-related smartphone apps. There is even less information about consumers' behavior and use of such apps. Although our study was performed in a small cohort in a short time span it definitely shows the high acceptance as well as satisfaction rate of target population where the anxieties and demands to connect with the health care providers are higher.

The HealthRADAR system that we used in this study provided insightful trends on daily indicators of post intervention ACS recovery, such as chest pain, dyspnea, blood pressure control, feelings of anxiety, and the limitations of the physical activity. This gave physician important recovery information not often discussed during routine follow-up visits and at time points to which they would not otherwise have access. The utilization of this method provided the health care provider with an easy, portable way to monitor subjective quality of recovery on a real-time basis. Continued collection of aggregate data on this patient population will provide the care team with a method of identifying patients who fall outside the normal variances of postoperative recovery. This will also allow physician to plan follow-up visits on a more individualized basis. A recent study has summarized methods of assessing the quality of smart phone health-related apps and proposed a set of criteria that can used during the developmental stages of such apps to optimize the desired outcome [20].

India spearheading the digital movement records the second highest smart phones sales globally [21]. This statistic can be exploited effectively to increase health related awareness and disease follow up and thus bridge the gap, in a diverse country like

India where a huge and disproportionate gap still exists between the patient and care providers, especially in conditions associated with medical emergencies with high mortality, like cardiology.

The limitation of our study includes a small sample size and a short follow up. However, it provides a firm platform to develop and study such app based systems not only for an enhanced patient satisfaction but also to potentially access cost effectiveness and optimal utilization of health care services.

5. Conclusion

An app based system coupled with routine hospital based follow up of patients who had undergone PCI following an ACS event, shows higher satisfaction rate and comparable clinical outcome when compared to traditional hospital based follow up protocol alone. It has a high acceptance rate in an Indian population and thus this system should be explored further to optimize long term patient care.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijcha.2021.100832.

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Prediction of Cardio Vascular Disease in High Risk Cohort- Comparison of 'Traditional' versus 'Artificial Intelligence Based' Risk Scoring Models

Abstract

Background: Several risk prediction models for Cardio-vascular disease(CVD) already exist. They combine mutiple risk factors to create a risk prediction score for occurrence of cardiovascular (CV) event in any individual. This is a simplistic approach because the risk factors interact in a complex manner in any individual. We planned to study a novel and so an Artificial Intelligence(AI) based CVD risk score(AICVD) by comparing its efficacy to other commonly used risk scores in young patients of Acute coronary syndrome(ACS).

Design: Single center, Observational, Non-interventional study.

Participants: Cohort of Patients more than 18 but upto 40 years age with Acute coronary syndrome(ACS) presenting between 1st January 2019 to 31st October 2019.

Methods: 314 young patients [mean age 36.14 ± 4.17 years] presenting with (ACS) were enrolled. The three clinically most pertinent risk assessment models [Framingham Risk score (FRS), World Health Organization risk prediction charts (WHO/ISH), and QRISK3 scores] and Artificial Intelligence based novel CVD risk score (AICVD) were applied on day 1 of presentation, and tried to see whether one risk score versus other risk score could have predicted the event earlier had we applied it before the occurrence of acute coronary syndrome. Risk factors considered included those already in traditional scoring systems (age, ethnicity, systolic blood pressure, body mass index, total cholesterol, high density lipoprotein(HDL) cholesterol ,total cholesterol: HDL cholesterol ratio, smoking, family history of CAD ~~coronary heart disease~~ in a first degree relative aged less than 60 years, type 1 diabetes, type 2 diabetes, treated hypertension, rheumatoid arthritis, atrial fibrillation, migraine, systemic lupus erythematosus (SLE), atypical antipsychotics, a measure of systolic blood pressure variability (standard deviation of repeated measures), corticosteroids, erectile dysfunction, severe mental illness, chronic kidney disease (stage 3, 4 or 5) and new risk factors (diet, alcohol, tobacco, dyslipidemia, physical activity, family history of heart disease, history of heart disease, heart rate, respiratory rate, chronic heart symptoms and psychological stress).

Results: WHO/ISH provided the lowest high risk estimate with only 1(0.9%) patient estimated to be having >20% 10-year risk. The FRS estimated high risk (>20% 10-year risk) in 3(1%) patient. The QRISK3 estimated high risk (>10% 10-year risk) in 20 (6.5%) patients. In comparison, AICVD risk prediction model stood tall by identifying 73 (23.2%) patients for having high-risk of CV events at 7 years ($p < 0.001$)

Conclusion: Perhaps, this is the first study which has compared artificial intelligence based novel risk prediction model with the three most commonly applied models in the young Indian patients. We found that a cohort of young Indian patients presenting with ACS, when studied retrospectively, was identified as 'high risk' most likely by AICVD risk prediction model rather than the traditional counterparts. The WHO/ISH risk prediction charts and FRS were the poorest predictors. Performance of QRISK3 score also remained less than satisfactory. These findings suggested that AICVD risk prediction model is a promising tool ~~to~~ for the assessment ~~for~~ CV risk in Indian population.

Introduction

Cardiovascular risk assessment is a fundamental component of cardiovascular disease (CVD)prevention. CVD is conclusively the leading global cause of morbidity and mortality,[1] accounting for approximately one third of all deaths.[2] There is a widespread epidemic of CVD in the low and middle-income countries specially india sub-continent. [3-9] Most of the CVD risk prediction models have been developed and validated in western population and there is a need to interpret risk factors association with CVD in Indian population.

Several risk prediction models for Cardio-vascular disease(CVD) already exist like the Framingham Risk score (FRS), World Health Organization risk prediction charts (WHO/ISH) and QRISK models. They combine multiple risk factors to create a risk prediction score for occurrence of cardiovascular (CV) event in any person. This may be a simplistic approach because the risk factors interact in a complex manner in any individual. So, an Artificial Intelligence(AI) based models which takes the confounding nature of this interplay into consideration may be superior to the conventional risk scores. This study was envisaged to compare the relative efficacy of various conventional versus an AI based risk score in predicting the occurrence of CV event. We planned to do so by applying various risk score in each individual of a proven high-risk cohort of subjects who were young and had already suffered an ACS. We tried to analyze which score was more predictive of the high-risk CVD nature of these subjects.

Out of the available risk scoring systems, FRS has been the most widely accepted. Though having been validated in a number of populations, it is not free of limitations.[10]It has been found that FRS tends to overestimate the CV risk in low risk populations. Also, it does not consider many important risk factors like physical inactivity, obesity, family history of premature CV event, tobacco consumption etc. Another pitfall is its significant reliance on age as a risk factor. This has greater implication on Indian population in which age of CV event is almost 10 years earlier than western counterparts.[7,11,12]

WHO/ISH has been validated in South Asian populations but applicability stands true only in age 40 years and above.[13,14]ASCVD 10 year risk prediction model though can be applied to other races but uses data primarily on non-Hispanic whites and African Americans in the

United States.[15,16] Also it can only be applied in population > 40 years old. QRISK3 score, though can be applied to Indian ethnicity patients >25 years age, but it has been developed for the UK population and is intended for use in the UK.[17,18]

There are no firm data for atherosclerotic CVD risk in Indian population less than 40 years of age, although generally the incidence is low in this population. However, persons with a positive history for CVD in a first degree relative (sibling or parent), those with familial hypercholesterolemia (FH), or those who have had imaging studies done (such as CAC scoring) yielding abnormalities may present for advice. Expert opinion and observational database reports have generally provided the data for such persons.

The basic objective of this study was to compare Artificial Intelligence based risk score (AICVD risk score) with already existing traditional risk scores in the high risk Indian population of young (<40 years) patients presenting with ACS. Since the event had already happened in this patient cohort, it obviously was a high risk population. We applied four risk scores on day one of the presentation and tried to see if any one risk score could have better predicted the high-risk nature of the individual. Next step will be to apply the score to the general population to see whether it holds true in prospective sense in the apparently normal population.

Methods

This was a single center, observational, non-interventional study conducted from 1st January 2019 to 31st October 2019 in a leading tertiary care public sector hospital in India. 314 Patients >18 years but <40 years of age[mean age 36.14 ± 4.17 years] with ACS were enrolled[2]The three clinically most commonly used risk prediction models [Framingham Risk score (FRS), World Health Organization risk prediction charts (WHO/ISH), and QRISK3 scores] and Artificial Intelligence based novel risk score(AICVD) were applied to estimate what would have been their predicted risk of CV events if they had presented just prior to suffering the acute MI. While FRS, QRISK3 and WHO/ISH provides the CV event risk at 10 year, AICVD provides the estimated risk at 7 years. Risk factors considered included those already in traditional scoring systems and new risk factors as presented in Table 1.

Table 1- Clinical and biochemical parameters (along with applicable ranges) included in various cardiovascular risk assessment models.

Variable	*FRS*	*QRISK3*	*WHO/ISH*	*AICVD*
Age	*Yes (30-74 Years)*	*Yes (25-84 Years)*	*Yes(≥40 Years)*	*Yes (20-91years)*

Gender	*Yes*	*Yes*	*Yes*	*Yes*
Ethnicity	*No*	*Yes*	*Yes*	*Indian Population*
History Of Diabetes	*Yes*	*Yes*	*Yes*	*Yes*
Smoking History	*Yes*	*Yes*	*Yes*	*Yes*
Family History Of Premature CVD	*No*	*Yes*	*No*	*Yes*
History Of Atrial Fibrillation	*No*	*Yes*	*No*	*Yes*
History Of Chronic Kidney Disease	*No*	*Yes*	*No*	*Yes*
History Of Rheumatoid Arthritis	*No*	*Yes*	*No*	*Yes*
History Of SLE	*No*	*Yes*	*No*	*No*
History Of Blood Pressure Treatment	*Yes*	*Yes*	*No*	*Yes*
Systolic Blood Pressure	*Yes*	*Yes*	*Yes*	*Yes*
Standard Deviation Of Repeated BP Measures	*No*	*Yes*	*No*	*No*
Diastolic Blood Pressure	*No*	*No*	*No*	*Yes*
Body-Mass Index	*No*	*Yes*	*No*	*Yes*
Total Cholesterol	*Yes*	*No*	*Yes*	*No*
HDL-Cholesterol	*Yes*	*No*	*No*	*No*
Dyslipidaemia	*No*	*No*	*No*	*Yes*
Total Cholesterol/HDL Ratio	*No*	*Yes*	*No*	*No*
History Of Migraine	*No*	*Yes*	*No*	*No*
Mental Illness	*No*	*Yes (Psychosis, Depression,Neurosis)*	*No*	*Yes (Psychological Stress)*
History Of Atypical Antipsychotic medications	*No*	*Yes*	*No*	*No*
History Of Corticosteroids	*No*	*Yes*	*No*	*No*
History Of Erectile Dysfunction	*No*	*Yes*	*No*	*No*
Dietary Habits	*No*	*No*	*No*	*Yes*
Alcohol	*No*	*No*	*No*	*Yes*
Tobacco	*No*	*No*	*No*	*Yes*
Physical Activity	*No*	*No*	*No*	*Yes*
Family History Of Heart Disease	*No*	*No*	*No*	*Yes*
Patient's History Of Heart Disease	*No*	*No*	*No*	*Yes*
Heart Rate	*No*	*No*	*No*	*Yes*
Respiratory Rate	*No*	*No*	*No*	*Yes*
Chronic Heart Symptoms	*No*	*No*	*No*	*Yes*

Definitions

All the variables were defined as per standard definitions. Hypertension was defined as per 2017 ACC/AHA guidelines for Hypertension.[23] For diabetes, recommendations from 2019 guidelines by the American *Diabetes* Association (ADA) were used.[24] Moderate alcohol consumption was defined as having up to 1 drink per day for women and up to 2 drinks per day for men. Smoking categorized as light if consumption is <7 cigarettes per day, moderate if >7 but <20 cigarettes per day and heavy smokers as 20 or more cigarettes per day. Dyslipidemia, defined as elevated total or low-density lipoprotein(LDL) cholesterol levels, or low levels of high-density lipoprotein (HDL) cholesterol. Physical activity is categorized assedentary when only physical activity is that associated with activities of daily living. Moderately active consists of walking 1.5 to 3 miles daily at a pace of 3 to 4 miles per hour (or the equivalent). Active, whena person walks more than 3 miles daily at the same pace, or equivalent exercise.

Estimation of CV risk

Based on the information collected, risk of having a major CV event (CV death, MI or stroke) was calculated for each patient using the four different risk scores- FRS, QRISK3,

WHO/ISH, AICVD. The FRS and the Q RISK 3 calculators are available for download from the websiteshttps://www.framinghamheartstudy.org/risk-functions/cardiovascular disease /10-year-risk.php# and https://qrisk.org/three respectively.The WHO risk prediction charts are included as part of the 'Guideline for assessment and management of cardiovascular risk' available at the WHO website (http://www.who.int/cardiovascular_diseases/publications/ Prevention_of_Cardiovascular_Disease/en/).The chartapplicable for South-East Asian region D (which includes Bangladesh, Bhutan, Democratic People's Republic of Korea, India, Maldives, Myanmar and Nepal) was used in the present study. For AICVD risk score we used an Artificial Intelligence based application developed by Microsoft incorporation. (Figure 1)

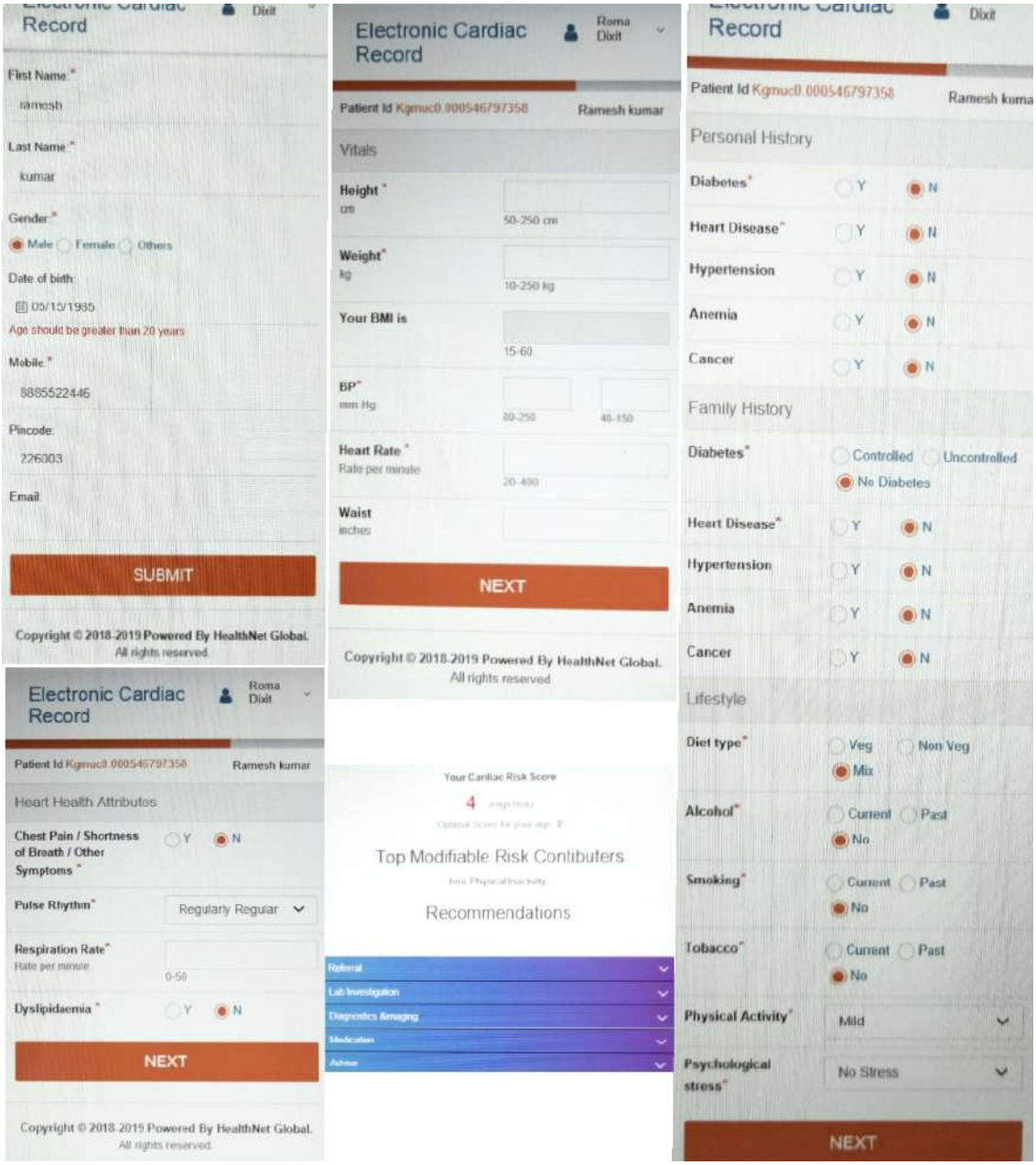

Figure1: Example of score calculation in a dummy patient using Microsoft incorporation software. After filling the required data, score is calculated and software provides a cardiac risk score. It also compares the calculated risk with optimal risk at particular age. As the Optimal Threshold values for different age and gender vary, the values are scored as the risk score rather than the percentages.

<1 (of Optimal Score) - Low Risk
1 - 1.5 (of Optimal Score) - Moderate Risk
> 1.5 (of Optimal Score) - High Risk

Statsitical analysis

The data were managed on Microsoft excel spreadsheet (version 2007, Microsoft Corp, Seattle, Washington) and analyzed using SPSS for Windows (release 16.0, SPSS Inc, Chicago, IL, USA). All the values were expressed as mean (±standard deviation) or as percentages. Standard descriptive analysis was performed to analyze the baseline characteristics of the study population. The categorized risk estimates derived from the different risk scores were compared using Chi squared test ($\chi 2$). A p value <0.001 was considered statistically significant.

Results

The baseline characteristics of the study population are presented in Table 2. The mean age of the study subjects was 36.14 ± 4.17 years. 272 (86.6%) patients were males and 42(13.4%) were females. Out of the overall ACS admissions in the hospital, the young ACS (<40 years age) comprised 314(11.03%) patients. Of them 117 (37.26%) were anterior MI (AWMI), 64(20.38%) were inferior MI (IWMI), 1(0.32%) was lateral MI (LWMI) and 132(42.04%) were non- ST elevation MI (NSTEMI). Of the study cohort, the age group with maximum ACS presentation was 36-40 years old(59.9%) and minimum was that of very young ACS <25 years old which constituted only 1.3% patients of the study population.

The conventional, major CV risk factors were common in the study subjects (table 3). 62 (19.7%) patients had hypertension while diabetes mellitus was present in 52 (16.5%) patients out of which 3 patients had type 1 diabetes. The most frequent risk factors seen in the study population were tobacco chewing and smoking, seen in 139 (44.3%) patients. Of them ~~139(44.26%) smokers~~,14(10.07%) were heavy smokers while 99(71.22%) were moderate smokers.The family history of sudden death below 60 years in first degree relative ~~expiry <60year age~~ was there in 31(9.9%) patients. Family history of heart disease was there in

53(16.9%) patients and 10 (3.2%) patients were known case of heart disease and were already under OPD follow up. Dyslipidaemia was present in 75(23.9%) patients. 139(44.3%) patients were ~~had~~ vegetarian ~~food habit~~ while 175(55.7%) had ~~followed~~ mixed dietary habits. 9(2.9%) patients had history of more than moderate alcohol intake. 57(18.2%) patients had active lifestyle while 155(49.4%) patients had moderately active lifestyle and102(32.5%) patients were ~~had~~ sedentary. ~~lifestyle.~~ None of the patient had CKD stage 3 or above. None of the patient reported migraine, erectile dysfunction, rheumatoid arthritis, SLE, severe mental illness, antipschycotics or chronic corticosteroid drug intake.

Estimated CV risk prediction according to the different risk scores

The risk of major CV events (CVD death, MI or stroke) was calculated in all patients using FRS, QRISK3 score, WHO/ISH and AICVD risk score. While FRS, QRISK3 and WHO/ISH provides the CV event risk at 10 year, AICVD provides the estimated risk at 7 years. As the FRS calculates risk in patients of minimum age 30 years old, so out of 314 patients score could be applied to only 289 patients. Similarly, 310 out of 314 patients were included in QRISK3 calculator due to minimum age variable being 25 years old. In comparison, only 115 patients could be included in WHO/ISH score because the score can not be applied to patients age <40 years. The AICVD score was applied on all 314 patients(Figure2). Of these patients FRS predicted high risk (>20% 10 year mortality) estimate only in 3(1%) patient. QRISK3 identified high risk (>10% 10 year risk) in 20 (6.5%) patients while WHO/ISH identified only 1 (0.9%) patient as high risk (>20% 10 year risk). AICVD stood tall by identifying 73 (23.2%) patients at~~s~~ high risk of CV event at 7 years . While FRS identified 37(12.8%) patients with moderate or higher risk, QRISK3 only categorize into low or high risk thus patients with more than low risk identified were 20 (6.5%). WHO/ISH predicted 8 ? 7%(6.96%) patients with moderate or high ~~more~~ 10 year risk. AICVD score predicted moderate or more risk in 197(62.74%) patients.On comparing AICVD risk prediction model with FRS, QRISK3 score and WHO/ISH models, AICVD score appeared to be statistically significant with a p value <0.001(Figure 3-6)

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Table 2: Baseline characteristics of study population

Variable	*Mean ± SD*
Age(years)	*36.14±4.17*

Height(cm)	*165.61±6.77*
Weight(kg)	*71.71±9.98*
BMI(kg/m2)	*26.13±2.94*
Systolic blood pressure(mm Hg)	*126.63±16.25*
Diastolic blood pressure(mm hg)	*78.25±7.96*
Heart rate per minute	*81.13±9.55*
Respiratory rate per minute	*12.66±.92*
Total Cholesterol (mg/dL)	*179.63±32.57*
High density Lipid(HDL) mg/dL	*45.31±5.69*
Cholesterol /HDL ratio	*4.06±1.14*

Table 3: Risk Factors

Variable	***Yes***	***No***
HT	*62 (19.7%)*	*252(80.3%)*
DM	*52(16.5%)* *Type 2 : 49(94.23%)* *Type 1 : 3(5.77%)*	*262(83.44)*
Tobacco	*139(44.3%)*	*175(55.7%)*
Family History of First Degree Relative Expiry <60year Age	*31(9.9%)*	*283(90.1%)*
Family History of Heart Disease	*53(16.9%)*	*261(83.1%)*
History Of Heart Disease	*10 (3.2%)*	*304 (96.8%)*
Dyslipidaemia	*75(23.9%)*	*239(76.1%)*
Alcohol (More Than Moderate)	*9(2.9%)*	*305(97.1%)*
Smoking	*139(44.3%)* *Heavy :14(10.07%)* *Moderate :99(71.22%)* *Light : 26(18.7%)*	*175(55.7%)*
Dietary Habit	*Vegetarian :139(44.3%)* *Mixed Diet : 175(55.7%)*	
Physical Activity	*Active : 57(18.2%)* *Moderately Active : 155(49.4%)* *Sedentary : 102(32.5%)*	

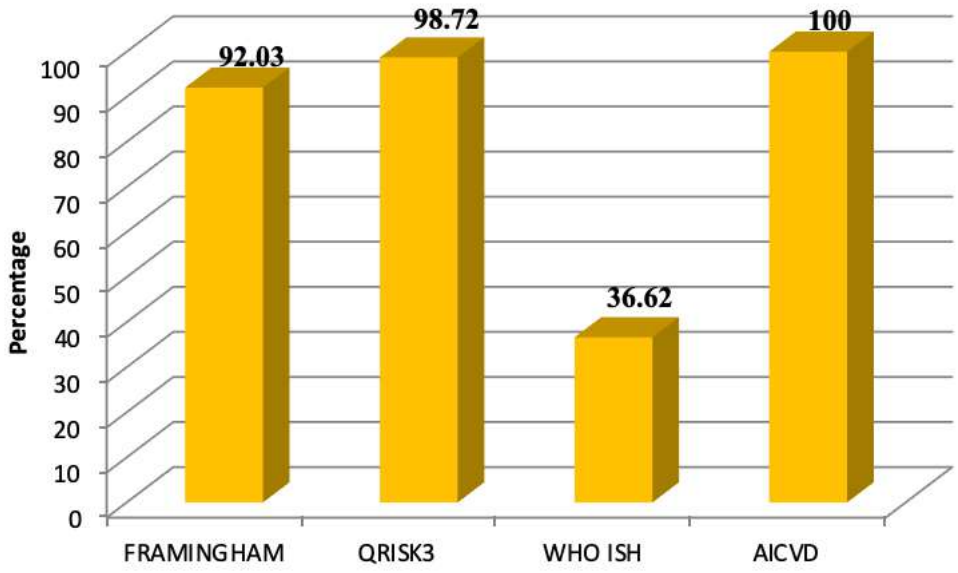

Figure2: Application of various scoring systems on study cohort

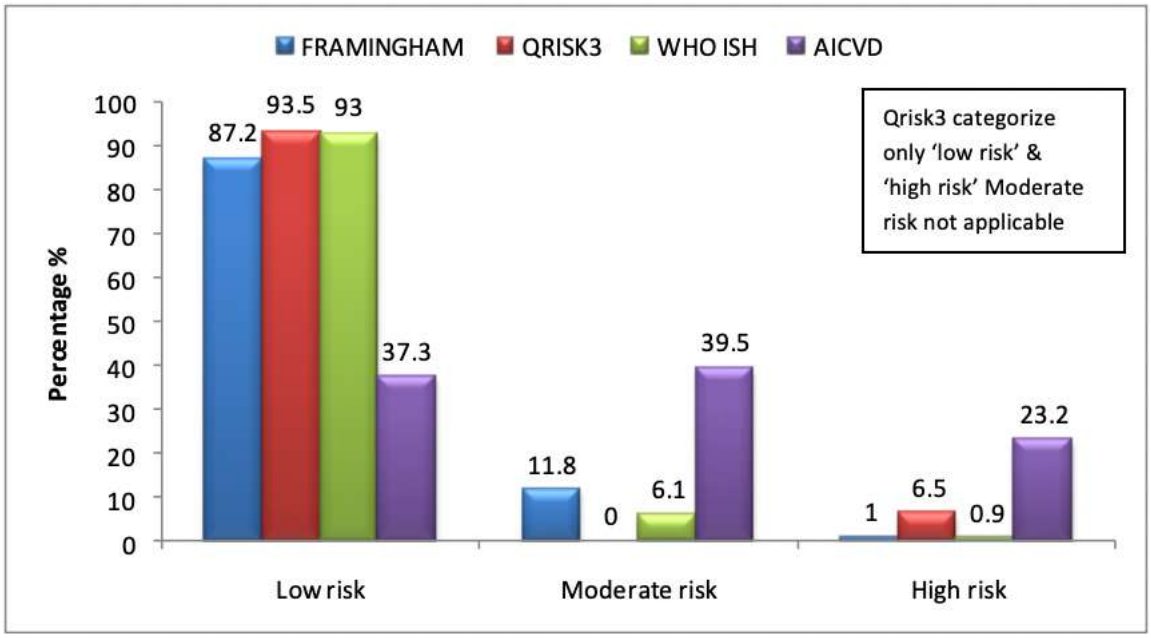

Figure 3: Predictability of the risk prediction models

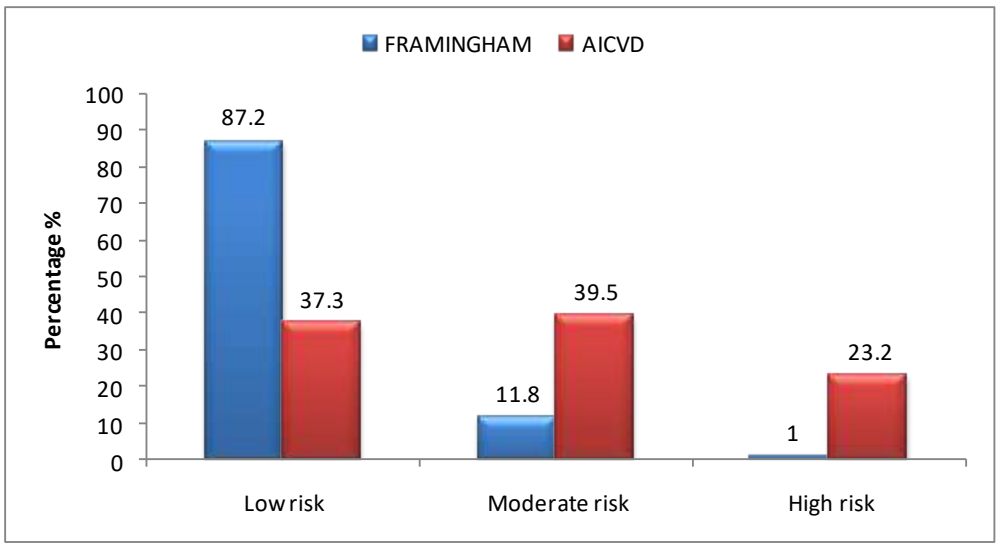

Figure 4: Comparing statistical significance of AICVD risk prediction model with FRS.Applied $\chi 2$ test for significance. p-value=<0.001

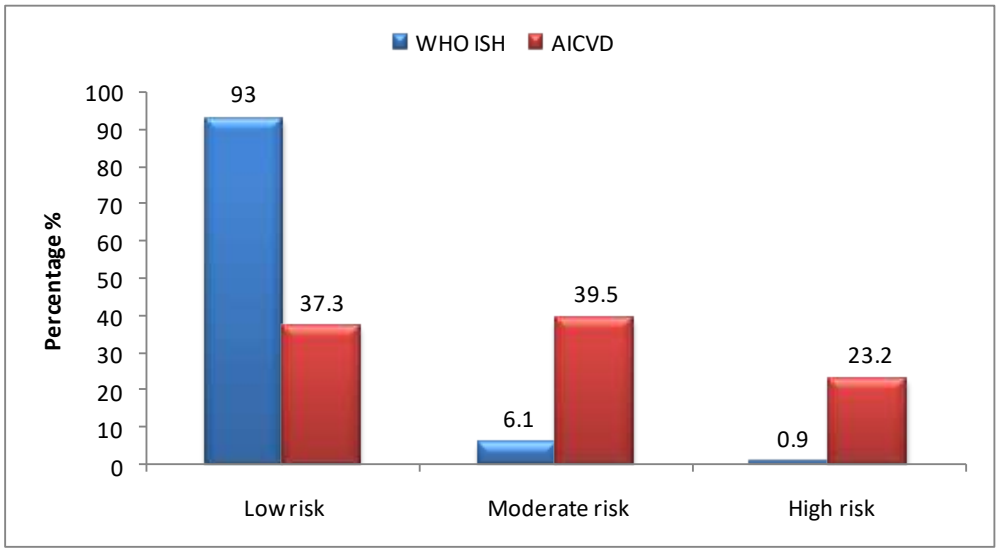

Figure 5.: Comparing statistical significance of AICVD risk prediction model with WHO/ISH.Applied $\chi 2$ test for significance. p-value=<0.001

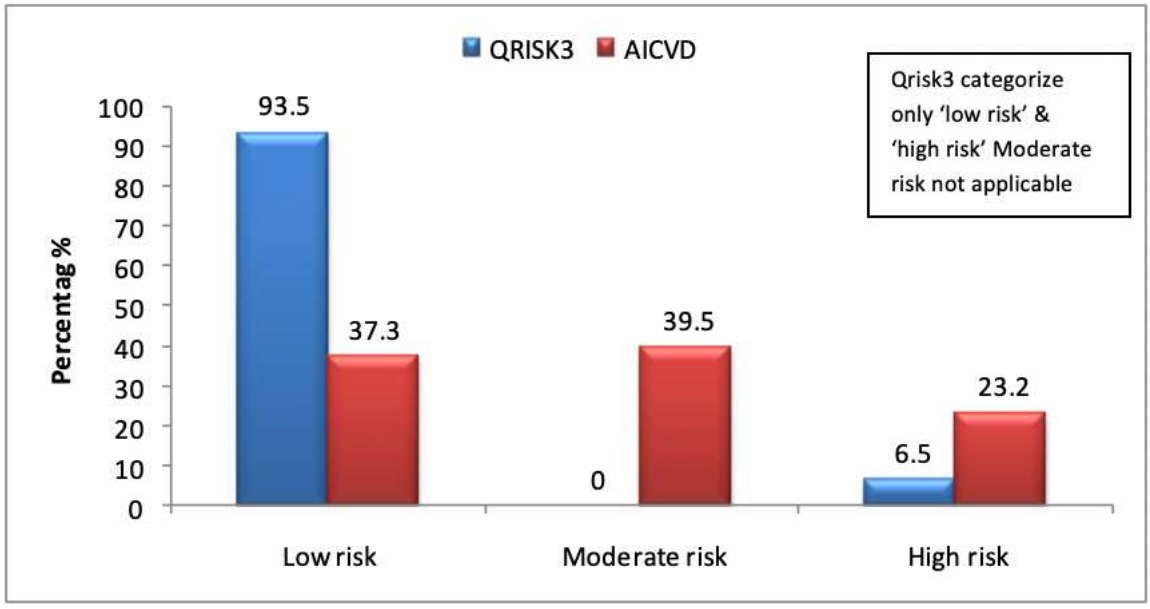

Figure 6.Comparing statistical significance of AICVD risk prediction model with QRISK3. Applied $\chi 2$ test for significance. p-value=<0.001

Discussion

Perhaps, this is the first study which has compared artificial intelligence based novel risk prediction model with the three most commonly applied models in the young Indian patients. We found that a cohort of young Indian patients presenting with ACS, when studied retrospectively, was identified as 'high risk' most likely by AICVD risk prediction model rather than the traditional counterparts. The WHO/ISH risk prediction charts and FRS were the poorest predictors. Performance of QRISK3 score also remained less than satisfactory.

The CV event risk prediction is an essential aspect of preventive cardiology. CV risk prediction let the clinician to offer the patient fair advice regarding intensity of risk reduction therapy either by ~~whether~~ lifestyle modification or drug intervention. The prime example of drug intervention as primary prevention approach is use of statin and aspirin in high risk individuals. Additionally, knowing the likelihood of CV risk not only improves patient's compliance toward his health but also gets the family prepared for any untoward incident.

The CV risk assessment is done by determining various risk factors and applying them in an algorithm to calculate a risk score. Many such risk calculators are available but the most popular and commonly used risk assessment tool is Framingham risk score (FRS).[25]FRS is the oldest risk calculation algorithm which was created way back based on a data derived from Framingham Heart Study which was initiated in 1948 ~~in~~ in the town of Framingham in Massachusetts, USA. The original FRS, published in 1998, was based on data derived from a

European population.[26]It was then modified in 2002 by the third Adult Treatment Panel (ATP III)[27]and finally updated in 2008 to Framingham general cardiovascular risk score, which was shown to have reliable predictive ability.The 2008 Framingham risk calculators for men and women are based on a sample general population from the north-eastern United States and is calculated using online calculator.[25]Individuals with low risk have 10% or less coronary heart disease (CHD) risk at 10 years, with intermediate risk 10-20%, and with high risk 20% or more.The sensitivity of Framingham risk calculators for men and women is 49% and 60% respectively while specificity in men and women is 85% and 84%, respectively.[25]Though having been validated in a number of populations, it is not free of limitations.[10]It has been found that FRS tends to overestimate the CV risk in low risk populations. Also, it does not consider many important risk factors like physical inactivity, obesity, family history of premature CV event, tobacco consumption etc. Another pitfall is its significant reliance on age as a risk factor. This has greater implication on Indian population in which age of CV event is almost 10 years earlier than western counterparts.[7,11,12]

To get through the shortcomings of FRS, many other CV risk prediction models have been created taking data from various ethnic subgroups. In 2007, the World health Organization collaborated with the International Society for Hypertension and developed risk prediction charts for each geographic region.[13]These charts took into consideration the various indigenous risk factors particular to that geographical region. The National Programme for Prevention and Control of Cancer, Diabetes, Cardiovascular diseases and Stroke (NPCDCS) recommend using WHO/ISH risk prediction model for CV risk assessment in Indian population.[28]In our study we faced a major shortcoming of non applicability of WHO/ISH risk prediction model in more than half (63.4%) of the study population due to unavailability of scoring system in patients of age <40 years old.

The QRISK and the updated QRISK2 algorithms were developed to predict cardiovascular risk in patients from different ethnic groups living in England and Wales.[29,30]The first QRISK model to estimate 10 year risk of cardiovascular disease was published in 2007.[29] It was followed by an updated model (QRISK2) in 2008.[30]In 2017 QRISK2 algorithm was updated to QRISK3 algorithm. It estimates CV risk at 10 years and is available as an online calculator.[18] The QRISK3 risk score has been developed for the UK population and is intended for use in the UK but it has been used in other countries as well.

In 2013, the ACC/AHA developed ASCVD risk calculator which calculates 10 year risk of CV event.[15]The motive of creating this score was to provide clinicians a better decision making regarding lipid management and use of statins.[31]Risk Calculator uses data primarily

on non-Hispanic whites and African Americans in the United States.[15,16] Also, the lower age limit to calculate risk score using this calculator is more than 40 years old.

In 2014, Joint British Societies' (JBS) risk prediction model was developed basically for healthcare providers to come up with a means of conveying CV risk to general population and hence necessary actions for amendment if needed.[32,33] JBS risk model includes data on ethnic Indians, albeit non-resident.

Despite availability of numerous risk prediction models, it has been shown that not just FRS, other Western risk assessment models also tend to systematically underestimate the risk in individuals of South Asian origin.[3,6,7] These findings underscore the importance of using population-specific risk estimation algorithms. It is important to consider that as CV risk depends heavily on environmental factors, the same risk prediction model can not be applied on all populations. Furthermore, it is well accepted that CVD occurs a decade earlier in Indian population compared to its western counterpart.[3-9] Besides, Indian population has a high risk of developing diabetes and that too at a younger age compared to populations of other ethnicity.[5,34]This has been attributed to genetic makeup as well as environmental factors.[4,5,9]Due to these factors, as has been shown in several studies, the risk prediction models based on data from western population tends to underestimate CV risk severity in Indian population.[3,6,7]Assessing CV risk in Indians is challenging because of unavailability of any prospective data on Indian population. As a result, clinicians in India are using the existing risk prediction models to estimate the risk of CV event. However, performance of these risk prediction models in Indian population has not been adequately exhibited.

It was found that FRS identified only 23.3% patients as intermediate to high risk in a cohort of patients suffering from metabolic syndrome.[11]A study by Kanjilal et al also stated comparable results.[12]The authors compared three risk prediction models FRS, SCORE and JBS(older version) in family members of patients suffering from CVD. It was observed that even with significantly elevated lipids and pro-inflammatory markers, all the risk prediction models could identify only less than 5% population as 'high risk'. In a study by Bansal et al. the four risk scoring systems were compared namely, FRS, WHO/ISH risk prediction charts, ASCVD risk score and JBS3 score in a cohort of patients presenting with acute MI.[35]They found superiority of JBS3 model over others in predicting patients as 'high risk'. In their study, WHO/ISH risk prediction charts had lowest predictability while ASCVD 10 year risk score and FRS had intermediate prediction accuracy. In an another study by same authors[36], these four risk prediction models were compared in patients presenting for general health checkup. Results of coronary artery calcium (CAC) score and carotid intima-mediathickness

(CIMT) were compared, which were chosen as a proxy markers for CVD. They found that JBS3 model had highest correlation with CAC and CIMT. A study by Garg et al.[37]on 1110 Indian patients of acute MI provided conflicting results. The authors estimated 10 years CV risk applying for prediction models including QRISK2, FRS-CVD, FRS-CHD, WHO/ISH risk prediction charts, ASCVD 10 year risk score and JBS3 risk score. Here, FRS-CVD had highest predicting accuracy by identifying 51.9% patients as high risk, while ASCVD 10 year risk model and WHO/ISH risk prediction charts predicted the least (28.3% and 16.2%, respectively). To deal with the limitation of lack of a sound data, some researchers have come up with calculating risk score after recalibrating the original prediction model. In a study by Chow et al.[38] investigators found that, in order to get a more accurate estimate in Indians, risk obtained from FRS can be recalibrated by multiplying the risk score with a correction factor (1.0 and 0.8 for rural men and women, respectively,1.81 and 1.54 for urban men and women respectively). But again, this method need to be validated prospectively. Another way is to check for various CV risk factors, determine their strength of association for CVD and developing an algorithm to predict CV risk. The Lipid Association of India has proposed an algorithm based on this approach that categorizes patients into various risk categories.[39]Nevetheless, this algorithm is yet to be validated in a prospective study.

Machine Learning, a term coined by Artur Samuel in 1959, meant "the ability to learn without being explicitly programmed." Machine Learning involves the use of algorithms to review data and learn from it, and making a determination or prediction as a result. Instead of hand coding software libraries with well defined specific instructions for a specefic task, the machine gets "trained" using large amounts of data and algorithms, and in turn gains the capability to perform specific tasks. "Deep Learning is a technique for implementing Machine Learning. Deep Learning was inspired by the structure and function of the brain, specifically the interconnecting of many neurons. Artificial Neural Networks (ANNs) are algorithms that are based on the biological structure of the brain. In ANNs, there are 'neurons' which have discrete layers and connections to other "neurons". Each layer picks out a specific feature to learn. It's this layering that gives deep learning its name, depth is created by using multiple layers as opposed to a single layer.[40]AI refers to the ability of machines to perform cognitive tasks like thinking, perceiving, learning, problem solving and decision making. Initially conceived as a technology that could mimic human intelligence, AI has evolved in ways that far exceed its original conception. With incredible advances made in data collection, processing and computation power, intelligent systems can now be deployed

to take over a variety of tasks, enable connectivity and enhance productivity. As AI's capabilities have dramatically expanded, so have its utility in a growing number of fields.

In a study by Ryan Poplin et al[41]using deep-learning models trained on data from 284,335 patients and validated on two independent datasets of 12,026 and 999 patients, cardiovascular risk factors not previously thought to be present or quantifiable in retinal images were predicted. Kevin M. Johnson et al[42] studied the scoring of CAD ~~coronary artery disease~~ characteristics on coronary CT angiograms by using machine learning on 6892 patients and concluded that compared with Coronary Artery Disease Reporting and Data System(CAD-RADS) and other scores, machine learning methods better discriminated patients who subsequently experienced an adverse event from those who did not.Using a DNN algorithm Chen-Ying Hung et al.[43]developed an intelligent decision support system for ischemic stroke risk assessment in a population-based electronic health record database. Using data mining and artificial neural network, Patil and Kumaraswamy(2009) proposed an intelligent and effective CV event prediction system.[44]Same authors presented an efficient approach for extracting significant patterns from the heart disease data warehouses for the efficient prediction of CV event using data mining and artificial neural network.[45]Using machine learning principles Soni et al[46] presented an intelligent and effective CV event prediction system using Weighted Associative Classifier. Despite extensive work in the field of AI, none of the AI based risk prediction model is yet validated in cardiology clinical practice.

Recognizing AI's potential to transform economies and the need for India to strategize its approach, Hon'ble Finance Minister, in his budget speech for 2018 – 2019, mandated NITI Aayog to establish the National Program on AI, with a view to guide ~~ing~~ the research and development innew and emerging technologies. In pursuance of the above, NITI Aayog has adopted a three-pronged approach – undertaking exploratory proof-of-concept AI projects in various areas, crafting a national strategy for building a vibrant AI ecosystem in India and collaborating with various experts and stakeholders.[47]

Apollo Hospitals and Microsoft developed the Cardiovascular Risk Score in Indian population based on the available data at Apollo Hospitals using AI and Machine Learning (ML).[48] The retrospective data analysis arm of the project included 31,599 participants aged between 18 to 91 between year 2010 to 2017. A multi-step risk factors selection process was used to build the prediction model. Cox-proportional hazard model analysis provided an Area under ROC (Receiver Operating Characteristic) curve (AUC-ROC) score of 0.86 on model trained with clinical parameters.

In our study, AICVD risk scoring model, based on an application developed by Microsoft incorporation, was used and compared with commonly used risk prediction models in contemporary practice. The 10-year risk of major CV events (CVD death, MI or stroke) was calculated in all patients using FRS, QRISK3 score, WHO/ISH and 7 year risk of CV event was calculated using AICVD risk score. As the FRS calculates risk in patients of minimum age 30 years old so out of 314 patients, score could be applied to only 289 patients. Similarly, 310 out of 314 patients were included in QRISK3 calculator due to minimum age variable being 25 years old. In comparison, only 115 patients could be included in WHO/ISH score because the score can not be applied to patients age <40 years. The AICVD score was applied on all 314 patients. Of these patients FRS predicted high risk (>20% 10 yearrisk) estimate only in 3(1%) patient. QRISK3 identified high risk (>10% 10 year risk) in 20(6.5%) patients while WHO/ISH identified only 1(0.9%) patient as high risk(>20% 10 year risk). On the other hand AICVD ~~stood tall by~~ identified ~~ying~~ 73(23.2%) patient as high risk for CV event at 7 years. While FRS identified 37(12.8%) patients with moderate or higher risk, QRISK3 only categorize into low or high risk thus patients with more than low risk identified in were 20(6.5%) patients. WHO/ISH predicted ?8(6.96%) patients with moderate or more 10 year risk. AICVD score predicted moderate or more risk in 197(62.74%) patients. In patients aged <35 years, while FRS identified 1(1.8%) patient as high risk, QRISK3 identified 3(3.9%) patients as high risk while AICVD score identified 18(22.2) patients as high risk. FRS identified 2(3.57%) patients in moderate or more risk, QRISK3 identified 3(3.9) as more than low risk. AICVD identifies 52 (64.2%) as high risk. In very young patients <30 years old, QRISK3 identifies 1(4.8%) patient as high risk and AICVD identifies 5(20%) patients as high risk. AICVD identifies 17(68%) patients as more than low risk.We concluded that in Indian patients, AICVD risk prediction model has highest prediction potential out of the commonly used risk prediction models.

Limitations

Our study had various limitations that needs to be mentioned. Firstly, several of our patients were already on statins which they had been taking as a part of their primary prevention therapy when they had presented to physician for hypertension/diabetes treatment. Additionally, as already known, serum lipids are affected in ACS ~~acute coronary syndromes~~ which can lead to their transient lowering. But as we had obtained samples right at the patient presentation so this factor was not likely of much clinical relevance because impact of ACS

on serum lipids is less marked ~~rs~~ in initial 24 hours. Secondly, many of the patients were already on antihypertensive therapy plus an acute event could have lead to decrease in SBP. Both these alterations could have lead to underestimation of CV risk in our study. But as all the risk prediction models used take into account these factors, so our comparative results are unlikely to be affected. Thirdly, as already has been discussed, the most appropriate method of developing a risk prediction tool is conducting a prospective study while ours was a retrospective one. But as clinicians are still awaiting a clinically applicable risk prediction model appropriate for Indian population, our study provides valuable information having significant clinical implications. Finally, the sample size of our study was relatively small. However, as we included only young patients presenting with ACS, we were able to collect reasonable number of hard CVevents to derive meaningful conclusions from it.

Conclusions

~~Perhaps~~, tThis is the first study which has compared artificial intelligence based novel risk prediction model with the three most commonly applied models, in the young Indian patients. We found that a cohort of young Indian patients presenting with ACS, when studied retrospectively, was identified as 'high risk' most likely by AICVD risk prediction model rather than the traditional counterparts. The WHO/ISH risk prediction charts and FRS were the poorest predictors. Performance of QRISK3 score also remained less than satisfactory. These findings suggested that AICVD risk prediction model is a promising tool to assess for CV risk in Indian population.

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