MACHINE LEARNING-BASED ONE-YEAR OUTCOME PREDICTION AFTER PERCUTANEOUS CORONARY INTERVENTION

I-RUK CHANMANACHAROEN

Graduate School Srinakharinwirot University

2024

การทำนายผลการรักษาโดยการเรียนรู้ของเครื่องภายหลังการถ่างขยายหลอดเลือดหัวใจผ่านทางผิวหนังในระยะเวลา 1 ปี

ไอรัก จันทร์มานะเจริญ

ปริญญานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตร
วิศวกรรมศาสตรมหาบัณฑิต สาขาวิชาวิศวกรรมชีวการแพทย์
คณะวิศวกรรมศาสตร์ มหาวิทยาลัยศรีนครินทรวิโรฒ
ปีการศึกษา 2567

MACHINE LEARNING-BASED ONE-YEAR OUTCOME PREDICTION AFTER PERCUTANEOUS CORONARY INTERVENTION

I-RUK CHANMANACHAROEN

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of MASTER OF ENGINEERING
(M.Eng. (Biomedical Engineering))
Faculty of Engineering, Srinakharinwirot University
2024

THE THESIS TITLED

MACHINE LEARNING-BASED ONE-YEAR OUTCOME PREDICTION AFTER PERCUTANEOUS CORONARY INTERVENTION

BY

I-RUK CHANMANACHAROEN

HAS BEEN APPROVED BY THE GRADUATE SCHOOL IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE MASTER OF ENGINEERING IN M.ENG. (BIOMEDICAL ENGINEERING) AT SRINAKHARINWIROT UNIVERSITY

....

(Assoc. Prof. Dr. Chatchai Ekpanyaskul, MD.)

Dean of Graduate School

....

ORAL DEFENSE COMMITTEE

.... Major-advisor

(Dr.Wongwit Senavongse, Ph.D.)

.... Chair

(Asst. Prof.Arthorn Sanpanich, Ph.D.)

.... Committee

(Dr.Theerasak Chanwimalueng, Ph.D.)

Title	MACHINE LEARNING-BASED ONE-YEAR OUTCOME PREDICTION AFTER PERCUTANEOUS CORONARY INTERVENTION
Author	I-RUK CHANMANACHAROEN
Degree	MASTER OF ENGINEERING
Academic Year	2024
Thesis Advisor	Dr. Wongwit Senavongse , Ph.D.

Cardiovascular disease (CVD), a leading non-communicable disease, remains one of the primary causes of mortality worldwide, with its prevalence increasing annually. In Thailand, CVD accounts for approximately 35% of total deaths, imposing a significant burden on the healthcare system (World Health Organization, 2021). Among the available treatment options, percutaneous coronary intervention (PCI) is widely performed to alleviate blood vessel blockages. However, the procedure carries notable risks, including in-hospital and post-discharge mortality. Accurate prediction of adverse outcomes following PCI is therefore critical for improving patient care and supporting clinical decision-making. Recently, machine learning techniques have emerged as powerful tools for predictive analysis and decision support in healthcare. This study aims to evaluate and compare the predictive performance of three widely used machine learning algorithms—Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)—alongside traditional logistic regression in assessing in-hospital and one-year mortality outcomes in PCI patients. The results indicate that the Random Forest model demonstrated the highest predictive performance for both in-hospital and one-year mortality. Specifically, the in-hospital mortality model achieved an accuracy of 0.900 (95% CI: 0.890–0.909), while the one-year mortality model attained an accuracy of 0.778 (95% CI: 0.764–0.790). These findings highlight the potential of machine learning algorithms, particularly Random Forest, in providing reliable predictions and assisting clinicians in identifying high-risk patients undergoing PCI. In conclusion, this study underscores the effectiveness of machine learning in improving mortality outcome predictions and emphasizes its utility in clinical decision-making to enhance patient outcomes within Thailand's healthcare system.

Keyword : Cardiovascular Disease, Percutaneous Coronary Intervention (PCI), Machine Learning, Clinical Decision Support, Healthcare Analytics, Mortality Prediction

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my supervisor, Dr. Wongwit Senavongse, for his invaluable guidance, support, and encouragement throughout the entire process of this thesis. His expertise and constructive feedback have been instrumental in shaping this work.

I would also like to extend my sincere appreciation to my physician advisors, Assistant Professor Worawut Roongsangmanoon and Dr. Anuchate Pattanateepapon, for their insightful advice, professional guidance, and unwavering support, which significantly contributed to the quality of my work.

I extend my heartfelt appreciation to the Cardiovascular Intervention Association of Thailand for providing the essential dataset, the Thai PCI Registry, and for facilitating all the processes necessary for this study. Their support has been invaluable in achieving my research objectives.

My heartfelt thanks go to my family for their unconditional love, patience, and encouragement throughout my academic journey. I am truly grateful for their unwavering belief in me. Additionally, I would like to thank my friends for their support, motivation, and always being there when I needed them.

Finally, I would like to extend my appreciation to everyone who has contributed, directly or indirectly, to the completion of this thesis. Your support has been deeply cherished. This work would not have been possible without all of you. Thank you for being part of this important milestone in my life.

I-RUK CHANMANACHAROEN

TABLE OF CONTENTS

Page

ABSTRACT .... D

ACKNOWLEDGEMENTS .... E

TABLE OF CONTENTS .... F

LIST OF TABLES L

LIST OF FIGURES .... O

CHAPTER 1 INTRODUCTION 1

Background 1

Objective of the Study 2

Significance of Study 2

Potential Clinical Impact of Research on Predictive Models for Post-PCI Mortality Risk 3

1. Personalized Risk Assessment 3

2. Enhanced Clinical Decision-Making 4

3. Improved Patient Outcomes 4

4. Efficient Resource Allocation 4

5. Reduction in Healthcare Costs 4

6. Support for Preventative Care Initiatives 4

7. Standardization and Consistency in Care 4

8. Advancing Precision Medicine 5

9. Facilitation of Clinical Research and Innovation 5

Research challenges 5

Knowledge Gap Between Biomedical Engineers and CAD Physicians in Collaborative Work on Machine Learning for Post-PCI Mortality Prediction .. 5

Divergent Expertise and Terminology 5

Challenges in Data Interpretation and Integration 6

Difficulty in Translating Predictions into Clinical Practice 7

The Importance of Collecting and Utilizing Domestic Data for Training Prediction Models 7

Population-Specific Variability 8

Alignment with Local Clinical Practices 8

Addressing Data Completeness and Quality 8

Enhancing Clinical Adoption and Trust 9

Strengthening Data Sovereignty and Ethical Considerations 9

Research Scope 10

Definitions and outcomes 10

Abbreviations of the research 14

Project Plan 16

CHAPTER 2 LITERATURE REVIEW 17

Coronary Artery 17

The coronary arteries are essential blood vessels that deliver oxygen-rich blood to the heart. While the endocardium can receive blood through diffusion, the myocardium, and epicardium rely on these arteries. They are divided into two primary types: the right coronary artery and the left coronary artery[18].17

Right coronary artery (RCA) 17

Left coronary artery (LCA) 17

Venous drainage of the heart 18

Atherosclerosis 19

Cardiovascular diseases (CVDs) 21

Angina 21

Interventions to treat angina. 22

Cardiac Catheterization for Balloon Angioplasty and Stenting 22

Coronary artery bypass grafting 23

Cerebrovascular disease 24

Percutaneous coronary intervention (PCI) 24

PCI procedure 24

Medication for PCI patients 25

Aspirin 25

GP IIb/IIIa Inhibitors 25

Prasugrel (P2Y12 Inhibitors) 25

Ticagrelor (P2Y12 Inhibitors) 25

Clopidogrel (Clopid) 25

Fondaparinux (Fonda) 25

Low Molecular Weight Heparin (LMWH) 26

Unfractionated Heparin (UFH, Unheparin) 26

Oral Anticoagulants 26

Angiotensin-converting enzyme Inhibitors (ACE Inhibitors) 26

Beta-Blockers 26

Statins 27

Spironolactone....................27

Vitamin K (Reversal Agent)....................27

Non-Vitamin K Oral Anticoagulants (NOACs)....................27

Machine learning....................32

XGBoost (Extreme Gradient Boosting)....................32

Support Vector Machine (SVM)....................33

Random Forest....................33

Application of Machine learning in interventional cardiology and heart failure....................34

Related works....................37

Comparing different studies' methodologies and results....................42

Logistic Regression....................47

Mathematical Foundation of Logistic Regression....................47

Interpreting the Coefficients in Logistic Regression....................47

CHAPTER 3 RESEARCH METHODOLOGY....................49

Data Source....................49

Definitions and outcomes....................49

Handing with missing data....................49

Data Preparation....................50

Feature Selection:....................55

Model Training:....................55

Model Evaluation:....................56

Performance metrics....................56

Ethics considerations....................58

CHAPTER 4 RESULT 59

In-hospital mortality 59

1-year mortality 64

CHAPTER 5 SUMMARY DISCUSSION AND SUGGESTION 72

Summary 72

In-hospital mortality outcome 72

1-year mortality outcome 72

Discussion and Suggestion 73

The problems we found while working with the work are. 73

The reason supp why random forest is better than other algorithms in this work. 74

1. Handling Imbalanced Data 74

2. Non-linearity in Data 75

3. Feature Importance and Interactions 75

4. Overfitting Risk 75

5. Data Size 76

6. Feature Scaling 76

7. Domain-Specific Factors 76

Clinical Implementation Recommendations 80

Framework for Implementing the Model in Clinical Practice 80

Validation Steps Before Clinical Deployment 81

Potential Challenges in Real-World Implementation 82

REFERENCES 85

APPENDIX 93

DATA APPROVAL 94

ETHICAL APPROVAL 95

CASE RECORD FORM.. 96

VITA 122

LIST OF TABLES

Page

Table 1 Clinical Characteristics of in-hospital mortality 11

Table 2Clinical Characteristics of 1-year Mortality 12

Table 3 Clinical Characteristics of 1-year Mortality (continuous) 13

Table 4 List of Abbreviations 14

Table 5 List of Abbreviations (continuous) 15

Table 6 Grant Graph 16

Table 7 Comprehensive Table of Medications Used in PCI Patients 28

Table 8 Comprehensive Table of Medications Used in PCI Patients (continuous) 29

Table 9 Comprehensive Table of Medications Used in PCI Patients (continuous) 30

Table 10 Comprehensive Table of Medications Used in PCI Patients (continuous) 31

Table 11 Related works 37

Table 12 Related works (Continued) 38

Table 13 Related works (Continued) 39

Table 14 Related works (Continued) 40

Table 15 Related works (Continued) 41

Table 16 Related works (Continued) 42

Table 17 Comparing different studies' methodologies and results 42

Table 18 Comparing different studies' methodologies and results (continuous) 43

Table 19 Comparing different studies' methodologies and results (continuous) 44

Table 20 Comparing different studies' methodologies and results (continuous) 45

Table 21 Data distribution of the in-hospital mortality dataset after splitting into a train-test group 50

Table 22 Data distribution of in-hospital mortality dataset after splitting into a train-test group (continuous) 51

Table 23 Data distribution of in-hospital mortality dataset after splitting into a train-test group (continuous) 52

Table 24 Data distribution of 1-year mortality dataset after splitting into a train-test group 52

Table 25 Data distribution of 1-year mortality dataset after splitting into a train-test group (continuous) 53

Table 26 Data distribution of 1-year mortality dataset after splitting into a train-test group (continuous) 54

Table 27 Data distribution of 1-year mortality dataset after splitting into a train-test group (continuous) 55

Table 28 Missing data percentages of in-hospital mortality 59

Table 29 Missing data percentages of in-hospital mortality (continuous) 60

Table 30 Univariate result for in-hospital mortality 60

Table 31 Univariate result for in-hospital mortality (continuous) 61

Table 32 Multivariate result for in-hospital mortality 62

Table 33 Model performance for in-hospital mortality 63

Table 34 Missing data percentages of 1-year mortality. 64

Table 35 Missing data percentages of 1-year mortality. (continuous) 65

Table 36 Missing data percentages of 1-year mortality. (continuous) 66

Table 37 Univariate result for 1-year mortality 66

Table 38 Univariate result for 1-year mortality(continuous) 67

Table 39 Univariate result for 1-year mortality (continuous) 68

Table 40 Multivariate result for 1-year mortality 69

Table 41 Model performance for 1-year mortality 70

Table 43 The description of each feature used in the training process for in-hospital mortality. 77

Table 44 The description of each feature used in the training process of 1-year mortality. 78

Table 45 The description of each feature used in the training process of 1-year mortality. (continuous) 79

Table 46 The description of each feature used in the training process of 1-year mortality. (continuous) 80

LIST OF FIGURES

Page

Figure 1Right coronary artery and left coronary artery. 18

Figure 2 Venous drainage of the heart. 19

Figure 3 Normal artery and an artery with plaque buildup. 20

Figure 4 Balloon angioplasty was inserted (A), inflated to open clogged arteries (B), and Artery blood flow improved (C). 22

Figure 5 Coronary Artery Bypass Grafting (CABG) 23

Figure 6 Growth in cardiac AI/ML in PubMed (*the data collected before the end of the year.) 35

Figure 7 PubMed content on Cardiac AI/ML publications recorded in 2020. (A) Publication distribution per disease category. (B) Publication distribution by data modality. (C) Publication distribution by aim. (D) Method for publishing distribution. 35

Figure 8 Confusion matrix. 56

Figure 9 Area Under the Receiver Operating Characteristic (AUROC) 58

Figure 10 The confusion matrix of the RF model with in-hospital mortality outcome 64

Figure 11The confusion matrix of the RF model with in-hospital mortality outcome 71

Figure 12 Data approval.. 94

Figure 13 Ethical approval 95

Figure 14 Thai PCI registry (demographics, episode of care, physical exam, history, and risk factors) 96

Figure 15 Thai PCI registry (CATH LAB VISIT) 97

Figure 16 Thai PCI registry (CATH LAB VISIT (continued)) 98

Figure 17 Thai PCI registry (Test performed) 99

Figure 18 Thai PCI registry (before PCI) 100

Figure 19 Thai PCI registry (Best Estimate of coronary anatomy) 101

Figure 20 Thai PCI registry (Best Estimate of coronary anatomy (continued)) 102

Figure 21 Thai PCI registry (PCI procedure, procedure information, mechanical ventricular support) 103

Figure 22 Thai PCI registry (Arterial access, Procedure medication) 104

Figure 23 Thai PCI registry (Lesion and devices) 105

Figure 24 Thai PCI registry (Lesion and devices (continued)) 106

Figure 25 Thai PCI registry (Lesion and devices (continued)) 107

Figure 26 Thai PCI registry (Investigation, pre-procedure, post-procedure) 108

Figure 27 Thai PCI registry (Intra and post-procedure clinical events) 109

Figure 28 Thai PCI registry (Discharge) 110

Figure 29 Thai PCI registry (Discharge (continuous)) 111

Figure 30 Thai PCI registry (before discharge) 112

Figure 31 Thai PCI registry (Hospital expense) 113

Figure 32 Thai PCI registry (Discharge medication) 114

Figure 33 Thai PCI registry (Follow-up 6-month) 115

Figure 34 Thai PCI registry (Follow-up 6-month (continued)) 116

Figure 35 Thai PCI registry (Follow-up 6-month expenses) 117

Figure 36 Thai PCI registry (Follow-up 12) 118

Figure 37 Thai PCI registry (Follow-up 12 (continuous)) 119

Figure 38 Thai PCI registry (Follow-up 12 expenses) 120

CHAPTER 1
INTRODUCTION

Background

Cardiovascular disease is found in more than billions of non-communication diseases around the world.[1] Moreover, this disease is the top three diseases that cause death according to the World Heart Federation (WHF) report.[2] This research focuses on the patient who receives the percutaneous coronary intervention (PCI) by the doctor's decision. Whether they are coming to the hospital because of a heart attack, myocardial infarction, myocardial ischemia, coronary artery disease, or another related disease, the doctor desires to use the PCI technique to be the treatment method.

Percutaneous coronary intervention (PCI) is a procedure used to open a blocked artery. Arteries are blood vessels that transport oxygen-rich blood throughout the body. If arteries contain a buildup of a fatty, waxy substance (plaque), you may require a PCI. Alternatively, patients might get a PCI to remove blockages after a heart attack. Coronary angioplasty is another term for PCI. This treatment can improve blood flow in a patient’s heart and reduce the symptoms of blocked arteries like chest pain and dyspnea. However, all heart treatments have some risks. Risks of a PCI procedure include major bleeding at the catheter insertion site due to the anticoagulant medicine[3], blood clots in the heart stent, stroke, heart failure, aortic dissection, revascularization, and death.

This research brought a dataset from the Thai PCI registry and applied it to several machine learning classifiers also logistic regression models to find the best models for the prediction of mortality outcome events after percutaneous coronary intervention (PCI). This research aims to find some important parameters from thirty-three in 19,701 patients. Prognostic models may predict patients at high risk for complications and low risk for undesirable outcomes following PCI. Big data analytics offers chances to explore and generate knowledge, increase clinical research, and improve healthcare. Predictive models may be constructed quickly and cost-effectively by analyzing vast amounts of electronic clinical data. These models can provide valuable insights into healthcare management issues[4].

Objective of the Study

1. To externally validate the risk prognostic models of adverse outcomes in after PCI
2. To update the risk prognostic models of adverse outcomes in after PCI
3. To assess prognostic factors that are associated with adverse outcomes after PCI.

Significance of Study

Percutaneous Coronary Intervention (PCI) has emerged as a critical treatment for managing coronary artery disease in Thailand. Insights from the Thai Percutaneous Coronary Intervention Registry (TPCIR) highlight the growing utilization and outcomes of PCI procedures. For example, between May 2006 and October 2007, 27 cardiac centers reported a total of 4,156 PCI procedures.[5]

In recent years, heart disease cases in Thailand have exhibited an upward trend. Data from 2022 indicate 958 heart disease patients per 100,000 population, a notable increase from 810 per 100,000 in 2017.[6]

Despite advancements in PCI, significant obstacles remain to providing timely access to treatment across the country. A study conducted across 1,180 hospitals from 2018 to 2019 revealed that only 49.15% of patients received timely coronary catheterization. Regional disparities are evident, particularly in the northeastern provinces, where a lack of cardiac catheterization centers limits access to care.[7]

Although these findings shed light on PCI usage and access in Thailand, comprehensive, up-to-date national statistics remain scarce. Efforts to enhance data collection and reporting are crucial to understanding trends and improving cardiovascular healthcare nationwide.

Nowadays, artificial intelligence is very famous in the classification research field because it can help us to find something that could not be found by human eyes. [8] It can reduce the load of doctor's work, time used for each patient, and risk of outcome events for some patients. Since 1988 many researchers from all over the world have tried to use machine learning to predict the risk of cardiovascular disease patients by collecting clinical data and it has had an increasing impact in the cardiovascular field. After the literature review, These two years was found that many countries have been interested in the risk of outcome events after patients received percutaneous coronary interventions such as; Japan[9], the United States[10], Iran[11], Canada[12], China[13, 14] and more. This topic is still not being presented much in Thailand. Last year, the Thai PCI registry collected data to predict patients' risk by using the statistical technique to find the index to identify the risk.

This research tries to use the PCI registry records of patients that are already available to quantify symptoms, physical characteristics, and clinical laboratory test results, which can be used to perform biostatistics analysis aimed at highlighting trends and correlations that would otherwise go unnoticed by physicians.[15] This research uses machine learning to identify and classify the most crucial characteristics in PCI registry records to develop models that can predict one-year outcomes for patients after percutaneous coronary interventions.

Potential Clinical Impact of Research on Predictive Models for Post-PCI Mortality Risk

The development and use of predictive models for assessing post-percutaneous coronary intervention (PCI) mortality risk are expected to produce significant advancements in clinical practice. Several areas of impact can be highlighted, as outlined below.

1. Personalized Risk Assessment

Through predictive models, a more precise stratification of patient risk is enabled. High-risk patients can be identified, and interventions can be tailored accordingly. Improved monitoring and alternative therapeutic approaches are expected to be facilitated.

2. Enhanced Clinical Decision-Making

Decision-making processes are supported by data-driven insights generated by these tools. Crucial choices, such as the selection of stent types or adjustments to pharmacological therapies, can be guided by the predictions provided. Proactive management of patients is thereby encouraged.

3. Improved Patient Outcomes

Outcomes for patients are likely to be improved as adverse events are reduced through early identification of risk. Preventative measures are expected to be implemented more effectively, leading to enhanced recovery and quality of life.

4. Efficient Resource Allocation

The allocation of healthcare resources can be optimized by utilizing these models. Critical care resources, such as intensive care beds, can be directed toward patients identified as high-risk. This ensures that limited resources are used most effectively.

5. Reduction in Healthcare Costs

Costs associated with post-PCI complications are anticipated to be reduced. Early intervention and preventative care, informed by predictive insights, can decrease hospital readmissions and extended stays, resulting in savings for healthcare systems.

6. Support for Preventative Care Initiatives

Preventative care strategies are expected to be enhanced by identifying trends and risk factors through longitudinal data analysis. Public health strategies and patient education programs can be informed by these findings.

7. Standardization and Consistency in Care

Standardized care delivery can be facilitated by predictive models. Treatment decisions are expected to become more consistent and evidence-based, reducing variability across providers and institutions.

8. Advancing Precision Medicine

The principles of precision medicine are supported through the integration of individual patient data into predictive modeling. The shift from generalized protocols to customized care pathways is expected to be accelerated.

9. Facilitation of Clinical Research and Innovation

Insights generated by predictive models can be utilized to identify patterns and gaps in clinical practice. Further research and innovation in cardiovascular medicine can be facilitated by these findings.

A profound impact on clinical practice is anticipated as predictive models for post-PCI mortality risk are developed and implemented. Improvements in patient outcomes, healthcare efficiency, and cost-effectiveness are expected to be achieved. By aligning with precision medicine principles, this research is likely to redefine cardiovascular care and establish a foundation for future advancements.

Research challenges

Knowledge Gap Between Biomedical Engineers and CAD Physicians in Collaborative Work on Machine Learning for Post-PCI Mortality Prediction

The collaboration between biomedical engineers specializing in machine learning and physicians treating coronary artery disease (CAD) presents both significant opportunities and unique challenges. While both fields aim to improve patient outcomes, particularly in predicting post-percutaneous coronary intervention (PCI) mortality risk, a distinct knowledge gap exists between these domains that can hinder effective interdisciplinary collaboration.

Divergent Expertise and Terminology

Biomedical engineers working with electronic health records (EHRs) focus on data-driven methodologies, including preprocessing, feature engineering, and the development of machine learning models. Their expertise lies in understanding data structures, statistical frameworks, and computational tools, often relying on algorithmic precision to extract meaningful insights. In contrast, CAD physicians bring a deep understanding of pathophysiology, clinical workflows, and patient care. Their expertise is grounded in medical intuition and practical experience, often informed by years of treating diverse patient populations.

This divergence in expertise leads to a critical barrier: differing terminologies and conceptual frameworks. For instance, while an engineer may discuss "predictor importance" or "data imputation," a physician may prioritize the clinical relevance of certain variables, such as ejection fraction or lesion complexity. The lack of shared language can make it challenging to align project goals and translate technical outputs into clinically actionable insights.

Challenges in Data Interpretation and Integration

Another gap lies in the interpretation and integration of EHR data. Biomedical engineers may approach EHR data from a statistical and computational perspective, prioritizing large-scale pattern recognition and model accuracy. However, physicians often emphasize the nuances of individual patient data, which may not always align with the generalizability sought by engineers. For instance, a machine learning model might identify age or comorbidities as significant predictors of post-PCI mortality risk, but physicians may question whether the model adequately accounts for contextual factors like treatment protocols or patient adherence to medications.

Additionally, the quality and completeness of EHR data present substantial challenges. Engineers often grapple with missing, inconsistent, or unstructured data, which require advanced preprocessing techniques. Physicians, however, may be more concerned with ensuring that the datasets accurately represent real-world clinical scenarios. Bridging this gap demands a mutual understanding of both the technical limitations of EHRs and the clinical significance of data selection.

Difficulty in Translating Predictions into Clinical Practice

The goal of developing machine learning models for post-PCI mortality prediction is to create tools that are both accurate and practical for clinical use. However, translating model predictions into actionable insights for CAD physicians is one of the hardest aspects of collaboration. Engineers may focus on optimizing model performance metrics such as accuracy, sensitivity, and specificity, but these metrics do not always align with clinical utility. On the other hand, physicians require interpretable, reliable, and seamlessly integrated models into existing clinical workflows.

The lack of interpretability in complex machine learning models, such as deep neural networks, is a particularly difficult challenge. Physicians are unlikely to trust or use a model if they cannot understand how it arrived at a prediction, especially when life-and-death decisions are involved. Explaining the rationale behind predictions in a way that aligns with clinical reasoning is a critical hurdle.

To bridge the knowledge gap and overcome these challenges, interdisciplinary efforts must prioritize the development of a shared understanding and communication framework. Both biomedical engineers and CAD physicians need to engage in cross-disciplinary education to appreciate each other's priorities and constraints. Additionally, incorporating clinicians into the model development process from the outset can help ensure that the resulting tools are both technically robust and clinically meaningful. Addressing these gaps is essential to harness the full potential of machine learning in improving post-PCI patient outcomes.

The Importance of Collecting and Utilizing Domestic Data for Training Prediction Models

Besides this, the collection and utilization of country-specific data play a pivotal role in developing accurate and reliable predictive models, particularly in the field of healthcare. For prediction models aimed at assessing post-percutaneous coronary intervention (PCI) mortality risk, the relevance of domestic data cannot be overstated. The unique characteristics of a country's population, healthcare infrastructure, and clinical practices necessitate the use of localized datasets to ensure the model's effectiveness and applicability.

Population-Specific Variability

Healthcare outcomes are influenced by a myriad of factors, including genetic predispositions, lifestyle habits, and socioeconomic conditions, all of which can vary significantly across countries. For instance, the prevalence of comorbidities such as diabetes, hypertension, or hyperlipidemia, which are known risk factors for adverse outcomes after PCI, may differ from one population to another. Training a model on domestic data allows it to capture these nuances, ensuring that predictions are tailored to the specific needs and risks of the local population. Using foreign datasets, while potentially beneficial for broader insights, may fail to account for these crucial differences, leading to biased or less accurate predictions.

Alignment with Local Clinical Practices

Clinical guidelines, procedural techniques, and resource availability can vary widely between countries, further emphasizing the importance of localized data. For example, the choice of stent types, medications, or follow-up protocols after PCI might differ due to economic constraints or national healthcare policies. A predictive model trained on data from other regions may not adequately reflect these practices, potentially compromising its clinical utility. Utilizing domestic data ensures that the model is aligned with the realities of local medical care, thereby enhancing its relevance and trustworthiness among healthcare providers.

Addressing Data Completeness and Quality

Domestic data collection also allows for greater control over data quality, completeness, and contextual relevance. Relying on international datasets may introduce inconsistencies or gaps that could undermine the model's accuracy. By prioritizing local data sources, researchers can ensure that the information used for model training is representative of the patient population and adheres to national data collection standards. This approach not only enhances the reliability of the predictive model but also fosters transparency and accountability in its development.

Enhancing Clinical Adoption and Trust

Models developed using domestic data are more likely to gain acceptance among local clinicians. Physicians are more inclined to trust predictions derived from datasets that reflect their own patient demographics and clinical environments. This trust is critical for the successful integration of predictive tools into routine medical practice, ultimately improving patient outcomes and fostering innovation in healthcare delivery.

Strengthening Data Sovereignty and Ethical Considerations

From an ethical perspective, the use of domestic data reinforces the principle of data sovereignty, ensuring that sensitive patient information remains under the jurisdiction of the originating country. This approach aligns with global trends advocating for localized data governance and protecting patient privacy while enabling the development of advanced healthcare solutions. Additionally, the use of domestic data can support national research initiatives, fostering the growth of local expertise in machine learning and predictive analytics.

Collecting and utilizing country-specific data for training prediction models is essential to ensure their accuracy, relevance, and ethical integrity. By leveraging localized datasets, researchers and clinicians can develop tools that are tailored to the unique characteristics of their population and healthcare system. This approach not only enhances the clinical utility of predictive models but also fosters trust, adoption, and long-term sustainability in healthcare innovation.

Research Scope

The Thai PCI registry dataset was used for this study. It is a prospective, multicenter, nationwide registry of patients treated with PCI in Thailand that is endorsed by the Cardiac Intervention Association of Thailand (CIAT). Training, validating, and testing the model with a dataset including up to 19,701 patient instances and 33 clinical characteristics.[15, 16] The primary endpoint was the incidence of all-cause mortality, which can be separated into 2 groups of datasets: in-hospital mortality and 1-year mortality. While random, 20% of the data was set aside for testing.[17]

Definitions and outcomes

The study's primary outcome was in-hospital death after PCI, while the secondary endpoint was all-cause mortality at 12 months. In-hospital events were logged immediately, and post-discharge events were tracked via follow-up calls. Deaths were confirmed by the Ministry of Interior's death certificates and adjudicated by the central investigator committee.

Table 1 Clinical Characteristics of in-hospital mortality

No.	Attribute Name	Label value
1	Age	
2	Gender	0: Female, 1: Male
3	BMI raw data	
4	Systolic blood pressure (SBP)	
5	Previous Heart Failure	1: Yes, 0: No
6	Previous COPD	1: Yes, 0: No
7	Previous PAD	1: Yes, 0: No
8	Previous Ischemic Heart Disease	1: Yes, 0: No
9	Previous Dyslipidemia	1: Yes, 0: No
10	Previous Diabetes Mellitus	1: Yes, 0: No
11	Previous PCI	1: Yes, 0: No
12	CAD Presentation	1: STEMI, 2: NSTEMI / Unstable Angina, 3: Stable CAD
13	Number Of Vessels	
14	Successful	
15	Hemoglobin	
16	Heart Failure	1: Yes, 0: No
17	Heart Failure Killip Class	CLASS 1: 1, 2: 2, 3: 3, 4: 4
18	LV Ejection Fraction Discharge	
19	eGFR raw data	
20	PCI procedure	1: Elective, 2: Urgent, 3: Emergency
21	Radial,	1: Yes, 0: No
22	In Hospital Mortality	1: Yes, 0: No

Table 2Clinical Characteristics of 1-year Mortality

No.	Attribute Name	Label value
1	Age	
2	Gender	0: Female, 1: Male
3	BMI raw data	
4	Systolic blood pressure (SBP)	
5	Heart rate	
6	Previous Heart Failure	1: Yes, 0: No
7	Previous Ischemic heart disease	1: Yes, 0: No
8	Previous dyslipidemia	1: Yes, 0: No
9	Previous diabetes mellitus	1: Yes, 0: No
10	Previous cerebrovascular	1: Yes, 0: No
11	History of smoking	1: Yes, 0: No
12	CAD Presentation	1: STEMI, 2: NSTEMI / Unstable Angina, 3: Stable CAD
13	PCI procedure	1: Elective, 2: Urgent, 3: Emergency
14	Aspirin	1: Yes, 0: No
15	Clopidogrel	1: Yes, 0: No
16	Fondaparinux	1: Yes, 0: No
17	Low molecular weight heparin (LMWH)	1: Yes, 0: No
18	Unfractionated Heparin	1: Yes, 0: No
19	Oral anticoagulant	1: Yes, 0: No
20	ACE inhibitor	1: Yes, 0: No
21	Beta-blocker	1: Yes, 0: No
22	Statin	1: Yes, 0: No
23	Spironolactone	1: Yes, 0: No
24	Number Of Vessels	
25	Lesion Complexity	1: A, 2: B1, 3: B2, 4: C

Table 3 Clinical Characteristics of 1-year Mortality (continuous)

No.	Attribute Name	Label value
26	Successful	1: Yes, 0: No
27	Glucose	
28	CK-MB	
29	Troponin I	
30	troponin T	
31	LDL	
32	Hemoglobin	
33	Heart Failure	1: Yes, 0: No
34	Heart Failure Killip Class	1: 1, 2: 2, 3: 3, 4: 4
35	LV Ejection Fraction	
36	eGFR Raw data	
37	Vitamin K	1: Yes, 0: No
38	Non-vitamin K oral anticoagulants ('NOAC's)	1: Yes, 0: No
39	1-year mortality	1: Yes, 0: No

Abbreviations of the research

Table 4 List of Abbreviations

Abbreviations	Definition
ACE Inhibitors	Angiotensin-converting enzyme Inhibitors
ACM	all-cause mortality
ACS	acute coronary syndrome
AL	Artificial Intelligence
ASA	Acetylsalicylic acid
BMI	body mass index
CABG	coronary artery bypass graft
CAD	coronary artery disease
CI	confident interval
CKD	Chronic kidney disease
CLOPID	Clopidogrel
CREC	Central Research Committee of Thailand
CRF	case record form
CVA	cerebrovascular accident
CVD	Cardiovascular disease
DM	Diabetes Mellitus
DOACs	Direct Oral Anticoagulants
DRF	Distribute random forest
DT	Decision tree
EC	ethics committee
eCRF	electronic case record form
eGFR	estimated glomerular filtration rate
Fonda	Fondaparinux
GP IIb/IIIa	Glycoprotein IIb/IIIa
Hb	Hemoglobin

Table 5 List of Abbreviations (continuous)

HF	heart failure
HR	heart rate
IHDPS	intelligent heart disease prediction system
KNN	K-Nearest Neighbors
LCA	Left coronary artery
LDL	Low-density Lipoprotein
LMWH	Low Molecular Weight Heparin
LR	logistic regression
LVEF	left ventricular ejection fraction
LVEF	LV Ejection Fraction
MACE	Major adverse cardiovascular events
MI	Myocardial infarction
ML	Machine Learning
NB	Naïve Bayes
NOACS	Non-Vitamin K Oral Anticoagulants
NSTEMI	non-ST elevation myocardial infarction
PAD	peripheral arterial disease
PCI	percutaneous coronary intervention
RCA	Right coronary artery
RF	Random forest
SBP	systolic blood pressure
SD	standard deviation
STEMI	ST-elevation myocardial infarction
SVM	Support vector machines
UFH	Unfractionated Heparin
XGBOOST	Extreme Gradient Boosting

Project Plan

The research is planned to start the process on 1st August 2023 and finish on 15 January 2024 at the Biomedical Engineering Department at Srinakharinwirot University.

Table 6 Grant Graph

No.	Task	Month							
		AUG-DEC	JAN-MAR	APR-JUN	JUL-AUG	SEP	OCT	NOV	DEC
1.	Literature reviews the related work								
2.	Plan and edit the research topic to support user demand								
3.	Collect and preprocess the dataset before using								
4.	External validate the model following the objective								
5.	Analyze and conclude the research result								
6.	Prepare the paper for the international conference								
7.	Working on the thesis chapters 1 to 3 for the first presentation								
8.	Working on chapters 4 to 6 the thesis for the second presentation								
9.	Edit and Summarize the final thesis submission								
10.	Present at the conference								

CHAPTER 2
LITERATURE REVIEW

Coronary Artery

The coronary arteries are essential blood vessels that deliver oxygen-rich blood to the heart. While the endocardium can receive blood through diffusion, the myocardium, and epicardium rely on these arteries. They are divided into two primary types: the right coronary artery and the left coronary artery[18].

Right coronary artery (RCA)

The right coronary artery supplies blood to the right atrium, right ventricle, and the sinoatrial (SA) and atrioventricular (AV) nodes, which regulate the heart's rhythm. It branches into smaller vessels, including the right posterior descending artery and the acute marginal artery. Along with the left anterior descending artery, the RCA also plays a role in delivering blood to the heart's central region or septum.

Left coronary artery (LCA)

The left coronary artery extends from the left aortic sinus to the coronary sulcus, traveling around the posterior and left sections of the pulmonary trunk. It supplies blood to the left atrium, left ventricle, the AV bundle, the anterior 60% of the interventricular septum, and approximately 30–45% of the SA node. The LCA is divided into the following branches:

- The left anterior descending artery, which delivers blood to the front portion of the left side of the heart.
- The circumflex artery, which originates from the LCA and encircles the heart muscle, transporting blood to the outer and posterior regions of the heart.[19]

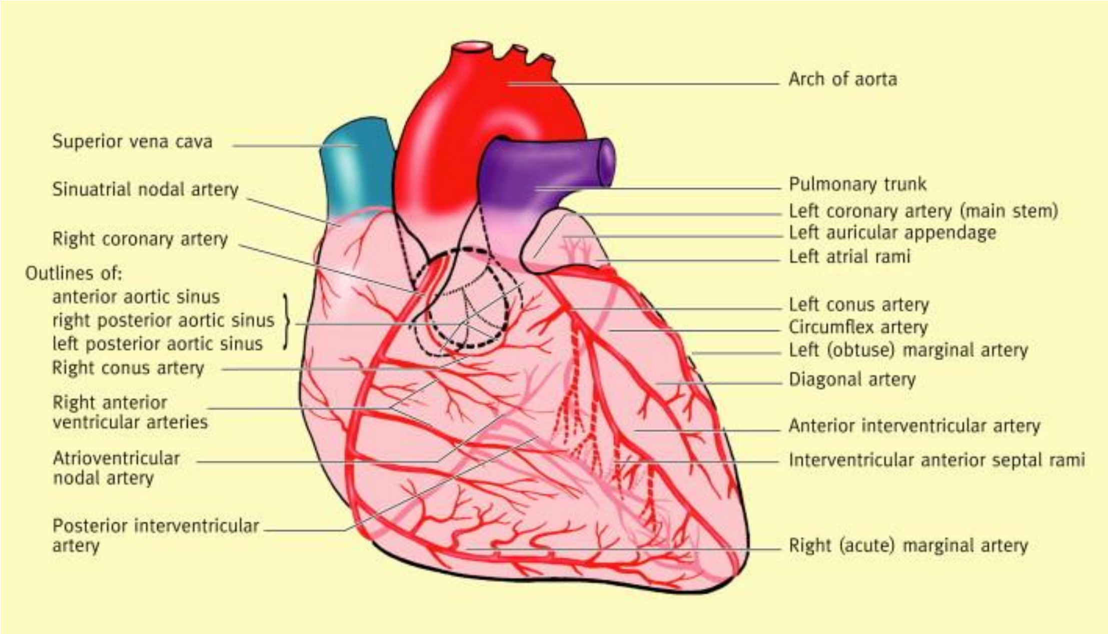


Figure 1Right coronary artery and left coronary artery.

Source: Mahadevan V. Anatomy of the heart. Surgery (Oxford). 2015;33(2):47-51.

Venous drainage of the heart

The coronary sinus, a large venous structure located on the posterior surface of the heart, is responsible for draining the majority of venous blood from the heart. Most cardiac veins empty into the coronary sinus, which subsequently drains into the right atrium. Additionally, smaller cardiac veins directly flow into the right atrium. The major tributaries of the coronary sinus include:

- Great Cardiac Vein (Anterior Interventricular Vein): The largest tributary of the coronary sinus, this vein originates at the apex of the heart and travels upward through the anterior interventricular groove. It then curves to the left, continuing to the heart's posterior surface, where it gradually widens to form the coronary sinus.
- Small Cardiac Vein: Positioned on the anterior surface of the heart, this vein runs along a groove between the right atrium and right ventricle. It traverses this groove to the posterior side of the heart, where it empties into the coronary sinus.

- **The middle cardiac vein** (also known as the posterior interventricular vein) originates at the apex of the heart and drains into the coronary sinus through the posterior interventricular groove.
- **The posterior cardiac vein** is situated on the back of the left ventricle. It enters the coronary sinus to the left of the great cardiac vein..[20]

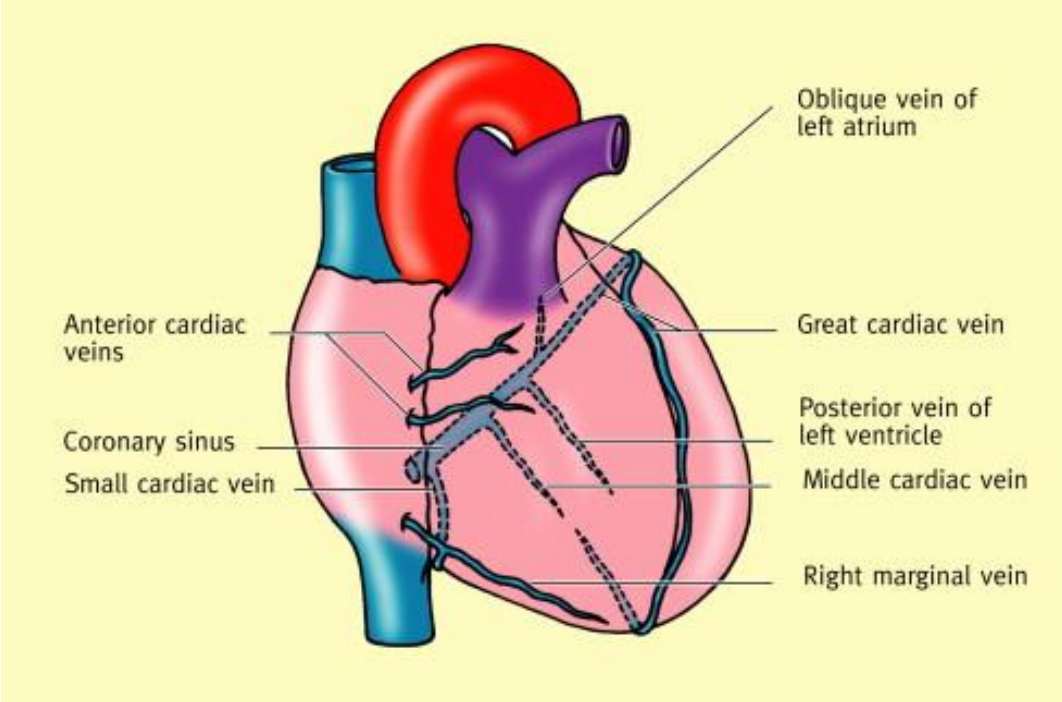


Figure 2 Venous drainage of the heart.

Source: Mahadevan V. Anatomy of the heart. Surgery (Oxford). 2015;33(2):47-51.

Atherosclerosis

Atherosclerosis is a prevalent condition characterized by the buildup of a sticky substance called plaque within the arteries. This disease develops gradually as plaques made up of cholesterol, fats, blood cells, and other substances in the bloodstream accumulate. The presence of plaque causes the arteries to narrow, reducing the flow of oxygen-rich blood to essential organs and tissues. Atherosclerosis can affect various arteries throughout the body and is referred to by different names depending on the location of the affected arteries. For example, when it impacts the heart's arteries, it is known as coronary artery disease (CAD). When it affects arteries in the brain, it is called vertebral artery disease. If it involves the arms, legs, and pelvis, it is referred to as peripheral artery disease (PAD), while the narrowing of the arteries in the kidneys is called renal artery stenosis.

Angina can occur due to reduced blood flow. If a plaque ruptures, it may lead to the formation of blood clots that can obstruct the artery or travel to other parts of the body. These blockages, whether complete or partial, can lead to serious complications such as heart attack, stroke, vascular dementia, erectile dysfunction, or even limb loss. In severe cases, atherosclerosis may result in death or permanent disability..[21]

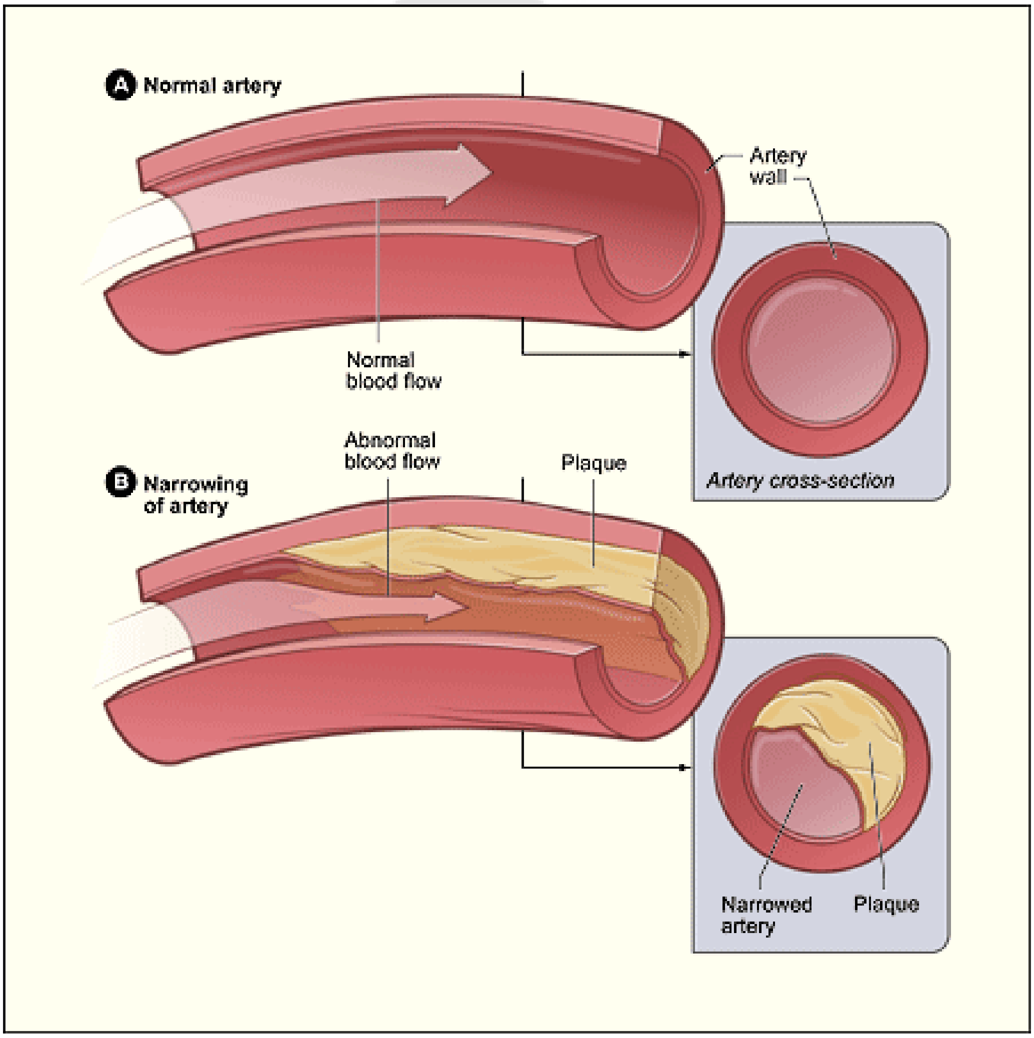


Figure 3 Normal artery and an artery with plaque buildup.

Source: https://www.nhlbi.nih.gov/health/atherosclerosis

Cardiovascular diseases (CVDs)

Cardiovascular diseases (CVDs) encompass various conditions affecting the heart and blood vessels. These include:

- **Coronary Heart Disease**: A condition impacting the blood vessels that supply oxygen and nutrients to the heart muscle.
- **Cerebrovascular Disease**: A disorder involving blood vessels that deliver blood to the brain.
- **Peripheral Arterial Disease**: A condition that affects the arteries supplying blood to the arms and legs.
- **Rheumatic Heart Disease**: Damage to the heart muscles and valves caused by streptococcal bacteria during rheumatic fever.
- **Deep Vein Thrombosis and Pulmonary Embolism**: Blood clots that form in the veins of the legs, which may break loose and travel to the heart or lungs.[22]

Angina

Angina is a symptom of heart disease rather than a standalone condition. It is most commonly caused by coronary artery disease (CAD), a specific type of heart disease. CAD occurs when fatty deposits, or plaque, build up within the inner walls of the coronary arteries, which are the primary blood vessels supplying oxygen and nutrients to the heart. This plaque accumulation, known as atherosclerosis, leads to the narrowing of arteries and reduced blood flow.

While CAD is the leading cause of angina, other conditions such as coronary artery spasms or abnormalities in the artery lining (endothelium) can also trigger similar symptoms. Because of this, doctors typically conduct a detailed medical history and perform various tests to determine the exact cause of angina symptoms and rule out other potential conditions, some of which may be serious.

If you experience persistent chest pain, intense pressure in the chest, or pain accompanied by symptoms such as nausea, sweating, dizziness, or shortness of breath, it is important to seek emergency medical attention. The treatment approach will depend on the underlying cause of the pain.

Interventions to treat angina.

Interventional procedures are medical treatments designed to address blockages in the heart's arteries by either opening them or bypassing them through surgery. Contrary to common belief, the main goal of these procedures is to alleviate chest pain symptoms rather than to lower the risk of future heart attacks. Studies have not demonstrated that angioplasty or bypass surgery significantly reduces the risk of death or recurrence of heart attacks in individuals with angina.

Cardiac Catheterization for Balloon Angioplasty and Stenting

Interventional procedures often begin with cardiac catheterization, a technique in which a long, slender tube called a catheter is inserted into a blood vessel in the arm or leg. The catheter is carefully guided through the blood vessels to reach the coronary arteries. Once positioned, the doctor performs a procedure to open the blocked artery, such as balloon angioplasty or the placement of a stent.[23]

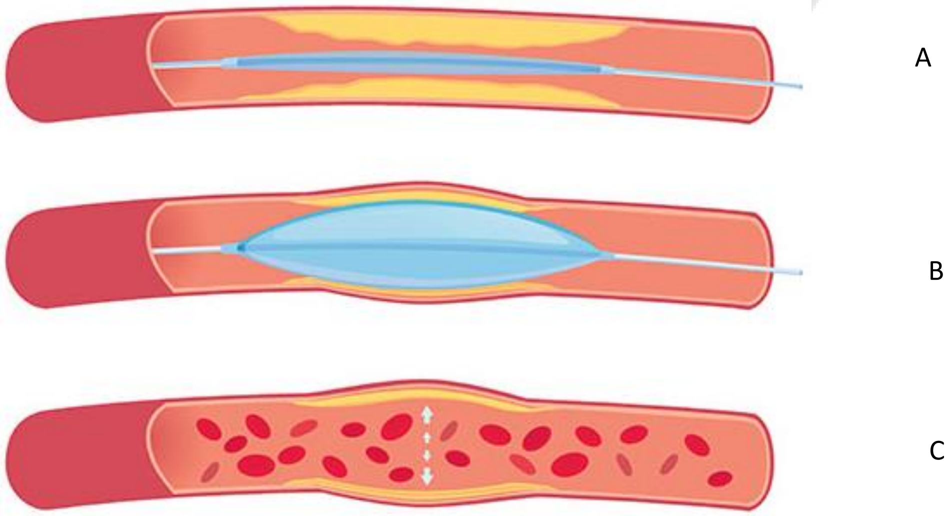


Figure 4 Balloon angioplasty was inserted (A), inflated to open clogged arteries (B), and Artery blood flow improved (C).

Source: https://cavsclinic.com/service-single.php?id=22

Coronary artery bypass grafting

Coronary artery bypass surgery reroutes blood flow around a blocked or partially obstructed artery in the heart. This is done by using a healthy blood vessel, typically taken from the chest or leg, which is attached below the blocked coronary artery. This new pathway improves blood flow to the heart muscle. While the surgery does not cure the underlying condition causing the blockage, such as atherosclerosis or coronary artery disease, it can help alleviate symptoms like chest pain and shortness of breath. Commonly referred to as CABG, this procedure may also reduce the risk of death from heart disease.[24]

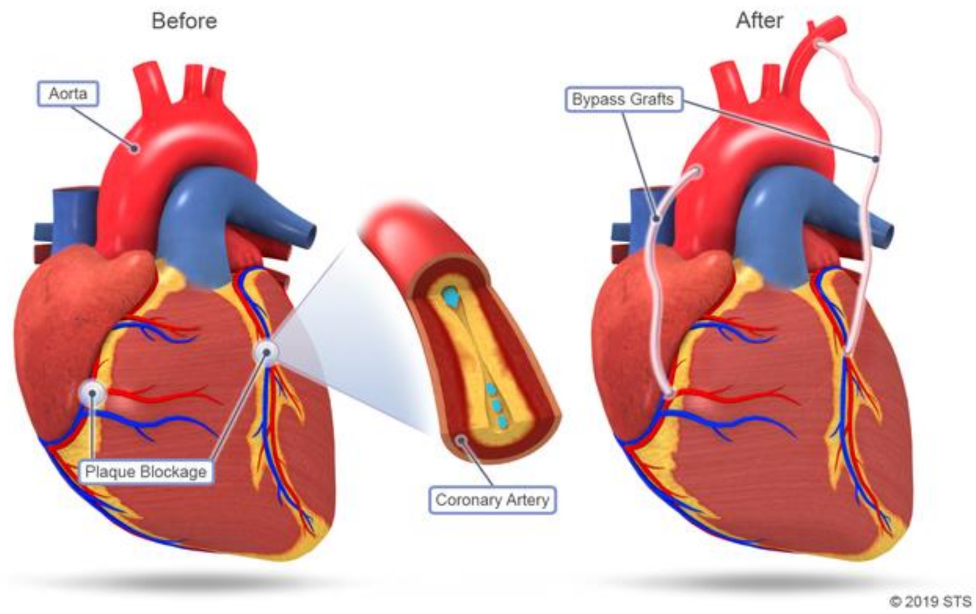


Figure 5 Coronary Artery Bypass Grafting (CABG)

Source: https://ctsurgerypatients.org/procedures/coronary-artery-bypass-grafting-cabg

Cerebrovascular disease

Cerebrovascular disease refers to disorders that impair blood flow to the brain. Stroke, brain aneurysm, brain hemorrhage, and carotid artery disease are all conditions. These are health emergencies that require immediate care, such as drugs and surgery. Though impairment or death may occur, some people recover completely.

Cerebrovascular disorders can result in a reduction in blood flow to your brain (ischemia) or bleeding (hemorrhage) in a portion of your brain. Both illnesses are commonly referred to as "stroke." Strokes and other vascular problems can be caused by blood vessel diseases in the brain.[25]

Percutaneous coronary intervention (PCI)

Percutaneous coronary intervention (PCI) is a minimally invasive procedure used to open narrowed or blocked sections of the coronary arteries, helping to restore blood flow, reduce symptoms, and improve heart function. Compared to coronary artery bypass surgery, PCI carries fewer risks, is less invasive, and requires a shorter recovery period.

This procedure is commonly used to treat conditions like coronary artery disease and acute coronary syndrome. However, doctors will evaluate whether PCI is the most appropriate treatment option for a patient. In some situations, medications or coronary artery bypass graft (CABG) surgery may provide more effective results for managing these conditions.[26]

PCI procedure

1. A small hollow tube (sheath) is placed into a blood vessel, either in the arm or near the upper thigh.
2. A thin, flexible tube (catheter) is guided through the sheath and advanced toward the heart.
3. Contrast dye is injected, and X-rays are used to visualize the catheter's movement in real time.
4. A balloon at the catheter's tip is inflated to clear the blockage in the artery.
5. If needed, a stent is inserted to maintain the artery's openness.[27]

Medication for PCI patients

Aspirin

Commonly known as aspirin, acetylsalicylic acid is a widely used medication for managing pain and fever associated with various conditions. It possesses anti-inflammatory and antipyretic properties. Additionally, ASA inhibits platelet aggregation, making it an effective treatment for preventing blood clots, strokes, and myocardial infarctions (heart attacks).[28]

GP IIb/IIIa Inhibitors

Glycoprotein IIb/IIIa inhibitors work by blocking the GP IIb/IIIa receptors, thereby reducing platelet aggregation. These inhibitors are commonly used in the management of coronary artery disease (CAD). Tirofiban and eptifibatide are two examples of GP IIb/IIIa inhibitors currently available on the market..[29]

Prasugrel (P2Y12 Inhibitors)

Prasugrel is a P2Y12 platelet inhibitor that is used to lower the risk of thrombotic cardiovascular events in patients with unstable angina or non-ST-elevation myocardial infarction (NSTEMI), as well as in STEMI patients who are treated with either primary or delayed PCI.[30]

Ticagrelor (P2Y12 Inhibitors)

Ticagrelor is a P2Y12 platelet inhibitor intended to prevent future myocardial infarction, stroke, and cardiovascular mortality in individuals with a history of myocardial infarction or acute coronary syndrome (ACS).[31-35]

Clopidogrel (Clopid)

Clopidogrel inhibits the P2Y12 receptor on platelets, blocking ADP-induced platelet aggregation. This reduces the risk of blood clots forming in stents or at the PCI site.[36]

Fondaparinux (Fonda)

Fondaparinux selectively binds to antithrombin III, enhancing its inhibition of factor Xa. This prevents the formation of thrombin and fibrin clots. It is used to prevent deep vein thrombosis (DVT) and pulmonary embolism and to reduce clot formation during PCI.[37]

Low Molecular Weight Heparin (LMWH)

LMWH binds to antithrombin III, accelerating its inhibition of factor Xa and thrombin (factor IIa). This reduces the blood's ability to clot. It is used to prevent thrombus formation during and after PCI, especially in high-risk patients.[38]

Unfractionated Heparin (UFH, Unheparin)

Unfractionated heparin enhances the activity of antithrombin III, inhibiting both factor Xa and thrombin (factor IIa). This interrupts the clotting cascade. It is used to prevent clot formation during PCI, particularly in acute coronary syndrome (ACS) patients.[38]

Oral Anticoagulants

- **Warfarin** inhibits vitamin K-dependent clotting factors (II, VII, IX, X).
- **Direct Oral Anticoagulants (DOACs)** directly inhibit thrombin or factor Xa.

It is used to reduce the risk of thrombosis, especially in patients with atrial fibrillation, mechanical heart valves, or venous thromboembolism post-PCI.[39]

Angiotensin-converting enzyme Inhibitors (ACE Inhibitors)

ACE inhibitors prevent the conversion of angiotensin I into angiotensin II, a substance that causes blood vessels to constrict. By blocking this process, ACE inhibitors lower blood pressure and decrease the workload on the heart. They are commonly used to enhance cardiac function, reduce afterload, and prevent heart failure, especially following PCI in patients with left ventricular dysfunction or hypertension.[40]

Beta-Blockers

Beta-blockers block β1-receptors in the heart, reducing sympathetic stimulation, heart rate, and contractility. It is used to reduce myocardial oxygen demand, heart rate, and blood pressure, preventing arrhythmias and recurrent ischemia post-PCI.[41]

Statins

Statins inhibit HMG-CoA reductase, the rate-limiting enzyme in cholesterol synthesis. This lowers LDL levels and stabilizes atherosclerotic plaques. It is used to lower LDL cholesterol and reduce inflammation, thereby preventing restenosis and recurrent coronary events post-PCI.[42]

Spironolactone

Spironolactone blocks aldosterone receptors in the kidneys, promoting sodium excretion and potassium retention, reducing fluid overload and cardiac workload. It is used to manage heart failure and reduce fluid overload in PCI patients with reduced ejection fractions.[43]

Vitamin K (Reversal Agent)

Vitamin K promotes the synthesis of clotting factors II, VII, IX, and X, restoring the blood's ability to clot. It is used to reverse the effects of warfarin-induced anticoagulation if excessive bleeding occurs post-PCI.[39]

Non-Vitamin K Oral Anticoagulants (NOACs)

NOACs directly inhibit either factor Xa (rivaroxaban, apixaban) or thrombin (dabigatran), thereby disrupting the coagulation cascade. It is used as an alternative to warfarin for preventing thrombosis in PCI patients, particularly those with atrial fibrillation or venous thromboembolism.[44]

Table 7 Comprehensive Table of Medications Used in PCI Patients

Medication	Class	Mechanism of Action	Why Used in PCI	Reference
Clopidogrel (Clopid)	Antiplatelet (P2Y12 inhibitor)	Inhibits P2Y12 receptors, preventing ADP-induced platelet aggregation	Prevents stent thrombosis and platelet aggregation	Patrono et al., 2017; European Heart Journal
Fondaparinux (Fonda)	Anticoagulant (Factor Xa inhibitor)	Enhances antithrombin III activity to inhibit factor Xa	Reduces thrombus formation during PCI	Yusuf et al., 2006; NEJM
Aspirin	Antiplatelet (COX-1 inhibitor)	Irreversibly inhibits COX-1, reducing thromboxane A2 production	Prevents platelet aggregation and thrombosis	Patrono et al., 2017; European Heart Journal
GP IIb/IIIa Inhibitors	Antiplatelet agents	Block IIb/IIIa receptors, preventing fibrinogen binding and platelet aggregation	Reduces acute thrombotic complications	G. W. Stone et al., 2007; JAMA

Table 8 Comprehensive Table of Medications Used in PCI Patients (continuous)

Medication	Class	Mechanism of Action	Why Used in PCI	Reference
Prasugrel	Antiplatelet (P2Y12 inhibitor)	Irreversibly inhibits P2Y12 receptors on platelets	Reduces thrombotic events post-PCI	Stephen et al., 2007; NEJM
Ticagrelor	Antiplatelet (P2Y12 inhibitor)	Reversibly inhibits P2Y12 receptors, preventing platelet aggregation	Provides faster and stronger platelet inhibition	Wallentin et al., 2009; NEJM
Low Molecular Weight Heparin (LMWH)	Anticoagulant	Inhibits factor Xa and thrombin (IIa)	Prevents thrombus formation during and after PCI	Hirsh et al., 2001; *Circulation*
Unfractionated Heparin (UFH)	Anticoagulant	Enhances antithrombin III activity, inhibiting factor Xa /IIa	Prevents acute clot formation during PCI	Hirsh et al., 2001; *Circulation*

Table 9 Comprehensive Table of Medications Used in PCI Patients (continuous)

Medication	Class	Mechanism of Action	Why Used in PCI	Reference
Oral Anticoagulants	Anticoagulant	Inhibit vitamin K-dependent factors (Warfarin) or factor Xa/thrombin (DOACs)	Prevent thromboembolism in high-risk patients	You JJ et al., 2012; *CHEST*
ACE Inhibitors	Antihypertensive	Block angiotensin-converting enzyme, reducing angiotensin II	Lowers BP, improves cardiac function post-PCI	Yusuf et al., 2011; *Lancet*
Beta-Blockers	Beta-adrenergic blockers	Block β1-receptors to reduce heart rate and myocardial oxygen demand	Prevent arrhythmias, ischemia, and recurrent events	Bangalore et al., 2006; *BMJ*
Statins	Lipid-lowering agents	Inhibit HMG-CoA reductase, lowering LDL cholesterol and stabilizing plaques	Reduce LDL, prevent restenosis and plaque rupture	Cannon et al., 2004; *NEJM*

Table 10 Comprehensive Table of Medications Used in PCI Patients (continuous)

Medication	Class	Mechanism of Action	Why Used in PCI	Reference
Spironolactone	Aldosterone antagonist	Blocks aldosterone receptors, reducing sodium and fluid retention	Manages heart failure and fluid overload	Pitt et al., 1999; *NEJM*
Vitamin K	Vitamin	Promotes synthesis of vitamin K-dependent clotting factors	Reverses warfarin-induced anticoagulation	Holbrook et al., 2012; *CHEST*
NOACs (Apixaban, Rivaroxaban, Dabigatran)	Anticoagulant	Directly inhibit factor Xa (apixaban, rivaroxaban) or thrombin (dabigatran)	Prevent thrombosis, alternative to warfarin	Connolly et al., 2009; *NEJM*

Machine learning

Machine learning (ML) has recently gained significant popularity across various data science fields worldwide. ML algorithms are highly adaptable, capable of handling data uncertainty without rigid constraints, and excel in processing large datasets.[45, 46] In cardiovascular care, ML has the potential to improve precision medicine and predict future adverse events following PCI. This is facilitated by the widespread use of electronic health record (EHR) systems in hospitals and the availability of extensive medical datasets.[10] [47]

XGBoost (Extreme Gradient Boosting)

XGBoost is an optimized gradient-boosting library that builds an ensemble of decision trees. It is highly efficient and scalable for structured/tabular data. The model minimizes the following regularized objective function:[48]

$$\mathrm{Obj} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

,where

$$\Omega(f_k) = \Upsilon^{T} + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$$

- l: Loss function (e.g., log loss for classification)
- Ω: Regularization term
- T: Number of leaves in a tree.
- w_j: Weights for leaf nodes.
- γ and λ : Regularization hyperparameters.

- Pros:
  - Handles missing data and imbalanced datasets well.
  - Faster and optimized compared to regular Gradient Boosting.
  - Supports parallel computing and regularization (L1 and L2).
- Cons:
  - Hyperparameter tuning can be complex and time-consuming.

- Risk of overfitting for small datasets if not carefully tuned.

Support Vector Machine (SVM)

SVM is a supervised learning model that works by finding the optimal hyperplane that separates classes in a high-dimensional space.[49]

$$\min_{w,b} \frac{1}{2} \|w\|^2$$

, Subject to

$$y_i(w * x_i + b) \geq 1, \forall_i$$

- w: Weight vector.
- b: Bias term.
- y_i: Class label (+1 or -1).

- Pros:
  - Effective for high-dimensional data and small datasets.
  - Works well with a clear margin of separation.
  - Can use kernel tricks (linear, polynomial, RBF, etc.) for non-linear data.
- Cons:
  - Computationally expensive for large datasets.
  - Requires careful kernel selection and tuning of hyperparameters.
  - Does not perform well with noisy or overlapping data.

Random Forest

Random Forest is an ensemble learning method that builds multiple decision trees using bootstrapped datasets and feature randomization. It aggregates the output of these trees (majority voting for classification).[50]

$$\hat{y} = mode(f_1(x), f_2(x), \ldots, f_n(x))$$

- f_i: Individual decision tree outputs.
- n: Number of trees.

- Pros:
  - Reduces overfitting compared to individual decision trees.
  - Works well with large datasets and high-dimensional data.
  - Handles missing values and categorical features effectively.

- Cons:
    - Slower prediction for large ensembles.
    - Less interpretable compared to single decision trees.
    - Memory-intensive for large datasets.

Application of Machine learning in interventional cardiology and heart failure

For the physician to plan the treatment or follow the response using a lot of patterns of patient data from electronic health records this is one of the big processes of work for physicians to identify the diagnostics patterns.(45) For this reason, machine learning, AI, or deep learning can support physicians by screening through the whole dataset and predicting the risks that physicians should be aware of or help them diagnose. It does not mean that technology can work instead of the physician, but the concept idea is helping them support what they think, screening some relative points that humans could not find, and reducing the load of their work due to the number of patients per physician. The literature review found that the trend of ML in cardiology has been very popular in recent years but wasn't much enough for Thailand.(15)

The record PubMed reports that several cardiac Artificial intelligent and Machine Learning have gain enormous interest in recent years and from the report found that Atherosclerosis is the most famous topic in this field due to the numerous of patients.(45)

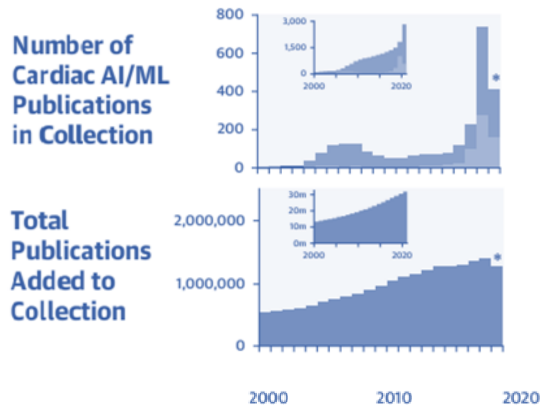


Figure 6 Growth in cardiac AI/ML in PubMed (*the data collected before the end of the year.)

Source: https://www.sciencedirect.com/science/article/pii/S0735109720378943

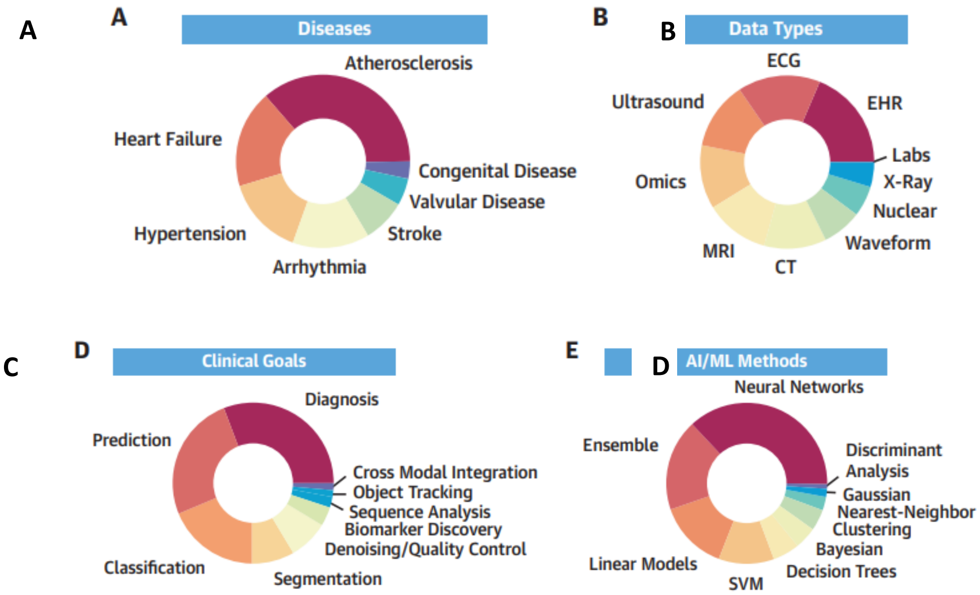


Figure 7 PubMed content on Cardiac AI/ML publications recorded in 2020. (A) Publication distribution per disease category. (B) Publication distribution by data modality. (C) Publication distribution by aim. (D) Method for publishing distribution.

Source: https://www.sciencedirect.com/science/article/pii/S0735109720378943

The algorithms that this study used are the ten most popular common algorithms in this field of work. The definitions of them are shown in the table below.

Table 15 Definition of algorithms in this study

No.	Name of algorithm	Definition
1	eXtreme Gradient Boosted trees (XGBoost)	This approach is an ensemble method, meaning it combines multiple versions of a model sequentially, with each iteration correcting the errors of the previous ones. It is user-friendly, fast, and an excellent choice for those starting with machine learning algorithms. [51]
2	Distribute random forest (DRF)	The model combines decision trees, each trained on a dataset subset, and aggregates their predictions for the final output. It offers high accuracy, evaluates variable importance, handles large, high-dimensional datasets, and is easy to construct. [52]
3	Logistic Regression (LR)	Logistic regression is a statistical technique used to describe and analyze the relationship between a dependent binary variable and one or more independent variables. These independent variables can be nominal, ordinal, interval, or ratio in nature. [53]
4	Support vector machine (SVM)	SVM performs classification by creating a hyperplane, which can be visualized as a line in 2D or a plane in 3D. This hyperplane separates data points such that those belonging to one category are positioned on one side, while data points of the other category are on the opposite side.

The Figure 7 will support this study for working on ML for predicting the risk for patients after PCI by using the electronic health record. The summary of the literature review is shown in the table below.

Related works

Table 11 Related works

Study	Number of patients	ML approach	ML algorithms	Description
Akhmetzhan Galimzhanov et al.[10]	1,815,595	Multiple ML models	LR, SVM, NB, RF, XGBoost	Develop a multiclass ML model to predict all-cause mortality, ischemic, and bleeding of patients undergoing PCI.
Saeed Tofighi et al.[11]	4,514	Multiple ML models, Deep Learning (DL)	XGBoost, DRF, LR, DL	Predict major adverse cardiovascular events (MACE) for 1-year follow-up.
Luyao Huang et al.[14]	151	ML model	LR	Finding the risk factors for in-hospital MACE
Xueyan Zhao et al.[3]	16,736	Multiple ML models	XGBoost, CRUSADE, ACUITY-HORIZONS	Predicting in-hospital hemorrhage in patients with acute myocardial infarction patients after PCI.
A.V.Senthil Kumar[54]	303	Combine technique	ANFIS (ANN+ Fuzzy logic (FL))	Developing the ANFIS for diagnosis of heart disease.

Table 12 Related works (Continued)

Study	Number of patients	ML approach	ML algorithms	Description
Nozomi Niimi et al.[9]	24,848	Multiple ML models	LR, XGBoost	Prediction of adverse events (acute kidney injury, bleeding, mortality) after PCI.
Jaihoon Amon et al.[12]	1,770	ML model	LR	Developing predictor of adverse events among initially stable ST-Elevation myocardial infraction patients after PCI.
Christopher M. Cook et al.[55]	1,008	Supervised Learning	AI called iFR pressure-wire pull back data	For iFR interpretation, the ML algorithm was compared against an expert team.
Vanisree K et al.[56]	200	Supervised Learning	Backpropagation (BP) Neural Network	Decision support system for diagnosis the congenital heart disease.
Milan Kumari et al.[57]	296	Supervised Learning, multiple ML models	BP, RIPPER, Decision Tree, ANN, SVM	Compare methods for predicting cardiovascular disease.
Nabeel Al-Milli[58]	166	Supervised Learning	BP	Using BP for predicting heart disease.

Table 13 Related works (Continued)

Study	Number of patients	ML approach	ML algorithms	Description
Branko Ster et al.[59]	2,182	Supervised Learning, multiple ML models	BP, Learning vector quantization (LVQ), Classification and Regression Trees (CART), Linear Discriminant analysis (LDA), Quadratic Discriminant Analysis (QDA), K-nearest neighbor (KNN), Lookahead Feature Construction (LFC), Assistant-I (ASI), Assistant-R (ASR), NB, Semi-naïve Bayes (SNB)	Comparing multi-methods of neural network in medical diagnosis.
Resul Das et al.[60]	297	Supervised Learning	BP, Neural network ensemble	Using SAS for diagnosis heart disease with neural network ensemble technique.
Gunta Srilakshmi et al.[52]	918	Multiple ML models	KNN, Decision Tree, RF, SVM, LR	Forecasting congestive heart failure.

Table 14 Related works (Continued)

Study	Number of patients	ML approach	ML algorithms	Description
C. Beulah Christalin Latha et al.[61]	303	Supervised Learning, multiple ML models	NB, Bayes Net, C4.5, Multilayer perception, Projective Adaptive Resonance Theory (PART)	Improve model by using bagging, boosting ensemble, majority voting, stacking for prediction of heart disease.
Peter W.F Wilson et al.[62]	5,345	ML algorithm	Logistic function with Weibull distribution	Finding index range of risk factors for predicting risk factors of coronary heart disease.
Azzalini et al[63].	2,648	ML algorithm	iso-osmolar contrast media (IOCM), low-osmolar contrast media (LOCM)	Determine whether there is a difference in the risk of CI-AKI following percutaneous coronary intervention (PCI) based on the type of contrast media (CM).
Robert Detrano et al.[64]	1,071	Multiple ML algorithms	LR, CADENZA (Bayesian method)	Testing CADENZA algorithm to diagnosis three groups of CAD patient.
Istaiak Mahmud et al.[65]	918	ML algorithm	Meta model	The development of metamodel to predict heart failure.

Table 15 Related works (Continued)

Study	Number of patients	ML approach	ML algorithms	Description
Senthilkumar Mohan et al.[66]	297	Supervised learning	* HRFLM * NB * Generalized linear model * LR * DL * Decision tree * RF * XGBoost * SVM * VOTE	Develop the HRFLM model to predict heart disease and compare the model with another popular algorithms.
Liaqat Ali et al.[67]	297	Multiple ML algorithms	L1 Linear SVM + L2 Linear & RBF SVM	Using an expert system that slacks two SVM models to improve prediction of heart failure
S. Jabeen Begum et al.[68]	303	Multiple ML algorithms	KNN * K-mean clustering	Using k-mean clustering and KNN algorithms to predict heart disease.
A. Sheik Abdullah et al.[69]	-	ML algorithm	Random forest	Data classification uses random forest classifiers to predict the risk of coronary heart disease.

Table 16 Related works (Continued)

Study	Number of patients	ML approach	ML algorithms	Description
Sellappan Palaniappan et al.[70]	909	Multiple ML algorithms	Decision trees * NB * Neural network	Develop a prototype intelligent heart disease prediction system (IHDPS)
Kemal Polat et al.[71]	270	Supervised Learning	Artificial immune recognition system (AIRS)	Prediction the heart disease by using AIRS

Comparing different studies' methodologies and results

Table 17 Comparing different studies' methodologies and results

Authors	Study type (enrollment period)	N	Methods	Outcome	ROC
Worawut R. et al.	multicenter registry (2018-2019)	22,741	* Cox regression model * Herrrell's C-statistic on STATA version 17.0	Bleeding	0.674
Nozomi Niimi et al.	Multicenter registry (2008-2020)	24,848	* LR * XGB	* AKI * Bleeding * In-hospital death	AKI (LR/XGB) 0.83/0.84 Bleeding 0.75/0.79 In hospital death 0.95/0.96

Table 18 Comparing different studies' methodologies and results (continuous)

Authors	Study type (enrollment period)	N	Methods	Outcome	ROC
Xueyan Zhao et al.	Multicenter registry (2013-2016)	16,736	* XGBoost * CRUSADE score * Acuity Horizons score	* In-hospital * bleeding * non-bleeding	* XGBoost model 0.837 * CRUSADE score 0.741 * Acuity Horizons score 0.731
Luyao Huang et al.	Single center registry (2019-2022)	188	* Univariate LR * Backward stepwise multivariate LR	* MACE * non-MACE	0.778
Saeed Tofighi et al.	Single center registry (2011-2019)	4,514	* GBM * DRF * LR * Deep learning	* MACE during 1 year follow up * non MACE	* GBM 0.91 * Deep learning 0.86 * LR 0.85 * DRF 0.92
Akhmetzhan Galimzhanov et al.	Multicenter registry (2016-2019)	1,815,595	* SVM * NB * RF * XGBoost * LR	*Death *Bleeding * CVE *Bleeding and death * Ischemic CVE and death * Bleeding and ischemic CVE * All	* SVM 0.84 * NB0.81 * RF 0.83 * XGBoost 0.86 * LR 0.83

Table 19 Comparing different studies' methodologies and results (continuous)

Authors	Study type (enrollment period)	N	Methods	Outcome	ROC
Masahiro Natsuaki et al.	Multicenter registry (2005-2007)	13,058	* Using Cox proportional hazard models to estimate the effects of the HBR and non-HBR for clinical events.	* Bleeding * MI * Death *Target lesion revascularization * Any coronary revascularization	0.66
Zhixun Bai et al.	Single center registry (2016-2020)	2,580	* CatBoost * RF * XGBoost * LR * KNN * GRACE Score	* Procedure success * All-cause mortality	* CatBoost 0.87 * RF 0.88 * XGBoost 0.83 * LR 0.82 * KNN 0.75 * GRACE Score 0.80
Shangyu Liu et al.	Single center registry (Jan2013-Dec2013)	10,724	* SVM * Decision tree * RF * Gradient boosting decision tree * Neural network * LR	* Procedure success * All-cause mortality	* SVM 0.47 * Decision tree 0.51 * RF0.71 * Gradient boosting decision tree 0.70 * Neural network 0.57 * LR 0.67

Table 20 Comparing different studies' methodologies and results (continuous)

Authors	Study type (enrollment period)	N	Methods	Outcome	ROC
Jinwan Wang et al.	Single center registry (2019-2020)	1,004	* DT * RF * LR * NB * SVM * XGBoost	* MACE during 6 months * non MACE	* DT 0.7035 * RF 0.7522 * LR 0.7434 * NB 0.7058 * SVM 0.7478 * XGBoost 0.7788
Chenxi Huang et al.	Multiple Center Registry (2009-2011)	947,091	Lasso regularization * Lasso regression No variable selection * XGBoost-Full Permutation selection * XGBoost	post-PCI AKI	Lasso regularization * Lasso regression 0.733 No variable selection * XGBoost-Full 0.759 Permutation selection * XGBoost 0.752

In conclusion, research in the field of Machine learning and Artificial Intelligence when used with cardiac disease has gained enormous interest more than 20 years ago. The algorithms that have always been used in this decade are eXtreme Gradient Boosted trees (XGBoost), Distribute random forest (DRF), Logistic Regression (LR), and Support vector machine (SVM), These are all effective algorithms. However, the efficiency and accuracy of algorithms depend on the parameters set, dataset, pre-processing procedure, and many other reasons. This is the reason this study decided to use the four algorithms above and compare their efficiency and accuracy in Chapter 4. The model developed by the group of datasets is learning by data learned so it will be most effective while using the model learned by its own country. This is the reason people around the world try to collect their datasets and train the model with many more datasets from their own country and another country to make it adaptable for international use. Nowadays in Thailand, not much work focuses on the risk of patients after PCI moreover the dataset for this study has to be followed up 12 months after the patient gets PCI.[(16)] This topic is quite specialized. After reviewing found that less than 10 works in Thailand and most of them were classified the risk by using statistical techniques to find the index of data. Or focusing on some outcome of PCI like bleeding.[(15)]

In summary, machine learning can work with huge groups of datasets. This study will classify the dataset for prediction of all one-year outcomes including Repeated Hospitalization, Myocardial Infraction, Heart Failure, Stroke, Repeated Revascularization (Unplanned PCI), Death, and Major Bleeding 1-year post-PCI index dates after the patient received PCI with multiple machine learning algorithms.

Logistic Regression

Logistic regression is a classic statistical technique used for binary classification tasks. It models the relationship between independent variables and a binary dependent variable (e.g., 0 or 1). Unlike linear regression, which forecasts continuous values, logistic regression estimates the likelihood of an outcome belonging to one of two categories. [72]

Mathematical Foundation of Logistic Regression

1. Logit Function (Link Function): Logistic regression models the log odds of the probability of an event occurring as a linear combination of independent variables. The log-odds also called the logit function, is expressed as:

$$logit(P) = \log\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

   - P: Probability of the positive class (y=1y=1y=1).
   - x_n : Independent variables.
   - β_0: Intercept term.
   - $\beta_1 \ldots . \beta_n$: Coefficients for each independent variable.

2. Sigmoid Function (Probability Mapping): To ensure the output is bounded between 0 and 1 (a valid probability), the logistic regression uses the sigmoid function:

$$P(y=1|x) = \sigma(z) = \frac{1}{1+e^{-z}}$$

, where

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

The sigmoid function maps the linear combination of inputs ($\boldsymbol{Z}$) to a probability between 0 and 1.

Interpreting the Coefficients in Logistic Regression

The coefficients (β_j) indicate the change in the log-odds of the dependent variable for a one-unit increase in the corresponding independent variable (x_j), assuming all other variables remain constant. When exponentiated, these coefficients represent the odds ratio:

$$Odds\ Ratio = e^{\beta_j}$$

- If $\beta_j > 0$, increasing x_j increases the odds of y=1.
- If $\beta_j < 0$, decreasing x_j increases the odds of y=1.

- Pros
  - **Interpretability**: The model is highly interpretable due to its linear nature and direct relationship between coefficients and log-odds.
  - **Efficiency**: Logistic regression is computationally efficient and can be applied to small and large datasets.
  - **Statistical Inference**: Traditional logistic regression (e.g., via Statsmodels) provides valuable statistical outputs like p-values, confidence intervals, and standard errors for coefficients, enabling hypothesis testing.
  - **Probabilistic Output**: Logistic regression outputs probabilities, allowing users to set custom thresholds for classification.
- Cons
  - **Linearity Assumption**: Logistic regression assumes a linear relationship between the log-odds and independent variables, which may not hold for complex, non-linear data.
  - **Sensitivity to Outliers**: Extreme values in independent variables can distort the model.
  - **Multicollinearity**: Highly correlated independent variables can reduce the reliability of coefficient estimates.
  - **Not Suitable for Non-Linear Problems**: Traditional logistic regression cannot capture non-linear relationships without feature transformation or interaction terms.[73-76]

CHAPTER 3
RESEARCH METHODOLOGY

Data Source

The dataset from the Thai PCI registry was used in this retrospective analysis. In brief, data regarding patients and procedural features, adjunctive treatment, complications, and clinical outcomes were collected prospectively from thirty-nine hospitals in Thailand. A total number of 19,701 PCI patients' data were collected. All patients had 1-year follow-up assessments as the outcome.[15, 16] The PCI registry forms are shown in the Appendix.

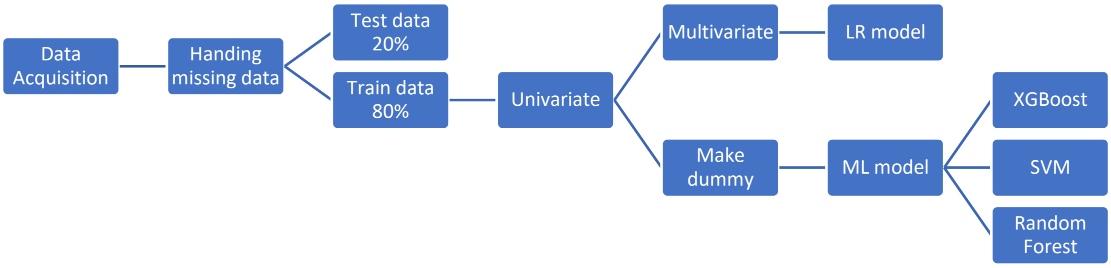
Definitions and outcomes

The attributes that this study uses can be grouped into 13 categories which are Demographics, Physical exam, History, Risk factor, CAD LAB VISIT, Test performed, Medication, Arterial access, Investigation, Pre-procedure, Post-procedure, INTRA and Post-procedure clinical events, Discharge, Discharge medication, and outcomes from follow-up after 12 months. The outcome of this study can be separated into two endpoints: The primary endpoint includes in-hospital all-cause mortality and mortality at 12 months post-PCI index date.

Handing with missing data

We have missing data in some variables due to the dataset we utilized. This study intends to deal with missing data by starting with an inspection of the missing percentage of each feature. If any feature is missing more than 35% of the data, we desire not to use that feature to keep the most patient data then if the feature is missing less than 35%, we try to reject patient data person by person. So, the work can assume that we use completed data to train the model without imputing any feature.

Data Preparation



Data Preparation: The dataset was split into 80% of the training group and 20% of the test group. This step uses sklearn.model_selection.train_test_split to split the data.

Table 21 Data distribution of the in-hospital mortality dataset after splitting into a train-test group

Characteristics		Train data N = 14919	Test data N = 3730
age	mean(SD)	64.23(11.63)	64.37(11.91)
sex	men n(%)	10297(69.02)	2539(68.07)
	female n(%)	4622(30.98)	1191(31.93)
bmi	mean(SD)	24.31(4.20)	24.25(4.19)
c_admissionsbp	mean(SD)	137.29(26.73)	137.37(26.36)
c_priorheart	yes n(%)	2074(13.90)	539(14.45)
	no n(%)	12845(86.10)	3191(85.55)
c_chroniclung	yes n(%)	509(3.41)	134(3.59)
	no n(%)	14410(96.59)	3596(96.41)
c_peripheral	yes n(%)	249(1.67)	77(2.06)
	no n(%)	14670(98.33)	3653(97.94)

Table 22 Data distribution of in-hospital mortality dataset after splitting into a train-test group (continuous)

Characteristics		Train data N = 14919	Test data N = 3730
c_dyslipidemia	yes n(%)	9055(60.69)	2302(61.72)
	no n(%)	5864(39.31)	1428(38.28)
c_priormi	yes n(%)	3537(23.72)	913(24.48)
	no n(%)	11380(76.28)	2815(75.47)
dm	yes n(%)	6689(44.84)	1647(44.16)
	no n(%)	8228(55.15)	2083(55.84)
c_priorpci	yes n(%)	4523(30.32)	1130(30.29)
	no n(%)	10396(69.68)	2600(69.71)
d_type	1 n(%)	3972(26.62)	966(25.90)
	2 n(%)	4520(30.30)	1194(32.01)
	3 n(%)	6427(43.08)	1570(42.09)
f_novessel	1 n(%)	12860(86.20)	3260(87.40)
	2 n(%)	1897(12.72)	437(11.72)
	3 n(%)	157(1.05)	33(0.88)
	4 n(%)	5(0.03)	0(0.00)
s_finalresult_fail	success n(%)	14216(95.29)	3553(95.25)
	fail n(%)	703(4.71)	177(4.75)
h_prehemoglobin	mean(SD)	12.62(2.10)	12.61(2.06)
i_heartfail	yes n(%)	1781(11.95)	446(11.96)
	no n(%)	13136(88.05)	3284(88.04)
i_heartfailclass	1 n(%)	13051(87.48)	3267(87.59)
	2 n(%)	435(2.92)	96(2.57)
	3 n(%)	314(2.10)	89(2.39)
	4 n(%)	1119(7.50)	278(7.45)

Table 23 Data distribution of in-hospital mortality dataset after splitting into a train-test group (continuous)

Characteristics		Train data N = 14919	Test data N = 3730
egfr_epi	mean(SD)	70.46(27.44)	70.54(26.96)
f_pcistat	1 n(%)	9386(62.91)	2330(62.47)
	2 n(%)	2333(15.64)	623(16.70)
	3 n(%)	3200(21.44)	777(20.83)
radial	yes n(%)	6530(43.77)	1643(44.05)
	no n(%)	8389(56.23)	2087(55.95)
death	alive (SD)	14540(97.46)	3626(97.21)
	death (SD)	379(2.54)	104(2.79)

Table 24 Data distribution of 1-year mortality dataset after splitting into a train-test group

Characteristics		Train data N = 14611	Test data N = 3653
age	mean(SD)	64.10(11.67)	64.33(11.57)
sex	men n(%)	10104(69.15)	2502(68.49)
	female n(%)	4507(30.85)	1151(31.51)
bmi	mean(SD)	24.29(4.18)	24.39(4.25)
c_priormi	yes n(%)	3481(23.82)	899(24.61)
	no n(%)	11130(76.18)	2754(75.39)
c_admissionsbp	mean(SD)	135.53(26.40)	137.87(26.22)
c_admissionhr	mean(SD)	75.76(16.38)	76.06(16.26)
c_cerebrovascular	yes n(%)	836(5.72)	205(5.61)
	no n(%)	13775(94.28)	3448(94.39)

Table 25 Data distribution of 1-year mortality dataset after splitting into a train-test group (continuous)

Characteristics		Train data N = 14611	Test data N = 3653
c_priorheart	yes n(%)	2025(13.86)	503(13.77)
	no n(%)	12586(86.14)	3150(86.23)
dyslipid2	yes n(%)	9700(66.39)	2438(66.74)
	no n(%)	4911(33.61)	1215(33.26)
dm	yes n(%)	6493(44.44)	1637(44.81)
	no n(%)	8118(55.56)	2016(55.19)
c_smoke	yes n(%)	8083(55.32)	2010(55.02)
	no n(%)	6528(44.68)	1643(44.98)
d_type	1 n(%)	3780(25.87)	948(25.95)
	2 n(%)	4497(30.78)	1114(30.50)
	3 n(%)	6334(43.35)	1591(43.55)
f_pcistat	1 n(%)	9306(63.69)	948(25.95)
	2 n(%)	2300(15.74)	1114(30.50)
	3 n(%)	3005(20.57)	1591(43.55)
f_aspirin	yes n(%)	14487(99.15)	3629(99.34)
	no n(%)	124(0.85)	24(0.66)
f_clopid	yes n(%)	13520(92.53)	3416(93.51)
	no n(%)	1091(7.47)	237(6.49)
f_fonda	yes n(%)	68(0.47)	16(0.44)
	no n(%)	14543(99.53)	3637(99.56)
f_lmwh	yes n(%)	1756(12.02)	442(12.10)
	no n(%)	12855(87.98)	3211(87.90)
f_unheparin	yes n(%)	13330(91.23)	3354(91.82)
	no n(%)	1281(8.77)	299(8.18)

Table 26 Data distribution of 1-year mortality dataset after splitting into a train-test group (continuous)

Characteristics		Train data N = 14611	Test data N = 3653
oral_aniticoag	yes n(%)	14071(96.30)	3529(96.61)
	no n(%)	540(3.70)	124(3.39)
j_ace	yes n(%)	5386(36.86)	1374(37.61)
	no n(%)	9225(63.14)	2279(62.39)
j_betablock	yes n(%)	9021(61.74)	2278(62.36)
	no n(%)	5590(38.26)	1375(37.64)
j_statin	yes n(%)	13609(93.14)	3384(92.64)
	no n(%)	1002(6.86)	269(7.36)
j_spironolactone	yes n(%)	1012(6.93)	250(6.84)
	no n(%)	13599(93.07)	3403(93.16)
j_vitamink	yes n(%)	361(2.47)	78(2.14)
	no n(%)	14250(97.53)	3575(97.86)
j_noacs	yes n(%)	137(0.94)	38(1.04)
	no n(%)	14474(99.06)	3615(98.96)
f_novessel	1 n(%)	12649(86.57)	3131(85.71)
	2 n(%)	1816(12.43)	474(12.98)
	3 n(%)	142(0.97)	47(1.29)
	4 n(%)	4(0.03)	1(0.03)
g_lesioncom_n	1 n(%)	640(4.38)	145(3.97)
	2 n(%)	2133(14.60)	545(14.92)
	3 n(%)	2703(18.50)	638(17.47)
	4 n(%)	9135(62.52)	2325(63.64)
s_finalresult_fail	success n(%)	13942(95.42)	3488(95.48)
	fail n(%)	669(4.58)	165(4.52)

Table 27 Data distribution of 1-year mortality dataset after splitting into a train-test group (continuous)

Characteristics		Train data N = 14611	Test data N = 3653
h_prehemoglobin	mean(SD)	12.64(2.07)	12.60(2.12)
i_heartfail	yes n(%)	1614(11.05)	380(10.40)
	no n(%)	12997(88.95)	3273(89.60)
i_heartfailclass	1 n(%)	12919(88.42)	3259(89.22)
	2 n(%)	419(2.87)	99(2.71)
	3 n(%)	308(2.11)	68(1.86)
	4 n(%)	965(6.60)	227(6.21)
egfr_epi	mean(SD)	70.82(27.35)	70.8(26.71)
death	alive (%)	13307(91.08)	337(9.23)
	death (%)	1304(8.92)	3316(90.77)

Feature Selection:

a. Univariate Analysis with LR (set reference): Consider each variable with a p-value $\leq$ 0.20.

b. Multivariate Analysis with LR (set reference): Identify variable combinations with a p-value $\leq$ 0.05.

Model Training:

For LR: Use the variables from multivariate analysis to train the model.

For ML:

1. Split the train data (80% of original data) again into the Training set for tuning the models and Validation set (may use cross-validation) to tune the hyperparameters.

- Grid Search CV was used for hyperparameters tuning.

2. Select the best hyperparameters.

3. Train the model using the entire Train data with the best hyperparameters ⟶ final model (one model).

Model Evaluation:

For LR and ML:

1. Use the Test data to evaluate the model's performance.
2. Compare the model performances.

The model planned to use in this study is the top four popular models that researchers usually use in this field of work. For example:

- XGBoost
- RF
- LR
- SVM

After comparing these algorithms by their performance to evaluate the best one for this study.

Performance metrics

In this study, eight standards to determine model performance which include confusion matrix, accuracy, sensitivity (or recall), specificity, precision, brier score, f1-score, and area under the receiver operating characteristics (AUROC). The details of each one are shown below.

- Confusion matrix

		Actual class	
		P	N
Predicted class	P	TP	FP
	N	FN	TN

Figure 8 Confusion matrix.

P: Positive, N: Negative

TP: True Positive, FP: False Positive, FN: False Negative, TN: True Negative

- Accuracy

The classification accuracy rating, often known as the accuracy score, is calculated by dividing the proportion of correct predictions by the total number of predictions.[65] It addresses the question, "How many of our predictions were correct?"

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Sensitivity or recall

Sensitivity or recall is the ratio of true positives to total (actual) positives in the data. This formula is also known as the formula of “True positive rate (TPR).”

$$Sensitivity\ or\ Recall = \frac{TP}{TP + FN}$$

- Specificity

Specificity is the ratio of true negative to total (actual) negative in the data.

$$Specificity = \frac{TN}{TN + FP}$$

- Precision

Precision is calculated by dividing the proportion of actual positive findings by the entire number of positive outcomes, including misdiagnosed ones. It is a statistic that calculates the proportion of real positives to total positives predicted by the model.[65] It provides a response to the question, "How many of our positive predictions came true?"

$$Precision = \frac{TP}{TP + FP}$$

- Brier Score

The Brier score measures the mean squared error for probabilistic predictions. It is calculated by squaring the difference between the binary class indicator and the predicted class probability, then averaging these values.

- F1 Score

The F1 score reflects the model's accuracy in each class. When a dataset is imbalanced, the F1-score measure is frequently used. It is a combination of recall and precision. As previously demonstrated, there is a trade-off between precision and recall; F1 may thus be used to assess how successfully our models make that trade-off.

$$F1\ Score = 2 * \left(\frac{Precision * Recall}{Presicion + Recall}\right)$$

- Area Under the Receiver Operating Characteristic (AUROC)

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = 1 - Specificity = \frac{FP}{TN + FP}$$

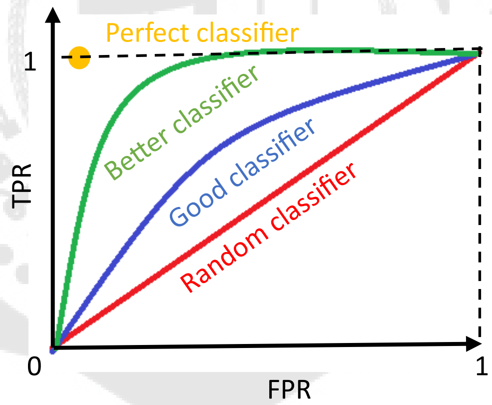


Figure 9 Area Under the Receiver Operating Characteristic (AUROC)

Ethics considerations

This study has a non-invasive operation with no risk of treatment that is given to the subject/patient. The risk of the subject is not greater than minimal risk. This study will use the demographics, clinical features, and patient history from the Cardiovascular Intervention Association of Thailand. This study was approved by The Human Research Ethics Committee of Srinakharinwirot University. The protocol code is SWUEC-671023

CHAPTER 4
RESULT

In-hospital mortality

For the in-hospital mortality after we handled the missing data, we reduced the number of usable patients from 19701 to 18649. While the LV Ejection Fraction was rejected due to the 87.485% of missing data in this feature. Missing data percentages in each outcome are shown below.

Table 28 Missing data percentages of in-hospital mortality

Feature name	Missing rate (%)
Age	0
Gender	0
BMI raw data	0.010152
Systolic blood pressure (SBP)	0.010152
Previous Heart Failure	0
Previous COPD	0
Previous PAD	0
Previous Ischemic Heart Disease	0
Previous Dyslipidemia	
Previous Diabetes Mellitus	0
Previous PCI	0
CAD Presentation	0
Number Of Vessels	0
Successful	0
Hemoglobin	4.319578
Heart Failure	0
Heart Failure Killip Class	0
LV Ejection Fraction Discharge	87 .48 5

Table 29 Missing data percentages of in-hospital mortality (continuous)

Feature name	Missing rate (%)
eGFR raw data	3.35516
PCI procedure	0
Radial,	0
In Hospital Mortality	0

After rejecting the LV Ejection Fraction Discharge, we select the feature by univariate and multivariate in this step the result as Table 26-27. Univariate Analysis with LR (set reference): Consider each variable with a p-value $\leq$ 0.20. If any feature has a p-value of more than 0.02 we will reject them.

Table 30 Univariate result for in-hospital mortality

	Term	coef	std err	P>|z|	2.50%	97.50%
1	age	0.0552	0.005	<0.001	0.046	0.065
2	sex (ref=male)	0.4337	0.106	<0.001	0.226	0.642
3	bmi	-0.0427	0.013	0.001	-0.068	-0.017
4	c_admissionsbp	-0.0316	0.002	<0.001	-0.036	-0.027
5	c_priorheart	0.5695	0.127	<0.001	0.322	0.817
6	c_chroniclung	0.4705	0.234	0.045	0.011	0.93
7	c_peripheral	1.409	0.225	<0.001	0.967	1.851
8	c_dyslipidemia	-0.5928	0.104	<0.001	-0.797	-0.388
9	c_priormi	-0.5543	0.144	<0.001	-0.837	-0.272
10	dm	0.5457	0.105	<0.001	0.339	0.752
11	c_priorpci	-1.0044	0.149	<0.001	-1.297	-0.712
12	d_type (reference=3)) [T.1]	2.8557	0.207	<0.001	2.451	3.261

Table 31 Univariate result for in-hospital mortality (continuous)

	term	coef	std err	P>|z|	2.50%	97.50%
	d_type (reference=3)) [T.2]	1.621	0.223	<0.001	1.184	2.059
13	f_novessel (reference=1)) [T.2]	0.3134	0.14	0.025	0.038	0.588
	f_novessel (reference=1) [T.3]	-1.3654	1.005	0.174	-3.335	0.604
	f_novessel (reference=1)) [T.4]	-15.9802	8.33E+03	0.998	-1.63E+04	1.63E+04
14	s_finalresult_fail	1.0973	0.161	<0.001	0.782	1.413
15	creatinine	0.1241	0.02	<0.001	0.085	0.163
16	h_prehemoglobin	-0.2025	0.024	<0.001	-0.25	-0.155
17	i_heartfail	3.3344	0.124	<0.001	3.092	3.577
18	i_heartfailclass (reference=1)) [T.2]	1.5909	5.053	<0.001	0.974	2.208
	i_heartfailclass (reference=1)) [T.3]	3.0775	14.417	<0.001	2.659	3.496
	i_heartfailclass (reference=1)) [T.4]	3.9432	29.021	<0.001	3.677	4.209
19	egfr_epi	-0.0286	0.002	<0.001	-0.032	-0.025
20	f_pcistat (reference=1)) [T.2]	1.9327	0.201	<0.001	1.538	2.327
	f_pcistat (reference=1)) [T.3]	3.0776	0.171	<0.001	2.743	3.412
21	radial	-1.3526	0.137	<0.001	-1.622	-1.084

In this group only f_novessel which stands for the number of vessels is not significant it means we have only twenty features that can be able to go to the dummy step before acquisition in training in the machine learning process. For the parallel step, we use the significant features in the multivariate part of feature selection. For the multivariate part, we accept the feature when the p-value <0.05. In this phase, we got only eight significant features left. The results are shown in Table 28.

Table 32 Multivariate result for in-hospital mortality

	term	coef	std err	P>|z|	2.50%	97.50%
1	age	0.0275	0.005	<0.001	0.017	0.038
2	c_admissionsbp	-0.0094	0.002	<0.001	-0.013	-0.005
3	c_peripheral	1.2075	0.287	<0.001	0.644	1.771
4	s_finalresult_fail	0.9783	0.205	<0.001	0.577	1.38
5	i_heartfailclass (reference=1)) [T.2]	1.0239	0.326	0.002	0.386	1.662
	i_heartfailclass (reference=1)) [T.3]	1.9813	0.229	<0.001	1.532	2.431
	i_heartfailclass (reference=1)) [T.4]	2.6211	0.157	<0.001	2.312	2.93
6	egfr_epi	-0.0184	0.002	<0.001	-0.023	-0.014
7	f_pcistat (reference=1)) [T.2]	1.4257	0.218	<0.001	0.999	1.853
	f_pcistat (reference=1)) [T.3]	1.8383	0.197	<0.001	1.482	2.254
8	radial	-0.7337	0.152	<0.001	-1.032	-0.435

In the next step, after we get the significant feature for training data we use them in the training, validating, and testing process. To find the best hyperparameter in this work we use Grid Search CV to tune the models the performance we get in this work for the in-hospital mortality outcomes is shown in Table 29.

Table 33 Model performance for in-hospital mortality

In-hospital death	LR		RF		SVM		XGB	
	Train	Test	Train	Test	Train	Test	Train	Test
Accuracy	0.89081 (0.886, 0.896)	0.88499 (0.874, 0.896)	0.90435 (0.899, 0.909)	0.900 (0.890, 0.909)	0.89222 (0.887, 0.897)	0.89115 (0.881, 0.901)	0.89631 (0.891, 0.901)	0.89464 (0.885, 0.905)
Recall/ Sensitivity	0.87071 (0.836, 0.902)	0.88462 (0.818, 0.942)	0.86807 (0.831, 0.898)	0.83654 (0.768, 0.910)	0.87599 (0.838, 0.907)	0.86538 (0.798, 0.923)	0.89446 (0.862, 0.925)	0.84615 (0.779, 0.914)
Specificity	0.89133 (0.886, 0.897)	0.88500 (0.874, 0.895)	0.90530 (0.900, 0.910)	0.90182 (0.892, 0.911)	0.89264 (0.888, 0.898)	0.89189 (0.882, 0.902)	0.89635 (0.891, 0.901)	0.89603 (0.887, 0.906)
Precision	0.17277 (0.155, 0.190)	0.18075 (0.146, 0.213)	0.19285 (0.174, 0.213)	0.19639 (0.159, 0.234)	0.17538 (0.158, 0.192)	0.18672 (0.151, 0.221)	0.18364 (0.166, 0.202)	0.18925 (0.154, 0.226)
ROC	0.88102 (0.864, 0.900)	0.88481 (0.852, 0.913)	0.88668 (0.868, 0.902)	0.86918 (0.834, 0.905)	0.88432 (0.866, 0.900)	0.87864 (0.845, 0.909)	0.89541 (0.879, 0.911)	0.87109 (0.837, 0.905)
F1	0.28834 (0.263, 0.312)	0.30016 (0.249, 0.345)	0.31559 (0.288, 0.342)	0.31810 (0.263, 0.369)	0.29225 (0.267, 0.316)	0.30717 (0.256, 0.353)	0.30472 (0.279, 0.330)	0.30931 (0.258, 0.358)
Brier	0.01907 (0.017, 0.021)	0.02103 (0.018, 0.024)	0.08117 (0.078, 0.084)	0.08146 (0.076, 0.087)	0.01933 (0.018, 0.021)	0.02126 (0.018, 0.025)	0.09233 (0.090, 0.100)	0.09310 (0.088, 0.0982)

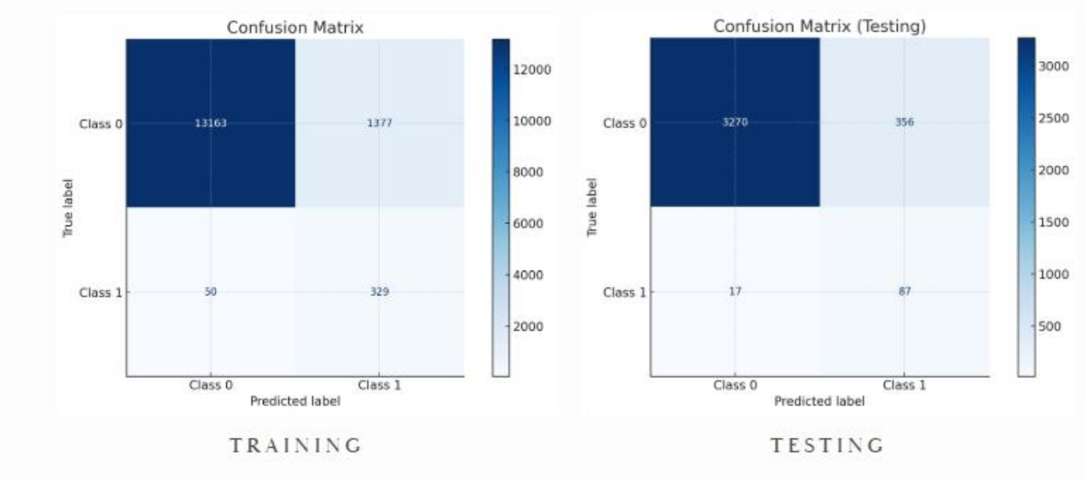


Figure 10 The confusion matrix of the RF model with in-hospital mortality outcome

1-year mortality

For the 1-year mortality after we handled the missing data, we reduced the number of usable patients from 19701 to 18264. While the Glucose, CK-MB, troponin I, troponin T, LDL, and LV Ejection Fraction were rejected due to the 39.536064, 87.838181, 89.619816, 65.641338, 60.296432, and 87.485 percent of missing data respectively. Missing data percentages in each outcome are shown below.

Table 34 Missing data percentages of 1-year mortality.

Feature name	Missing rate (%)
Age	0
Gender	0
BMI raw data	0
Systolic blood pressure (SBP)	0
Heart rate	0
Previous Heart Failure	0
Previous Ischemic heart disease	0
Previous dyslipidemia	0
Previous diabetes mellitus	0

Table 35 Missing data percentages of 1-year mortality. (continuous)

Feature name	Missing rate (%)
Previous cerebrovascular	0
History of smoking	0
CAD Presentation	0
PCI procedure	0
Aspirin	0
Clopidogrel	0
Fondaparinux	0
Low molecular weight heparin (LMWH)	0
Unfractionated Heparin	0
Oral anticoagulant	0
ACE inhibitor	1.603979
Beta-blocker	1.603979
Statin	1.603979
Spironolactone	1.603979
Number Of Vessels	0
Lesion Complexity	0.568499
Successful	0
Glucose	39.536064
CK-MB	87.838181
Troponin I	89.619816
troponin T	65.641338
LDL	60.296432
Hemoglobin	4.319578
Heart Failure	0
Heart Failure Killip Class	0
LV Ejection Fraction	84.712

Table 36 Missing data percentages of 1-year mortality. (continuous)

Feature name	Missing rate (%)
eGFR Raw data	3.35516
Vitamin K	0
Non-vitamin K oral anticoagulants ('NOAC's)	0
1-year mortality	0

After rejecting, we select the feature by univariate and multivariate in this step the result as Table 32-34. Univariate Analysis with LR (set reference): Consider each variable with a p-value $\leq$ 0.20.

Table 37 Univariate result for 1-year mortality

term	coef	std err	P>|z|	2.50%	97.50%
age	0.0532	0.003	<0.001	0.048	0.058
sex (ref=m)	0.4457	0.06	<0.001	0.329	0.562
bmi	-0.1127	0.008	<0.001	-0.128	-0.097
c_admissionsbp	-0.0073	0.001	<0.001	-0.01	-0.005
c_admissionhr	0.025	0.002	<0.001	0.022	0.028
c_priorheart	1.0346	0.067	<0.001	0.904	1.165
c_priormi	-0.1619	0.071	0.022	-0.3	-0.023
dyslipid2	0.3471	0.059	<0.001	0.231	0.463
dm	0.5371	0.059	<0.001	0.422	0.652
c_smoke	-0.2719	0.058	<0.001	-0.386	-0.158
d_type (reference=3) [T.1]	0.7774	0.071	<0.001	0.638	0.917
d_type (reference=3) [T.2]	0.4583	0.073	<0.001	0.316	0.601

Table 38 Univariate result for 1-year mortality(continuous)

term	coef	std err	P>|z|	2.50%	97.50%
f_pcistat (reference=1)) [T.2]	0.4017	0.082	<0.001	0.241	0.563
f_pcistat (reference=1)) [T.3]	0.9453	0.065	<0.001	0.817	1.074
f_aspirin	-0.3539	0.367	0.335	-1.073	0.365
f_clopid	-0.2883	0.123	0.019	-0.529	-0.048
f_fonda	-0.3096	0.378	0.412	-1.049	0.43
f_lmwh	-0.0493	0.088	0.575	-0.222	0.123
f_unheparin	-0.014	0.103	0.892	-0.216	0.188
oral_aniticoag	0.0421	0.151	0.781	-0.255	0.339
j_ace	0.8821	0.071	<0.001	0.743	1.021
j_betablock	0.6463	0.058	<0.001	0.532	0.761
j_statin	1.709	0.076	<0.001	1.56	1.858
j_spironolactone	-0.2477	0.105	0.018	-0.454	-0.042
f_novessel (reference=1)) [T.2]	0.0158	0.088	0.857	-0.156	0.188
f_novessel (reference=1)) [T.3]	-0.057	0.303	0.851	-0.651	0.538
f_novessel (reference=1)) [T.4]	2.3257	1	0.02	0.365	4.287
g_lesioncom_n (reference=1)) [T.2]	0.0456	0.177	0.797	-0.302	0.393
g_lesioncom_n (reference=1)) [T.3]	0.2357	0.171	0.167	-0.099	0.57
g_lesioncom_n (reference=1)) [T.4]	0.3624	0.16	0.024	0.048	0.676

Table 39 Univariate result for 1-year mortality (continuous)

term	coef	std err	P>|z|	2.50%	97.50%
s_finalresult_fail	0.7306	0.109	<0.001	0.517	0.944
creatinine	0.2063	0.013	<0.001	0.182	0.231
h_prehemoglobin	-0.316	0.014	<0.001	-0.344	-0.288
i_heartfail	1.586	0.066	<0.001	1.456	1.716
i_heartfailclass (reference=1)) [T.2]	0.9051	0.141	<0.001	0.628	1.182
i_heartfailclass (reference=1)) [T.3]	1.6396	0.133	<0.001	1.379	1.901
i_heartfailclass (reference=1)) [T.4]	1.8166	0.078	<0.001	1.663	1.97
egfr_epi	-0.0289	0.001	<0.001	-0.031	-0.027
c_cerebrovascular,	0.5347	0.105	<0.001	0.33	0.74
j_vitamink,	-0.4364	0.159	0.006	-0.748	-0.124
j_noacs	0.5024	0.249	0.044	0.015	0.99

In this group, seven features are not significant which means we got only twenty-six features that can be able to go to the dummy step before acquisition in training in the machine learning process. For the parallel step, we use the significant features in the multivariate part of feature selection. For the multivariate part, we accept the feature when the p-value <0.05. In this phase, we got only thirteen significant features left. The results are shown in Table 40.

Table 40 Multivariate result for 1-year mortality

term	coef	std err	P>|z|	2.50%	97.50%
age	0.0255	0.003	<0.001	0.019	0.032
bmi	-0.0692	0.009	<0.001	-0.086	-0.052
c_admissionsbp	-0.0048	0.001	<0.001	-0.007	-0.002
c_admissionhr	0.0169	0.002	<0.001	0.013	0.02
c_priorheart	0.4288	0.078	<0.001	0.275	0.583
dm	0.2791	0.07	<0.001	0.142	0.416
j_ace	0.3689	0.077	<0.001	0.217	0.52
j_betablock	0.2998	0.067	<0.001	0.168	0.432
j_statin	1.1106	0.091	<0.001	0.933	1.288
s_finalresult_fail	0.7384	0.123	<0.001	0.497	0.98
h_prehemoglobin	-0.1146	0.017	<0.001	-0.148	-0.081
i_heartfailclass	0.4403	0.154	0.004	0.138	0.743
i_heartfailclass	0.8093	0.153	<0.001	0.51	1.109
i_heartfailclass	1.0591	0.095	<0.001	0.872	1.246
egfr_epi	-0.0163	0.001	<0.001	-0.019	-0.014

In the next step, after we get the significant feature for training data we use them in the training, validating, and testing process. To find the best hyperparameter in this work we use Grid Search CV to tune the models the model's performance we get in this work for the 1-year mortality outcomes is shown in Table 41.

Table 41 Model performance for 1-year mortality

In-hospital death	LR		RF		SVM		XGB	
	Train	Test	Train	Test	Train	Test	Train	Test
Accuracy	0.75956 (0.753, 0.766)	0.75719 (0.743, 0.771)	0.77305 (0.766, 0.779)	0.77772 (0.764, 0.790)	0.76333 (0.756, 0.770)	0.75855 (0.746, 0.771)	0.76764 (0.761, 0.774)	0.75253 (0.738, 0.766)
Recall/ Sensitivity	0.72393 (0.698, 0.747)	0.68843 (0.637, 0.738)	0.68635 (0.660, 0.708)	0.66172 (0.610, 0.709)	0.73466 (0.711, 0.757)	0.69733 (0.644, 0.745)	0.75920 (0.736, 0.780)	0.67953 (0.631, 0.730)
Specificity	0.76306 (0.756, 0.770)	0.76417 (0.750, 0.779)	0.78154 (0.774, 0.788)	0.78951 (0.776, 0.803)	0.76614 (0.758, 0.773)	0.76478 (0.750, 0.780)	0.76847 (0.761, 0.776)	0.75995 (0.745, 0.774)
Precision	0.23041 (0.217, 0.242)	0.2288 (0.203, 0.253)	0.23540 (0.221, 0.248)	0.24213 (0.214, 0.270)	0.23538 (0.221, 0.248)	0.23153 (0.205, 0.257)	0.24318 (0.230, 0.2564)	0.22341 (0.197, 0.249)
ROC	0.74349 (0.730, 0.756)	0.7263 (0.670, 0.752)	0.73395 (0.721, 0.746)	0.72561 (0.699, 0.750)	0.75040 (0.738, 0.762)	0.73105 (0.704, 0.755)	0.76384 (0.751, 0.775)	0.71974 (0.693, 0.746)
F1	0.34956 (0.332, 0.364)	0.34345 (0.311, 0.375)	0.35057 (0.332, 0.366)	0.35453 (0.321, 0.387)	0.35653 (0.339, 0.372)	0.34763 (0.315, 0.380)	0.36837 (0.352, 0.384)	0.33627 (0.302, 0.3684)
Brier	0.06579 (.063, 0.069)	0.06752 (0.0615, 0.075)	0.18782 (0.186, 0.190)	0.18862 (0.186, 0.192)	0.06702 (0.064, 0.070)	0.06978 (0.063, 0.077)	0.16373 (0.161, 0.166)	0.16875 (0.164, 0.174)

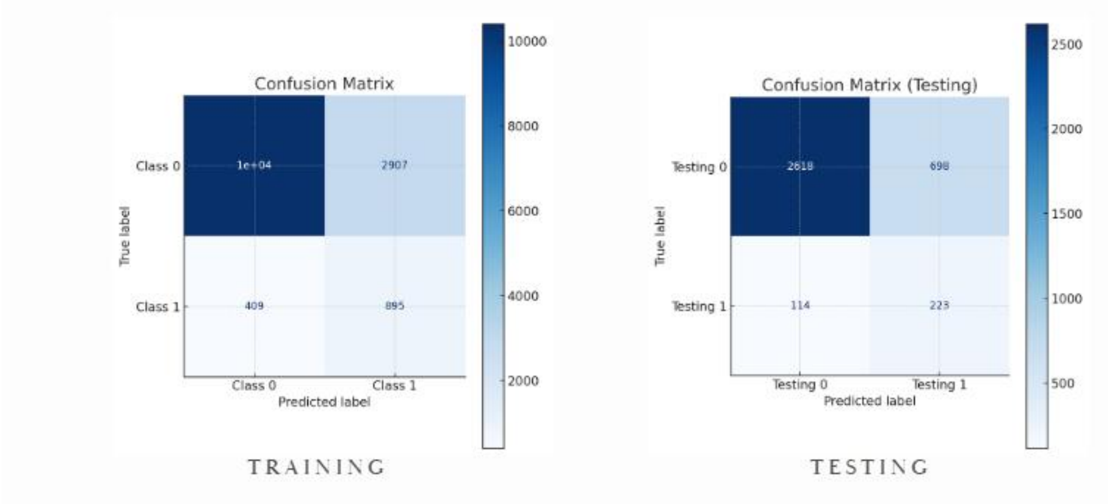


Figure 11The confusion matrix of the RF model with in-hospital mortality outcome

CHAPTER 5
SUMMARY DISCUSSION AND SUGGESTION

Summary

The results show that the mortality risk after PCI can be screened by the prediction model.

In-hospital mortality outcome

Following Table 33 the best model in this work is the Random forest models which reach 90% (95% CI:89-91) accuracy, 0.83654 (95% CI:0.768, 0.910) for sensitivity, 0.90182 (95% CI0.892, 0.911) of specificity, 0.19639 (95%CI: 0.159, 0.234) of precision, 0.86918 (95% CI: 0.834, 0.905) of ROC, 0.31810 (95% CI:0.263, 0.369) of F1 score, and 0.08146 (95% CI: 0.076, 0.087) of brier score.

1-year mortality outcome

Following to Table 41 the best model in this work is the Random forest models which reach 0.77772 (95% CI:0.764, 0.790) of accuracy, 0.66172 (95% CI: 0.610, 0.709) of sensitivity, 0.78951 (95%CI: 0.776, 0.803) of specificity, 0.24213 (95% CI: 0.214, 0.270) of precision, 0.72561 (95% CI:0.699, 0.750) of ROC, 0.35453 (95%CI: 0.321, 0.387) of F1 score, and 0.18862 (95% CI: 0.186, 0.192) of Brier score.

The in-hospital mortality risk model's performance is higher than that of one-year mortality risk models in every type of algorithm, including LR, XGBoost, SVM, and RF. This work assumed that this problem happened due to outsider factors that may affect the mortality rate in the one-year outcome because this work focused on only information collected in electronic health records and did not cover external factors after the patient leaves the hospital for 1 year. Besides this, the precision performance in both outcomes seems less effective than expected, but the problem is caused by extremely imbalanced data between the patients who survived and death.

From the description of each feature in tables thirty-eight to forty, this is the group of significant features in a multivariate process used to train the logistic regression model. This part can be updated with the feature that affects the risk prognostic models of adverse outcomes after PCI which is following to the objective.

However, from the test results, it was found that the efficiency of the model can be used to benefit the medical field and can be further improved. This is also in line with the objectives of the work, even though there are gaps that need to be developed or solved or try to deal with the problem in a different way.

Discussion and Suggestion

The problems we found while working with the work are.

a. Tuning the model while keeping all the data as much as we can makes the data very imbalanced, which is the reason it was extremely hard to make the higher precision index.
b. Due to the imbalanced data we have to avoid overfitting all the time.
c. According to the data we got in the case of the 1-year outcome, some patients may have outsider factors that can cause mortality while this prediction focuses on only clinical demographics in the medical electronic record, which we collected from the patient.
d. This work is quite hard to interpret by the author, so I need physicians to confirm the meaning of each feature. It follows the clinical procedure by interpreting the coefficient value in the univariate and multivariate process before using them to train the models. The meaning of each feature is shown in Table 43 to Table 46

The reason supp why random forest is better than other algorithms in this work

The better performance of Random Forest compared to XGBoost, SVM, and Logistic Regression in predicting the risk of mortality in post-PCI patients could be attributed to several factors, including the nature of the data and the characteristics of the algorithms. Here are some reasons why this might happen:

1. **Handling Imbalanced Data**

- **Random Forest** is inherently robust to imbalanced data because it uses bootstrapping and can weigh classes based on their prevalence.
- It randomly selects subsets of data and features for training individual trees, reducing the risk of overfitting to majority-class samples.
- It can easily be adjusted to account for imbalances by setting class_weight='balanced', which adjusts the weights inversely proportional to class frequencies.

In contrast:

- **XGBoost** can handle imbalances but requires careful tuning of parameters like scale_pos_weight or applying additional sampling techniques.
- **SVM** struggles with imbalanced datasets unless a proper cost-sensitive approach is employed.
- **Logistic Regression** often underperforms on imbalanced data because it tends to predict the majority class unless explicitly adjusted.

2. Non-linearity in Data

- Random Forest can capture complex, non-linear relationships between features and the target variable without explicit feature engineering.
- If the mortality risk depends on non-linear combinations of clinical factors, Random Forest might outperform Logistic Regression (which assumes linear relationships) and SVM (which may not generalize well on complex datasets).

3. Feature Importance and Interactions

- Random Forest evaluates feature importance and interactions implicitly through its ensemble of decision trees, which might better capture the relationships in medical data.
- Logistic Regression does not model feature interactions unless explicitly included as interaction terms.
- XGBoost captures interactions but might overfit or require more effort to tune.
- SVM lacks inherent feature importance and interpretability.

4. Overfitting Risk

- Random Forest reduces overfitting by averaging predictions over multiple trees, providing a robust performance even with noisy or redundant features.
- XGBoost is prone to overfitting if hyperparameters are not carefully tuned.
- SVM might overfit on noisy data, especially with non-linear kernels.
- Logistic Regression is less prone to overfitting but might underperform due to its simplicity.

5. Data Size

- If the dataset size is moderate to large, Random Forest is computationally efficient and can handle it well.
- XGBoost requires careful parameter tuning and is more computationally expensive.
- SVM scales poorly with large datasets.
- Logistic Regression scales well but might fail to capture complex patterns.

6. Feature Scaling

- Random Forest does not require feature scaling, making it more straightforward to apply to raw clinical data.
- SVM and Logistic Regression require careful preprocessing (e.g., standardization or normalization).
- XGBoost can handle unscaled features but might perform better with careful preprocessing.

7. Domain-Specific Factors

- In medical data, Random Forest's ability to deal with missing values, outliers, and categorical variables directly can be a significant advantage.
- Logistic Regression and SVM require preprocessing steps for these issues.

The superior performance of Random Forest in your scenario is likely due to its robustness to imbalanced data, ability to model complex relationships, ease of handling raw data, and reduced risk of overfitting. While other models can perform well, they often require more effort in preprocessing, feature engineering, and hyperparameter tuning to achieve comparable results.

Table 42 The description of each feature used in the training process for in-hospital mortality.

	Term	coef	Definitions
1	age	0.0275	The older patient has a higher risk of mortality.
2	c_admissionsbp	-0.0094	Higher systolic blood pressure decreases the risk of mortality.
3	c_peripheral	1.2075	If the patient has a PAD history, it will increase the risk of mortality.
4	s_finalresult_fail	0.9783	The PCI result failed to increase the risk of mortality.
5	i_heartfailclass (reference=1)) [T.2]	1.0239	The higher class of Killip increases the risk of mortality.
	i_heartfailclass (reference=1)) [T.3]	1.9813	The higher class of Killip increases the risk of mortality.
	i_heartfailclass (reference=1)) [T.4]	2.6211	The higher class of Killip increases the risk of mortality.
6	egfr_epi	-0.0184	Higher eGFR values indicate better kidney function, while lower values signify impaired kidney function
7	f_pcistat (reference=1)) [T.2]	1.4257	Urgent patients have more risk than elective patients but less than emergency patients.
	f_pcistat (reference=1)) [T.3]	1.8383	Emergency patients have the highest risk compared to other statuses.
8	radial	-0.7337	Radial access reduces mortality, particularly in high-risk patients because it reduces the bleeding risk and patients can mobilize sooner after the procedure.

Table 43 The description of each feature used in the training process of 1-year mortality.

	term	coef	Definitions
1	age	0.0255	The older patient has a higher risk of mortality.
2	bmi	-0.0692	In some populations, especially critically ill or hospitalized patients, mildly elevated BMI may be associated with better survival.
3	c_admissionsbp	-0.0048	Patients with extremely low SBP are more likely to be in shock or have poor perfusion, both of which increase mortality risk.
4	c_admissionhr	0.0169	Higher heart rates may signal physiological stress, cardiovascular strain, or worsening health, explaining the increased risk of mortality.
5	c_priorheart	0.4288	If the patient has a heart failure history, it will increase the risk of mortality.
6	dm	0.2791	If the patient has a diabetes mellitus history, it will increase the risk of mortality.

Table 44 The description of each feature used in the training process of 1-year mortality. (continuous)

	term	coef	Definitions
7	j_ace	0.3689	CE inhibitors are typically prescribed for patients with chronic conditions such as Hypertension, heart failure, and chronic kidney disease. These underlying conditions themselves are associated with higher mortality, which might explain the positive coefficient for ACE inhibitor use. The medication is not directly causing higher risk but is likely being used by a higher-risk population.
8	j_betablock	0.2998	The positive coefficient does not mean that beta blockers directly increase mortality. The association may reflect the severity of illness in patients who require beta blockers.
9	j_statin	1.1106	The positive coefficient does not mean that statins directly increase mortality. It is more likely that statins are used in a higher-risk population (e.g., patients with severe cardiovascular or metabolic disease).
10	s_finalresult_fail	0.7384	The PCI result failed to increase the risk of mortality.

Table 45 The description of each feature used in the training process of 1-year mortality. (continuous)

	term	coef	Definitions
11	h_prehemoglobin	-0.1146	Higher hemoglobin levels indicate better oxygen delivery, reduced physiological stress, and less severe illness.
12	i_heartfailclass	0.4403	The higher class of Killip increases the risk of mortality.
	i_heartfailclass	0.8093	The higher class of Killip increases the risk of mortality.
	i_heartfailclass	1.0591	The higher class of Killip increases the risk of mortality.
13	egfr_epi	-0.0289	Patients with better kidney function are associated with lower mortality

Clinical Implementation Recommendations

Framework for Implementing the Model in Clinical Practice

1) Integration into Clinical Workflow:

- Decision Support System (DSS): Embed the model into the hospital's Electronic Health Record (EHR) system as a clinical decision support tool.
- Point-of-Care Accessibility: Ensure the tool can provide real-time predictions during patient admission or post-PCI assessment.
- Risk Stratification Dashboard: Develop an intuitive user interface that displays risk predictions, key contributing factors, and recommendations.

2) Data Pipeline:

- Automated Data Extraction: Link the model to relevant clinical databases to retrieve necessary variables (e.g., patient demographics, procedural details, lab results) in real-time.
- Continuous Updates: Establish protocols to periodically update the model with new data for maintaining relevance.

3) Clinical Workflow Integration:

- Assign predictions to pre-defined action categories, such as:
  - High risk: Trigger alerts to prioritize closer monitoring or interventions.
  - Moderate risk: Recommend routine follow-up.
  - Low risk: Suggest standard care.

4) Interdisciplinary Collaboration:

- Involve cardiologists, nurses, data scientists, and IT specialists in designing and implementing the system.
- Provide training sessions to ensure clinicians understand the model's predictions and limitations.

Validation Steps Before Clinical Deployment

1) Retrospective Validation:

- Test the model on a separate dataset from a similar population to evaluate generalizability and performance metrics (e.g., sensitivity, specificity, AUC-ROC, calibration).

2) External Validation:

- Use datasets from other hospitals or populations to ensure the model works across different demographic and clinical settings.

3) Prospective Validation:
   - Conduct a prospective cohort study in a real clinical environment to evaluate the model's performance in live decision-making.
4) Clinical Trial:
   - Design a randomized controlled trial (RCT) to measure the model's impact on clinical outcomes, such as mortality reduction, length of stay, or re-admission rates.
5) Regulatory Approval:
   - Seek approval from relevant regulatory bodies (e.g., FDA, EMA) by providing evidence of the model's efficacy, safety, and reliability.
6) Ethical and Legal Review:
   - Conduct an ethical review to address patient consent, data privacy, and usage accountability.
   - Ensure compliance with data protection regulations like GDPR or HIPAA.

Potential Challenges in Real-World Implementation

1) Data Quality and Availability:
   - Challenge: Missing, inconsistent, or inaccurate data can affect model reliability.
   - Solution: Implement data quality control processes and imputation methods for handling missing values.
2) Model Interpretability:
   - Challenge: Clinicians may hesitate to trust or use predictions from a "black-box" model like Random Forest.
   - Solution: Provide explainability features, such as SHAP (SHapley Additive exPlanations), to show key factors influencing predictions.

3) Clinical Adoption Resistance:
    - Challenge: Clinicians may resist adopting a new tool due to concerns about workflow disruption or reliability.
    - Solution: Conduct training sessions, involve clinicians early in development, and demonstrate improved patient outcomes through pilot studies.
4) Workflow Integration:
    - Challenge: Integrating the tool seamlessly into EHR systems and clinical workflows can be technically challenging.
    - Solution: Work with IT teams to ensure smooth integration and minimal disruption to existing processes.
5) Generalizability:
    - Challenge: The model may not perform equally well across diverse patient populations or hospitals.
    - Solution: Regularly retrain the model on local data and evaluate performance across subgroups.
6) Ethical Concerns:
    - Challenge: Risk stratification might lead to biases or stigmatization of certain patient groups.
    - Solution: Monitor the tool for biases and ensure equitable care across all patient demographics.
7) Cost and Resource Allocation:
    - Challenge: Deploying and maintaining the system may require significant financial and human resources.
    - Solution: Demonstrate cost-effectiveness by showing reductions in adverse events, hospital stays, or readmissions.

To ensure successful implementation, the model must be rigorously validated, seamlessly integrated into clinical workflows, and accompanied by robust training and monitoring systems. Addressing challenges proactively through collaboration, ethical oversight, and iterative development will maximize the model's utility and impact in clinical practice.

REFERENCES

1. World health statistics 2023 – monitoring health for the sdgs. 2023. en.
2. Murray CJL. The global burden of disease study at 30 years. Nat Med. 2022;28(10):2019-26. en.
3. Zhao X, Wang J, Yang J, Chen T, Song Y, Li X, et al. Machine learning for prediction of bleeding in acute myocardial infarction patients after percutaneous coronary intervention. Ther Adv Chronic Dis. 2023;14:20406223231158561. eng.
4. Cichosz SL, Johansen MD, Hejlesen O. Toward big data analytics: Review of predictive models in management of diabetes and its complications. J Diabetes Sci Technol. 2015;10(1):27-34. eng. 20151014.
5. Kiatchoosakun S, Keelapang P, Kaewsuwana P, Chotinaiwattarakul C, Piumsomboon C. Percutaneous coronary intervention in the elderly: Results from the thai national percutaneous coronary intervention registry (tpcir). EuroIntervention. 2010;6(5):611-5. eng.
6. Ciba K. Number of heart disease patients thailand 2013-2022. 2024. https://www.statista.com/statistics/1402687/thailand-number-of-heart-disease-patients/?utm_source=chatgpt.com#statisticContainer
7. Kitigon Vichairuangthum PJ, , Kietchai Veerayannon. Factors associated with getting timely coronary catheterization of patients with acute ischemic heart disease of hospitals in thailand. American Journal of Public Health Research. 2021;9(3):106-13.
8. Chicco D, Jurman G. Machine learning can predict survival of patients with heart failure from serum creatinine and ejection fraction alone. BMC Medical Informatics and Decision Making. 2020;20(1):16.
9. Niimi N, Shiraishi Y, Sawano M, Ikemura N, Inohara T, Ueda I, et al. Machine learning models for prediction of adverse events after percutaneous coronary intervention. Scientific Reports. 2022;12(1):6262.
10. Galimzhanov A, Matetic A, Tenekecioglu E, Mamas MA. Prediction of clinical outcomes

after percutaneous coronary intervention: Machine-learning analysis of the national inpatient sample. International Journal of Cardiology. 2023:131339. en.

11. Tofighi S, Poorhosseini H, Jenab Y, Alidoosti M, Sadeghian M, Mehrani M, et al. Comparison of machine-learning models for the prediction of 1-year adverse outcomes of patients undergoing primary percutaneous coronary intervention for acute st-elevation myocardial infarction. Clin Cardiol. 2023. eng. 20230918.
12. Amon J, Wong GC, Lee T, Singer J, Cairns J, Shavadia JS, et al. Incidence and predictors of adverse events among initially stable st-elevation myocardial infarction patients following primary percutaneous coronary intervention. J Am Heart Assoc. 2022;11(17):e025572. eng. 20220903.
13. Zhao X, Wang J, Yang J, Chen T, Song Y, Li X, et al. Machine learning for prediction of bleeding in acute myocardial infarction patients after percutaneous coronary intervention. Ther Adv Chronic Dis. 2023;14:20406223231158561. eng. 20230304.
14. Huang L, Zhang J, Huang Q, Cui R, Chen J. In-hospital major adverse cardiovascular events after primary percutaneous coronary intervention in patients with acute st-segment elevation myocardial infarction: A retrospective study under the china chest pain center (standard center) treatment system. BMC Cardiovascular Disorders. 2023;23(1):198.
15. Roongsangmanoon W, Wongsoasup A, Chichareon P, Suwannasom P, Chandavimol M, Limpijankit T, et al. Validation of the academic research consortium high bleeding risk definition in thai pci registry. Int J Cardiol. 2023;388:131167. eng. 20230708.
16. Sansanayudh N, Chandavimol M, Srimahachota S, Limpijankit T, Hutayanon P, Kiatchoosakun S, et al. Patient characteristics, procedural details, and outcomes of contemporary percutaneous coronary intervention in real-world practice: Insights from nationwide thai pci registry. J Interv Cardiol. 2022;2022:5839834. eng. 20220712.
17. Chanmanacharoen IR, Jampa-Ngern S, Senavongse W. Comparison of machine learning models for prediction of in-hospital adverse outcomes after percutaneous

coronary intervention. 2024. 39-43.

18. Lanzer P. Panvascular medicine. 2. Lanzer P, editor.: Springer Berlin, Heidelberg; 2015. LXI, 5004.
19. Dalley AF. Moore's clinically oriented anatomy. Ninth edition.. Philadelphia : Wolters Kluwer; 2023.
20. Mahadevan V. Anatomy of the heart. Surgery (Oxford). 2015;33(2):47-51.
21. National Heart L, and Blood Institute. What is atherosclerosis? Maryland: National Heart, Lung, and Blood Institute; 2022 2023 [Mar 24,2022; Oct 28]. https://www.nhlbi.nih.gov/health/atherosclerosis
22. Organization WH. Cardiovascular diseases (cvds) [Internet]. Geneva: World Health Organization; 2021 2023 [Oct 24]. Availble from: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)
23. Cannon CP. The new heart disease handbook : Everything you need to know to effectively reverse and manage heart disease. Beverly, Mass. : Fair Winds Press; 2009.
24. Staff MC. Coronary artery bypass surgery. Arizona: Mayo Clinic; 2023 2023 [Oct 26]. https://www.mayoclinic.org/tests-procedures/coronary-bypass-surgery/about/pac-20384589
25. Clinic C. Cerebrovascular disease. Ohio: Cleavland Clinic; 2022 2023 [Oct 24]. https://my.clevelandclinic.org/health/diseases/24205-cerebrovascular-disease
26. Ahmad Y. Percutaneous coronary intervention (pci). Connecticut: Yale Medicine; 2023 2023 [Nov 5]. https://www.yalemedicine.org/conditions/percutaneous-coronary-intervention-pci#:~:text=Overview,blood%20flow%20to%20the%20heart.
27. Clinic C. Percutaneous coronary intervention. Ohio: Cleveland Clinic; 2021 2023 [Nov 5]. https://my.clevelandclinic.org/health/treatments/22066-percutaneous-coronary-intervention
28. Patrono C, Andreotti F, Arnesen H, Badimon L, Baigent C, Collet JP, et al. Antiplatelet agents for the treatment and prevention of atherothrombosis. Eur Heart J. 2011;32(23):2922-32. eng. 20111020.

29. Stone GW, Bertrand ME, Moses JW, Ohman EM, Lincoff AM, Ware JH, et al. Routine upstream initiation vs deferred selective use of glycoprotein iib/iiia inhibitors in acute coronary syndromesthe acuity timing trial. JAMA. 2007;297(6):591-602.

30. Stephen D. Wiviott MD, Eugene Braunwald, M.D., Carolyn H. McCabe, B.S., Gilles Montalescot, M.D., Ph.D., Witold Ruzyllo, M.D., Shmuel Gottlieb, M.D., Franz-Joseph Neumann, M.D., Diego Ardissino, M.D., Stefano De Servi, M.D., Sabina A. Murphy, M.P.H., Jeffrey Riesmeyer, M.D., Govinda Weerakkody, Ph.D., C. Michael Gibson, M.D., and Elliott M. Antman, M.D., for the TRITON–TIMI 38 Investigators. Prasugrel versus clopidogrel in patients with acute coronary syndromes. New England Journal of Medicine. 2007;357(20):2001-15.

31. Wishart DS, Feunang YD, Guo AC, Lo EJ, Marcu A, Grant JR, et al. Drugbank 5.0: A major update to the drugbank database for 2018. Nucleic Acids Res. 2018;46(D1):D1074-d82. eng.

32. Law V, Knox C, Djoumbou Y, Jewison T, Guo AC, Liu Y, et al. Drugbank 4.0: Shedding new light on drug metabolism. Nucleic Acids Res. 2014;42(Database issue):D1091-7. eng. 20131106.

33. Knox C, Law V, Jewison T, Liu P, Ly S, Frolkis A, et al. Drugbank 3.0: A comprehensive resource for 'omics' research on drugs. Nucleic Acids Res. 2011;39(Database issue):D1035-41. eng. 20101108.

34. Wishart DS, Knox C, Guo AC, Cheng D, Shrivastava S, Tzur D, et al. Drugbank: A knowledgebase for drugs, drug actions and drug targets. Nucleic Acids Res. 2008;36(Database issue):D901-6. eng. 20071129.

35. Wishart DS, Knox C, Guo AC, Shrivastava S, Hassanali M, Stothard P, et al. Drugbank: A comprehensive resource for in silico drug discovery and exploration. Nucleic Acids Res. 2006;34(Database issue):D668-72. eng.

36. Committee CS. A randomized blinded trial of clopidogrel versus aspirin in patients at risk of ischemic events (caprie). Lancet. 1996;348(9038):1329-39.

37. Yusuf S, Mehta SR, Chrolavicius S, Afzal R, Pogue J, Granger CB, et al. Comparison of fondaparinux and enoxaparin in acute coronary syndromes. N Engl J Med.

2006;354(14):1464-76. eng. 20060314.

38. Hirsh J, Anand SS, Halperin JL, Fuster V. Guide to anticoagulant therapy: Heparin : A statement for healthcare professionals from the american heart association. Circulation. 2001;103(24):2994-3018. eng.

39. You JJ, Singer DE, Howard PA, Lane DA, Eckman MH, Fang MC, et al. Antithrombotic therapy for atrial fibrillation: Antithrombotic therapy and prevention of thrombosis, 9th ed: American college of chest physicians evidence-based clinical practice guidelines. Chest. 2012;141(2 Suppl):e531S-e75S. eng.

40. Yusuf S, Islam S, Chow CK, Rangarajan S, Dagenais G, Diaz R, et al. Use of secondary prevention drugs for cardiovascular disease in the community in high-income, middle-income, and low-income countries (the pure study): A prospective epidemiological survey. Lancet. 2011;378(9798):1231-43. eng. 20110826.

41. Bangalore S, Parkar S, Messerli FH. How useful are beta-blockers in cardiovascular disease? Anadolu Kardiyol Derg. 2006;6(4):358-63. eng.

42. Cannon CP, Braunwald E, McCabe CH, Rader DJ, Rouleau JL, Belder R, et al. Intensive versus moderate lipid lowering with statins after acute coronary syndromes. N Engl J Med. 2004;350(15):1495-504. eng. 20040308.

43. Pitt B, Zannad F, Remme WJ, Cody R, Castaigne A, Perez A, et al. The effect of spironolactone on morbidity and mortality in patients with severe heart failure. Randomized aldactone evaluation study investigators. N Engl J Med. 1999;341(10):709-17. eng.

44. Connolly SJ, Ezekowitz MD, Yusuf S, Eikelboom J, Oldgren J, Parekh A, et al. Dabigatran versus warfarin in patients with atrial fibrillation. N Engl J Med. 2009;361(12):1139-51. eng. 20090830.

45. Quer G, Arnaout R, Henne M, Arnaout R. Machine learning and the future of cardiovascular care: Jacc state-of-the-art review. Journal of the American College of Cardiology. 2021;77(3):300-13.

46. Seetharam K, Balla S, Bianco C, Cheung J, Pachulski R, Asti D, et al. Applications of machine learning in cardiology. Cardiology and Therapy. 2022;11(3):355-68.

47. Bzdok D, Altman N, Krzywinski M. Statistics versus machine learning. Nature Methods. 2018;15(4):233-4.

48. Chen T, Guestrin C. Xgboost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; San Francisco, California, USA. Association for Computing Machinery; 2016. 785–94. https://doi.org/10.1145/2939672.2939785

49. Cortes C, Vapnik V. Support-vector networks. Machine Learning. 1995;20(3):273-97.

50. Breiman L. Random forests. Machine Learning. 2001;45(1):5-32.

51. Chantri P, จันตรี ผ, Srinakharinwirot University. Faculty of S, Khwanta S, ขวัญตา ศ. Students' performance prediction using machine learning: การใช้เทคโนโลยีการเรียนรู้ของเครื่อง เพื่อทำนายผลการเรียนของนักเรียน. Srinakharinwirot University; 2020.

52. . Forecasting congestive heart failure using deep learning [files/1311/Srilakshmi et al. - 2023 - Forecasting Congestive Heart Failure using Deep Le.pdf]. 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC); 2023. files/1312/10193602.html

53. solutions S. Directory of statistical analyses: What is logistic regression? Florida: Statistics solutions; 2023 2023 [Nov 3]. https://www.statisticssolutions.com/free-resources/directory-of-statistical-analyses/what-is-logistic-regression/

54. Kunmar AVS. Diagnosis of heart disease using fuzzy resolution mechanism. Journal of Artificial Intelligent 2012;5:47-55. en-gb.

55. Cook CM, Warisawa T, Howard JP, Keeble TR, Iglesias JF, Schampaert E, et al. Algorithmic versus expert human interpretation of instantaneous wave-free ratio coronary pressure-wire pull back data. JACC Cardiovasc Interv. 2019;12(14):1315-24. eng.

56. K V, Singaraju J. Decision support system for congenital heart disease diagnosis based on signs and symptoms using neural networks. IJCA. 2011;19(6):6-12. en.

57. Kumari M, Godara S. Comparative study of data mining classification methods in cardiovascular disease prediction. 2011;2(2). en.

58. Al-Milli N. Backpropogation neural network for prediction of heart disease. Vol.

2005;56. en.

59. Šter B, Dobnikar A. Neural networks in medical diagnosis: Comparison with other methods. Proceedings of the International Conference on Engineering Applications of Neural Networks. 1996.

60. Das R, Turkoglu I, Sengur A. Effective diagnosis of heart disease through neural networks ensembles. Expert Systems with Applications. 2009;36(4):7675-80.

61. Latha CBC, Jeeva SC. Improving the accuracy of prediction of heart disease risk based on ensemble classification techniques. Informatics in Medicine Unlocked. 2019;16:100203.

62. Wilson PWF, D'Agostino RB, Levy D, Belanger AM, Silbershatz H, Kannel WB. Prediction of coronary heart disease using risk factor categories. Circulation. 1998;97(18):1837-47. English.

63. Azzalini L, Vilca LM, Lombardo F, Poletti E, Laricchia A, Beneduce A, et al. Incidence of contrast-induced acute kidney injury in a large cohort of all-comers undergoing percutaneous coronary intervention: Comparison of five contrast media. Int J Cardiol. 2018;273:69-73. eng. 20180901.

64. Detrano R, Janosi A, Steinbrunn W, Pfisterer M, Schmid J-J, Sandhu S, et al. International application of a new probability algorithm for the diagnosis of coronary artery disease. The American Journal of Cardiology. 1989;64(5):304-10.

65. Mahmud I, Kabir MM, Mridha MF, Alfarhood S, Safran M, Che D. Cardiac failure forecasting based on clinical data using a lightweight machine learning metamodel. Diagnostics. 2023;13(15):2540. en.

66. Mohan S, Thirumalai C, Srivastava G. Effective heart disease prediction using hybrid machine learning techniques. IEEE Access. 2019;7:81542-54. en.

67. Ali L, Niamat A, Khan JA, Golilarz NA, Xingzhong X, Noor A, et al. An optimized stacked support vector machines based expert system for the effective prediction of heart failure. IEEE Access. 2019;7:54007-14. en.

68. Computer S, Engineering VCoE, Technology E-TI, Jabeen Begum DS. Heart diseases prediction using machine learning techniques. GOR. 2020;33(02). en.

69. Abdullah AS, Rajalaxmi RR. A data mining model for predicting the coronary heart disease using random forest classifier. IJCA. 2012. en.

70. Sellappan P, Awang R. Intelligent heart disease prediction system using data mining techniques. IJCSN International Journal of Computer Science and Network Security. 2008;8:108-15.

71. Polat K, Şahan S, Güneş S. Automatic detection of heart disease using an artificial immune recognition system (airs) with fuzzy resource allocation mechanism and k-nn (nearest neighbour) based weighting preprocessing. Expert Systems with Applications. 2007;32(2):625-31.

72. Introduction to the logistic regression model. Applied logistic regression. 2000. 1-30. https://onlinelibrary.wiley.com/doi/abs/10.1002/0471722146.ch1

73. Menard S. Applied logistic regression analysis. 2. SAGE Publications, Inc.; 2002.

74. McCullagh PaN, J.A. Generalized linear models. 4. Chapman and Hall; 1989.

75. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: Machine learning in python. Journal of Machine Learning Research. 2011. English.

76. David G. Kleinbaum MK. Logistic regression. 3. NY: Springer New York, NY; 2010. XVII, 702.

APPENDIX

DATA APPROVAL

สมาคมแพทย์มัณฑนากรหัวใจและหลอดเลือดแห่งประเทศไทย
Cardiovascular Intervention Association of Thailand

ที่ มฑ.งานวิจัย.001/2567

7 กุมภาพันธ์ 2567

เรื่อง อนุมัติการขอข้อมูลโครงการวิจัย Thai PCI Registry

เรียน คุณไอรัก จันทร์มานะเจริญ

ตามที่ท่านได้ขอข้อมูลโครงการวิจัย "การศึกษาปัจจัยที่มีความสัมพันธ์กับผลการรักษาผู้ป่วยด้วยการทำการถ่างขยายหลอดเลือดหัวใจผ่านทางผิวหนังในประเทศไทยแบบสหสถาบัน (Thai PCI Registry)" เป็นการศึกษาผลการรักษาผู้ป่วยด้วยการทำการถ่างขยายหลอดเลือดหัวใจผ่านทางผิวหนัง เพื่อใช้สำหรับเขียนบทความวิจัยเรื่อง Machine learning-based one-year outcome prediction after percutaneous coronary intervention ของนางสาวไอรัก จันทร์มานะเจริญ คณะวิศวกรรมศาสตร์ มหาวิทยาลัยศรีนครินทรวิโรฒ โดยมีนายแพทย์วรวุฒิ รุ่งแสงมนูญ เป็นที่ปรึกษา นั้น คณะกรรมการกำกับการเขียนบทความงานวิจัย โครงการวิจัย Thai PCI Registry มีมติอนุมัติการขอข้อมูลตามที่กล่าวขอ

จึงเรียนมาเพื่อได้โปรดทราบ

ขอแสดงความนับถือ

(พล.ต.รศ.ดร.นครินทร์ ศันสนยุทธ)
ประธานโครงการวิจัย Thai PCI Registry

ชั้น 3 อาคารชัยสงวน 2 1575 ถ.เพชรบุรีตัดใหม่ แขวงมักกะสัน เขตราชเทวี กรุงเทพฯ 10400
1993CIAT@gmail.com
02-070-6671 , 094-857-5588 Fax : 02-070-6672
www.ciat.or.th

3rd floor Chai Sa-Nguan II Bldg., 1575 New Petchburi Rd., Ratchatawee, Bangkok, 10400 Thailand
1993CIAT@gmail.com
(+66) 2-070-6671 , (+66) 94-857-5588 Fax : (+66) 2-070-6672
www.ciat.or.th

Figure 12 Data approval

ETHICAL APPROVAL

AF20-03-03.1
August, 2023

Certificate of Exemption

This is to certify that

Protocol Title: Machine learning-based one-year outcome prediction after percutaneous coronary intervention
Principal investigator: Miss I-ruk Chanmanacharoen
Institution: Faculty of Engineering, Srinakharinwirot University
Protocol code: SWUEC-671023

The Human Research Ethics Committee of Srinakharinwirot University agreed that this research study has met the criteria of the Exemption Determination Regulations and considered exempt from the full review process. If the changes are made to the research protocol regarding research methodology and target population, a new research protocol must be submitted for approval from the ethical committee. Upon completion of the research study, please submit the protocol closing form and the complete research report, or a copy of a published journal article. The Ethics and Research Standards Division will archive your research documents for 3 years after the date of approval.

Date of approval: 21/03/2024
Date of expiration: 20/03/2027

Sureeporn Patrasuwan
....
(Dr. Sureeporn Patrasuwan M.D.)
Chairman, Human and Research Ethics Committee (Panel 1)
Srinakharinwirot University

Ethics and Research Standards Devision
Innovation Building Prof. Dr. Saroch Buasri, Floor 17
Srinakhanarinwirot University, Thailand
Tel.: +66-26-495000, 17503, 17506 Fax: +66-22-042590

Figure 13 Ethical approval

CASE RECORD FORM

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

A. DEMOGRAPHICS	
A01: Gender: ☐ Male ☐ Female	A02: Date of Birth: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))

B. EPISODE OF CARE	
B01: Admission Date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))	B02: Admission Time: ☐☐:☐☐ (24 hr.)
B03: Refer Case: ☐ Yes ☐ No	
B04: Health benefits (Singular option only) ☐ Universal Coverage ☐ Public Office/State Enterprise ☐ Social Security ☐ Cash ☐ Private Health Insurance ☐ Others (please specify) ………………………...............	

C. PHYSICAL EXAM, HISTORY AND RISK FACTORS	
C01: Height: ☐☐☐ cm.	C02: Weight: ☐☐☐ kg.
C03: Admission SBP: ☐☐☐ mmHg	C04: Admission HR: ☐☐☐ /min
C05: Smoking status: ☐ Current smoker ☐ Ex-smoker ☐ Non-smoker	
C06: Hypertension ☐ Yes ☐ No	
C07: Dyslipidemia ☐ Yes ☐ No	C08: Cerebrovascular Disease ☐ Yes ☐ No
C09: Family History of Premature CAD ☐ Yes ☐ No	C10: Peripheral Arterial Disease ☐ Yes ☐ No
C11: Prior MI ☐ Yes ☐ No C12: Known CAD (Stenosis > 50%) ☐ Yes ☐ No	C13: Chronic Lung Disease ☐ Yes ☐ No
C14: Prior Heart Failure ☐ Yes ☐ No	C16: CKD ☐ Yes ☐ No
C15: Prior Valve Surgery/Procedure ☐ Yes ☐ No	C17: On Dialysis ☐ Yes ☐ No
C18: Prior PCI ☐ Yes ☐ No → *If Yes, **Most Recent PCI Date** (DD-MM-YYYY or at least year, if unknown YYYY=9999):* ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY(B.E.))	C19: Prior CABG ☐ Yes ☐ No → *If Yes, **CABG Date** (DD-MM-YYYY or at least year, if unknown YYYY=9999):* ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY(B.E.))
C20: Diabetes Mellitus ☐ Yes ☐ No → *If Yes,* (can choose > 1) ☐ Diet ☐ Oral ☐ Insulin ☐ GLP	

Version December 20th 2018 ~ 1 ~

Figure 14 Thai PCI registry (demographics, episode of care, physical exam, history, and risk factors)

Source: THAI PCI REGISTRY version Dec 20th ,2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

D. CATH LAB VISIT (Complete for each Cath lab visit)	
CLINICAL EVALUATION LEADING TO THE PROCEDURE	
D01: Symptom onset ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))	Time ☐☐:☐☐ (24 hr.)
D02: CAD Presentation: /Indication	☐ STEMI ☐ NSTEMI / Unstable Angina ☐ Stable CAD ☐ Others (please specify) ....
D03: → ***If STEMI*** (choose only 1)	☐ Primary PCI (PPCI) ☐ Rescue PCI ☐ Pharmacoinvasive ☐ PCI after 48 hours of onset
– Time at First Medical contact:	☐☐-☐☐-☐☐☐☐ /☐☐:☐☐
– Time arrived at PCI center:	☐☐-☐☐-☐☐☐☐ /☐☐:☐☐
– Time arrived at Cath Lab:	☐☐-☐☐-☐☐☐☐ /☐☐:☐☐
– Time of first Device:	☐☐-☐☐-☐☐☐☐ /☐☐:☐☐ (DD-MM-YYYY (B.E.)) (24 hr.)
D04: In referred STEMI case	
– Door in hospital 1	☐☐-☐☐-☐☐☐☐ /☐☐:☐☐
– Door out hospital 1	☐☐-☐☐-☐☐☐☐ /☐☐:☐☐
– Door in hospital 2	☐☐-☐☐-☐☐☐☐ /☐☐:☐☐
– Door out hospital 2	☐☐-☐☐-☐☐☐☐ /☐☐:☐☐ (DD-MM-YYYY (B.E.)) (24 hr.)
D05: If FMC to Device > 90 min, reason (s) of delay (can choose > 1)	
☐ Delay diagnosis	☐ Delay of in-hospital transfer
☐ Difficult vascular access	☐ Cardiac arrest and/or need for intubation before PCI
☐ Patient delays in providing consent for the procedure	☐ Difficulty crossing the culprit lesion during PCI
☐ Have to be referred to PCI center	☐ Others (please specify) ....

Version December 20th 2018 ~ 2 ~

Figure 15 Thai PCI registry (CATH LAB VISIT)

Source: THAI PCI REGISTRY version Dec 20th ,2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

D06: Thrombolytics: ☐ Yes ☐ No

Date/Time given: ☐☐-☐☐-☐☐☐☐ /☐☐:☐☐
(DD-MM-YYYY (B.E.)) (24 hr.)

Type of Thrombolytic : ☐ Streptokinase
☐ Alteplase
☐ Tenecteplase

D07: → *If Non STEMI /Unstable Angina*

ASA used last 7 days: ☐ Yes ☐ No

Severe angina > 2 episodes in 24 hr.: ☐ Yes ☐ No

ST-T segment (EKG) at presentation ☐ Normal ☐ Abnormal

→ *If abnormal* (can choose > 1)

☐ Transient ST Elevation ☐ ST Depression ☐ T-wave inversion

D08: → *If Stable CAD (with non-invasive test) / other indications* (can choose > 1)

☐ Positive non-invasive test ☐ Stage PCI ☐ Heart Failure (LV Dysfunction)
☐ Pre-Op ☐ Referred from other hospital for PCI
☐ Suspected CAD, no non-invasive test performed
☐ Others (please specify) ……………………………………......................

Stress or Imaging Studies Performed: ☐ Yes → If Yes, specify test performed (choose at least one)
☐ No

Version December 20th 2018 ~ 3 ~

Figure 16 Thai PCI registry (CATH LAB VISIT (continued))

Source: THAI PCI REGISTRY version Dec 20th ,2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

Test performed	Yes	No		Result		Risk/Extent of Ischemia
Standard exercise Stress Test : (w/o imaging)	☐	☐	→ *If Yes,*	☐ Negative ☐ Positive ☐ Indeterminant ☐ N/A	→ *If Positive,*	☐ Low ☐ Intermediate ☐ High ☐ N/A
Stress Echocardiogram :	☐	☐	→ *If Yes,*	☐ Negative ☐ Positive ☐ Indeterminant ☐ N/A	→ *If Positive,*	☐ Low ☐ Intermediate ☐ High ☐ N/A
Stress Testing w/SPECT MPI :	☐	☐	→ *If Yes,*	☐ Negative ☐ Positive ☐ Indeterminant ☐ N/A	→ *If Positive,*	☐ Low ☐ Intermediate ☐ High ☐ N/A
Stress Testing w/CMR :	☐	☐	→ *If Yes,*	☐ Negative ☐ Positive ☐ Indeterminant ☐ N/A	→ *If Positive,*	☐ Low ☐ Intermediate ☐ High ☐ N/A
Cardiac CTA :	☐	☐	→ *If Yes,*	☐ Negative ☐ 1 VD ☐ 3 VD ☐ Indeterminant	☐ Positive ☐ 2 VD ☐ LM ☐ N/A	
Coronary Calcium Score :	☐	☐	→ *If Yes,*	Calcium Score : ☐☐☐☐		

Version December 20th 2018 ~ 4 ~

Figure 17 Thai PCI registry (Test performed)

Source: THAI PCI REGISTRY version Dec 20th ,2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

EQ-5D-5L : Before PCI	☐ Can do it	☐ Cannot do it
**if Cannot do it, please specify the reason **	☐ Death	☐ Incapable
1. Mobility (Please select the most appropriate)		
I have no problems in walking about		☐
I have slight problems in walking about		☐
I have moderate problems in walking about		☐
I have severe problems in walking about		☐
I am unable to walk about		☐
2. Self-care (Please select the most appropriate)		
I have no problems washing or dressing myself		☐
I have slight problems washing or dressing myself		☐
I have moderate problems washing or dressing myself		☐
I have severe problems washing or dressing myself		☐
I am unable to wash or dress myself		☐
3. Usual activities (e.g. work, study, housework, family or leisure activities) (Please select the most appropriate)		
I have no problems doing my usual activities		☐
I have slight problems doing my usual activities		☐
I have moderate problems doing my usual activities		☐
I have severe problems doing my usual activities		☐
I am unable to do my usual activities		☐
4. Pain/ Discomfort (Please select the most appropriate)		
I have no pain or discomfort		☐
I have slight pain or discomfort		☐
I have moderate pain or discomfort		☐
I have severe pain or discomfort		☐
I have extreme pain or discomfort		☐
5. Anxiety/ Depression (Please select the most appropriate)		
I am not anxious or depression		☐
I am slight anxious or depression		☐
I am moderate anxious or depression		☐
I am severely anxious or depression		☐
I am extremely anxious or depression		☐

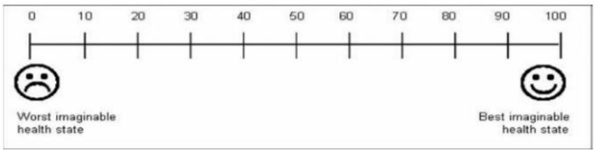
Version December 20th 2018 ~ 5 ~

Figure 18 Thai PCI registry (before PCI)

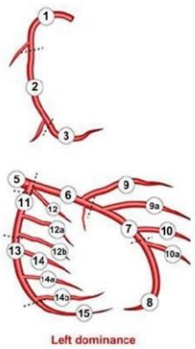
Source: THAI PCI REGISTRY version Dec 20th ,2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

How are your health today?, 100 is means best and 0 means worst.
Please mark the cross (X) into the picture below and write the number in the box ☐



Your health today = ☐☐☐

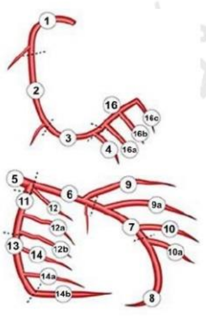
E. BEST ESTIMATE OF CORONARY ANATOMY				
E01: Dominance	☐ **Left**			
E02: Coronary Territory	**Native Artery Percent Stenosis in ≥ 2mm vessels**			
Segment No.1	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.2	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.3	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.5	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.6	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.7	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.8	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.9	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.10	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.11	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.12	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.13	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.14,15	________ %	☐ No Significant stenosis	☐ N/A	

Version December 20th 2018 ~ 6 ~

Figure 19 Thai PCI registry (Best Estimate of coronary anatomy)

Source: THAI PCI REGISTRY version Dec 20th ,2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

E03: Dominance	☐ **Right**			
E04: **Coronary Territory**	**Native Artery** **Percent Stenosis in ≥ 2mm vessels**			
Segment No.1	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.2	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.3	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.4	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.5	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.6	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.7	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.8	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.9, 10	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.11	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.12	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.13	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.14	________ %	☐ No Significant stenosis	☐ N/A	
Segment No.16	________ %	☐ No Significant stenosis	☐ N/A	

E05: Previous CABG	☐ Yes ☐ No		
E06: Coronary Territory	**Grafts Supply Coronary Territory**		
LAD	________ %	☐ No Significant stenosis	☐ N/A
Diagonal Branches	________ %	☐ No Significant stenosis	☐ N/A
LCX	________ %	☐ No Significant stenosis	☐ N/A
OMs, LPDA, LPL Branches	________ %	☐ No Significant stenosis	☐ N/A
Ramus	________ %	☐ No Significant stenosis	☐ N/A
RCA	________ %	☐ No Significant stenosis	☐ N/A
RPDA, RPL, AM Branches	________ %	☐ No Significant stenosis	☐ N/A
E07: Conclusion	Left main disease ☐ Yes ☐ No And/or ☐ No other stenosis ☐ SVD ☐ DVD ☐ TVD		
E08: Calculated syntax score	☐ Yes	☐ No	If, Yes ☐☐

Version December 20th 2018 ~ 7 ~

Figure 20 Thai PCI registry (Best Estimate of coronary anatomy (continued))

Source: THAI PCI REGISTRY version Dec 20th ,2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

F. PCI PROCEDURE (Complete for each Cath lab visit in which a PCI was attempted or performed)

F01: Operator's Name: ....

F02: PCI Status : ☐ Elective ☐ Urgent ☐ Emergency

F03: Cardiogenic Shock at Start of PCI : ☐ Yes ☐ No

PROCEDURE INFORMATION

F04: Procedure Date/Time: ☐☐-☐☐-☐☐☐☐ /☐☐:☐☐

(DD-MM-YYYY (B.E.)) (24 hr.)

F05: Fluoroscopy Time: ☐☐☐.☐☐min

F06: Dose (Air Kerma): ☐☐☐☐☐.☐☐mGy

F07: DAP (Dose Area Product): ☐☐☐☐☐☐.☐☐ mGy.cm^2/ cGy.cm^2/ Gy.cm^2

F08: Contrast Name: (can choose > 1) ☐ Ultravist ☐ Optiray ☐ Visipaque

☐ Others (please specify) ....

F09: Total Volume of contrast: ☐☐☐ml

MECHANICAL VENTRICULAR SUPPORT

F10: IABP ☐ Yes → *If Yes, Timing (must choose only 1)*

- ☐ In place before CAG
- ☐ Inserted after CAG but before PCI
- ☐ Inserted after PCI had begum
- ☐ Inserted after finish PCI

☐ No

F11: Other Mechanical Ventricular Support

☐ Yes → *If yes (must choose at least 1)*

- ☐ LVAD
- ☐ ECMO
- ☐ Others ....

☐ No

Version December 20th 2018 ~ 8 ~

Figure 21 Thai PCI registry (PCI procedure, procedure information, mechanical ventricular support)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

ARTERIAL ACCESS	
F12: Initial Access Site: (can choose > 1)	☐ Rt. Femoral ☐ Rt. Brachial ☐ Rt. Radial ☐ Lt. Femoral ☐ Lt. Brachial ☐ Lt. Radial ☐ Others ....
F13: More than one attempt	☐ Yes ☐ No
F14: Cross-over	☐ Yes ☐ No If yes, Final access site (can choose > 1) ☐ Rt. Femoral ☐ Rt. Brachial ☐ Rt. Radial ☐ Lt. Femoral ☐ Lt. Brachial ☐ Lt. Radial ☐ Others ....
F15: Closure Method(s)	(can choose > 1) ☐ Manual Compression ☐ Wristband ☐ C-arm ☐ Closure Device (☐ Angioseal ☐ Proglide ☐ Anscare ☐ Others (please specify) ....)

F16: PROCEDURE MEDICATION (Administered within 24 hours prior to and during the PCI procedure)

Category	Medication	Administered
Anticoagulants	Fondaparinux	☐ Yes ☐ No
	Low Molecular Weight Heparin	☐ Yes ☐ No
	Unfractionated Heparin	☐ Yes ☐ No
Aspirin	Aspirin	☐ Yes ☐ No
Glycoprotein IIb/IIa Inhibitors	GP IIb/IIIa Inhibitors	☐ Yes ☐ No
P2Y12 Inhibitors	Clopidogrel	☐ Yes ☐ No
	Ticlopidine	☐ Yes ☐ No
	Prasugrel	☐ Yes ☐ No
	Ticagrelor	☐ Yes ☐ No

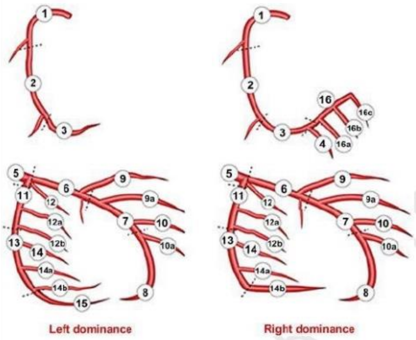
F17: ACT Measured	☐ Yes ☐ No
No. of lesions treated	☐
No. of vessels treated	☐
No. of Guiding catheter used	☐☐
No. of Guidewire used	☐☐
No. of Balloon used	☐☐
No. of Stent used	☐☐

Version December 20th 2018 ~ 9 ~

Figure 22 Thai PCI registry (Arterial access, Procedure medication)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: □□-□□□□

G. LESION AND DEVICES (Complete for each PCI attempted or performed) Please fill out form G 1 sheet per lesion, if doing PCI more than 1 lesion. Please complete additional G form for the number of lesion.	
G01: Dominance	□ Left □ Right
G02: Segment Number (see picture attached)	□□□ □ Others 
G03: If presentation is 'STEMI', 'Non-STEMI, or 'Unstable angina'	**PCI for Culprit Lesion** □ Yes □ No □ Unknown
G04: Stenosis Immediately Prior to PCI :	□□□% → If 100%, Chronic Total Occlusion □ Yes □ No
G05: IVUS-guided	□ Yes → If yes (can choose > 1) □ Pre PCI □ Post PCI □ No
G06: OCT-guided	□ Yes → If yes (can choose > 1) □ Pre PCI □ Post PCI □ No
G07: FFR-guided → *If Yes, FFR Ratio* :	□ Yes → If yes (can choose > 1) □ Pre PCI FFR □.□□ □ Post PCI FFR □.□□ □ No
G08: Pre-procedure TIMI Flow :	□ 0 □ 1 □ 2 □ 3
G09: Previously treated lesion :	□ Yes □ No

Version December 20th 2018 ~ 10 ~

Figure 23 Thai PCI registry (Lesion and devices)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

→ *If Yes, Timeframe :*	☐ <1 month ☐ ≥1 and <6 months ☐ ≥6 and <12 months ☐ ≥1 and < 2 years ☐ ≥ 2 years ☐ N/A
→ *If Yes, Previous treated with Stent :*	☐ Yes ☐ No
→ *If Yes, In-Stent Restenosis :*	☐ Yes ☐ No
→ *If Yes, Stent Type:*	☐ DES ☐ BMS ☐ BRS ☐ N/A
→ *If Yes, In-Stent Thrombosis :*	☐ Yes ☐ No
→ *If Yes, Stent Type:*	☐ DES ☐ BMS ☐ BRS ☐ N/A
G10: Lesion in Graft :	☐ Yes ☐ No
→ *If Yes, type of graft*	☐ LIMA ☐ RIMA ☐ Radial artery ☐ Other artery ☐ SVG
→ *If Yes, location in graft*	☐ Ostium ☐ Shaft ☐ Distal anastomosis
→ *If Yes, distal protection device*	☐ Yes ☐ No
G11: Lesion Complexity :	☐ A ☐ B1 ☐ B2 ☐ C
G12: Lesion Length (mm) :	☐☐☐ mm
G13: Ostium Lesion	☐ Yes ☐ No
G14: Thrombus Present :	☐ Yes ☐ No
G15: Bifurcation Lesion :	☐ Yes → *If yes; Medina classification* ☐-☐-☐ ☐ No
G16: POBA only	☐ Yes ☐ No
→ *If yes……………………………*	☐ None balloon ☐ Brand …………………………… Diameter ☐.☐☐ Length ☐☐mm Max inflation pressure ☐☐ ATM
G17: Stent	
Direct (without balloon predilatation)	☐ Yes ☐ No
- Stent1	☐ BMS ☐ DES ☐ BRS Brand ………………… Diameter ☐.☐☐ Length ☐☐mm
- Stent2	☐ BMS ☐ DES ☐ BRS Brand………………… Diameter ☐.☐☐ Length ☐☐mm

Version December 20th 2018 ~ 11 ~

Figure 24 Thai PCI registry (Lesion and devices (continued))

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

- Stent3	☐ BMS ☐ DES ☐ BRS Brand....................... Diameter ☐.☐☐ Length ☐☐mm
G18: Balloon post-dilate	☐ Yes → If yes, Brand .... Diameter ☐.☐☐ Length ☐☐mm Max inflation pressure ☐☐ ATM ☐ No
G19: Plaque Modification	☐ Yes → *If yes, please choose (can choose >1)* ☐ Rotablator ☐ Laser ☐ Tornus ☐ Cutting balloon ☐ Scoring Balloon (NSE, Scoreflex, Angiosculpt) ☐ Others (please specify)................................ ☐ No
G20: Aspiration catheter (included Angiojet)	☐ Yes ☐ No
G21: Post procedure TIMI flow:	☐ 0 ☐ 1 ☐ 2 ☐ 3
G22: Final Result *→ If Success, residual stenosis post procedure* *→ If fail, why : choose only 1*	☐ Success ☐ Fail ☐☐% ☐ Wire uncrossable ☐ Balloon uncrossable ☐ Stent uncrossable ☐ Nondilatable lesion ☐ Others (please specify)..
G23: Procedure complications	☐ Yes → If yes (can choose >1) ☐ Residual Dissection ☐ Perforation ☐ No Reflow ☐ Major Side branch occlusion ☐ Acute Stent Thrombosis ☐ Catheter Thrombosis ☐ Device loss, dislodge, rupture ☐ Others (please specify).. ☐ No

Figure 25 Thai PCI registry (Lesion and devices (continued))

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

H. INVESTIGATION (Complete for each Cath lab visit in which a PCI was attempted or performed)			
H01: LVEF	☐☐ %		☐ Not performed
H02: Pre-procedure (performed at your facility or referral hospital)			
CK-MB	☐☐☐☐.☐☐	ng/mL / unit/L	☐ N/A
Troponin I	☐☐☐☐☐.☐☐	ng/L	☐ N/A
Troponin T	☐☐☐☐☐.☐☐	ng/L	☐ N/A
Creatinine	☐☐.☐☐	mg/dL	☐ N/A
Hemoglobin	☐☐.☐	g/dL	☐ N/A
Hct	☐☐.☐	%	☐ N/A
WBC	☐☐.☐	*x 10^3/mm^3*	☐ N/A
Mean Platelet Volume	☐☐.☐	fL	☐ N/A
Blood sugar	☐ Random		☐ Fasting ☐☐☐ mg/dL ☐ N/A
HbA1C	☐☐.☐	%	☐ N/A
LDL-C	☐☐☐	mg/dL	☐ N/A

H03: Post-Procedure			
CK-MB *(Peak value 6-24 hrs)*	☐☐☐☐.☐☐	ng/mL/ unit/L	☐ N/A
Troponin I *(Peak value 6-24 hrs)*	☐☐☐☐☐.☐☐	ng/L	☐ N/A
Troponin T *(Peak value 6-24 hrs)*	☐☐☐☐☐.☐☐	ng/L	☐ N/A
Creatinine *(Highest value)* ☐☐-☐☐-☐☐☐☐/☐☐:☐☐ (DD-MM-YYYY (B.E.)) / 24 hr.)	☐☐.☐☐	mg/dL	☐ N/A
Hemoglobin *(Lowest within 72 hrs.)*	☐☐.☐	g/dL	☐ N/A
Hct	☐☐.☐	%	☐ N/A

Version December 20th 2018 ~ 13 ~

Figure 26 Thai PCI registry (Investigation, pre-procedure, post-procedure)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

I. INTRA AND/OR POST-PROCEDURE CLINCAL EVENTS (Complete for each Cath Lab visit)				
I01: Myocardial Infarction : (Positive Biomakers)	☐ Yes	☐ No		
I02: Cardiogenic Shock :	☐ Yes	☐ No		
I03: Heart Failure	☐ Yes	☐ No		
→ **KILLIP CLASS**	☐ I	☐ II	☐ III	☐ IV
I04: CVA/Stroke :	☐ Yes	☐ No		
→ *If Yes, Hemorrhagic* Stroke :	☐ Yes	☐ No	☐ N/A	
I05: Tamponade:	☐ Yes	☐ No		
I06: New Requirement for Dialysis :	☐ Yes	☐ No		
I07: Vascular Complications Req Rx :	☐ Yes	☐ No		
I08: AV Fistula	☐ Yes	☐ No		
I09: Pseudoaneurysm	☐ Yes	☐ No		
I10: Infection	☐ Yes	☐ No		
I11: RBC/Whole Blood Transfusion :	☐ Yes → If Yes, drop of Hb Prior to transfusion: ☐☐.☐g/dL Unit of PRC/whole bleed given ☐☐ ☐ No			
I12: Bleeding Event w/in 72 Hours :	☐ Yes	☐ No		
→ **Bleeding at Access Site** :	☐ Yes	☐ No		
→ **Hematoma at Access Site** :	☐ Yes	☐ No		
→ **Size** :	☐ < 3 cm	☐ 3 - 5 cm	☐ >5 - 10 cm	☐ >10 cm
→ **Retroperitoneal Bleeding** :	☐ Yes	☐ No		
→ **GI Bleed** :	☐ Yes	☐ No		
→ **GU Bleed** :	☐ Yes	☐ No		
→ **Intracranial Bleed** :	☐ Yes	☐ No		

Version December 20th 2018 ~ 14 ~

Figure 27 Thai PCI registry (Intra and post-procedure clinical events)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

I13: Arrhythmia that required treatment:	☐ Yes → *If Yes (can choose >1)* ☐ Tachyarrhythmia ☐ Bradyarrhythmia ☐ No
I14: ET-tube Intubation:	☐ Yes ☐ No
I15: Temporary Pacemaker:	☐ Yes → *If Yes* ☐ prophylaxis use ☐ treat bradyarrhythmia ☐ No
I16: Cardioversion /defibrillation	☐ Yes ☐ No
I17: Medical treatment for arrhythmia	☐ Yes ☐ No
I18: Other	☐ Repeat Angiogram *Date:* ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.)) ☐ Others (please specify).. ☐ No

J. DISCHARGE (Complete this section for each episode of care)
J01: CABG: ☐ Yes → *If Yes, CABG Indication* ☐ PCI complication ☐ PCI failure without clinical deterioration ☐ PCI/CABG hybrid procedure → *Location:* ☐ At your facility ☐ Transferred to other facility → *If at your facility, CABG Date:* ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.)) ☐ No
J02: LVEF: (At Discharge) ☐☐% ☐ N/A
J03: Discharge Date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))

Figure 28 Thai PCI registry (Discharge)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

J04: Deceased, ☐ Yes → *Death in Lab*: ☐ Yes ☐ No

→ *Deceased date*: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.)

→ *Primary Cause of Death (Choose only 1)*:

☐ Cardiac ☐ Neurologic ☐ Renal ☐ Vascular

☐ Infection ☐ Pulmonary ☐ N/A ☐ Others (please specify)..................................

☐ No (Alive)

→ *Discharge Location*:

☐ Home ☐ Referral Hospital ☐ Left against medical advice (AMA)

☐ Others (please specify) ....

J05: → Pre Discharge risk factors & life style modification :

Cardiac rehab	☐ Yes	☐ No	☐ N/A
Smoking cessation education	☐ Yes	☐ No	
Exercise education	☐ Yes	☐ No	
Nutrition education	☐ Yes	☐ No	

Figure 29 Thai PCI registry (Discharge (continuous))

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

EQ-5D-5L : Before discharge	☐ Can do it	☐ Cannot do it
if Cannot do it, please specify the reason	☐ Death	☐ Incapable
1. Mobility (Please select the most appropriate)		
I have no problems in walking about		☐
I have slight problems in walking about		☐
I have moderate problems in walking about		☐
I have severe problems in walking about		☐
I am unable to walk about		☐
2. Self-care (Please select the most appropriate)		
I have no problems washing or dressing myself		☐
I have slight problems washing or dressing myself		☐
I have moderate problems washing or dressing myself		☐
I have severe problems washing or dressing myself		☐
I am unable to wash or dress myself		☐
3. Usual activities (e.g. work, study, housework, family or leisure activities) (Please select the most appropriate)		
I have no problems doing my usual activities		☐
I have slight problems doing my usual activities		☐
I have moderate problems doing my usual activities		☐
I have severe problems doing my usual activities		☐
I am unable to do my usual activities		☐
4. Pain/ Discomfort (Please select the most appropriate)		
I have no pain or discomfort		☐
I have slight pain or discomfort		☐
I have moderate pain or discomfort		☐
I have severe pain or discomfort		☐
I have extreme pain or discomfort		☐
5. Anxiety/ Depression (Please select the most appropriate)		
I am not anxious or depression		☐
I am slight anxious or depression		☐
I am moderate anxious or depression		☐
I am severely anxious or depression		☐
I am extremely anxious or depression		☐

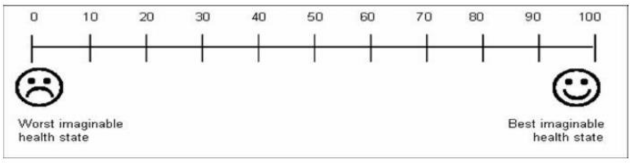
Version December 20th 2018 ~ 17 ~

Figure 30 Thai PCI registry (before discharge)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY　　Registry ID: ☐☐-☐☐☐☐

How are your health today?, 100 is means best and 0 means worst.
Please mark the cross (X) into the picture below and write the number in the box ☐



Your health today = ☐☐☐

Expenses incurred from hospitalization apart than those charged by the hospital.

– **Patient**

Total transportation cost ☐☐,☐☐☐baht

Total food cost ☐☐,☐☐☐baht

Total accommodation cost ☐☐,☐☐☐baht

If no admission, what is your average income <u>per month</u> ☐☐☐,☐☐☐baht

Total spent duration of not working ☐☐☐ days

– **Caretaker**

Total transportation cost ☐☐,☐☐☐baht

Total food cost ☐☐,☐☐☐baht

Total accommodation cost ☐☐,☐☐☐☐baht

Your average income <u>per month</u> ☐☐☐,☐☐☐baht

Total time spent during the patient recovering. ☐☐☐days

Version December 20th 2018　　~ 18 ~

Figure 31 Thai PCI registry (Hospital expense)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

DISCHARAGE MEDICATION (Prescribed at discharge – complete for each episode of care in which a PCI was attempted or performed)			
Category	**Medication**	**Administered**	
Discharge medications are not required for patients who expired or were discharge to 'Other acute care Hospital', 'Hospice' or 'AMA'			
ACE Inhibitor	ACE Inhibitor	❐ Yes	❐ No
ARBs	ARBs	❐ Yes	❐ No
Aspirin	Aspirin	❐ Yes	❐ No
Beta Blockers	Beta Blocker	❐ Yes	❐ No
Lipid Lowering Agents	Statin	❐ Yes	❐ No
	Non-Statin	❐ Yes	❐ No
P2Y12 Inhibitors	Clopidogrel	❐ Yes	❐ No
	Ticlopidine	❐ Yes	❐ No
	Prasugrel	❐ Yes	❐ No
	Ticagrelor	❐ Yes	❐ No
Aldosterone Antagonist	Spironolactone	❐ Yes	❐ No
Anticoagulant	Vitamin K Antagonist	❐ Yes	❐ No
	NOACs	❐ Yes	❐ No

Version December 20th 2018 ~ 19 ~

Figure 32 Thai PCI registry (Discharge medication)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

K. FOLLOW-UP (6 Month)	☐ Hospital Visit	☐ Phone Follow up	☐ Medical Record Review
K01: Date of follow-up			☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY(B.E.))
K02: Repeated Hospitalization : (due to Cardiovascular problems)	☐ Yes	☐ No	date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.)) Primary diagnosis : ____________
K03: Myocardial Infarction :	☐ Yes	☐ No	date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
K04: Heart Failure :	☐ Yes	☐ No	date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
K05: Stroke :	☐ Yes	☐ No	date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
→ *If Yes* :	☐ Ischemic	☐ Hemorrhagic	☐ N/A
K06: Repeated Revascularization	☐ Yes	☐ No	date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
– **Unplanned PCI**	☐ Yes	☐ No	
– **Staged PCI**	☐ Yes	☐ No	
K07: Death	☐ Yes	☐ No	date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
– **Sudden Death**	☐ Yes	☐ No	
– **Cardiovascular Death**	☐ Yes	☐ No	
K08: Major bleeding :	☐ Yes	☐ No	date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
K09: Others: (please specify)			date: ☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))

Version December 20th 2018 ~ 20 ~

Figure 33 Thai PCI registry (Follow-up 6-month)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

EQ-5D-5L : Follow up 6 month	☐ Can do it	☐ Cannot do it
**if Cannot do it, please specify the reason **	☐ Death	☐ Incapable
1. Mobility (Please select the most appropriate)		
I have no problems in walking about		☐
I have slight problems in walking about		☐
I have moderate problems in walking about		☐
I have severe problems in walking about		☐
I am unable to walk about		☐
2. Self-care (Please select the most appropriate)		
I have no problems washing or dressing myself		☐
I have slight problems washing or dressing myself		☐
I have moderate problems washing or dressing myself		☐
I have severe problems washing or dressing myself		☐
I am unable to wash or dress myself		☐
3. Usual activities (e.g. work, study, housework, family or leisure activities) (Please select the most appropriate)		
I have no problems doing my usual activities		☐
I have slight problems doing my usual activities		☐
I have moderate problems doing my usual activities		☐
I have severe problems doing my usual activities		☐
I am unable to do my usual activities		☐
4. Pain/ Discomfort (Please select the most appropriate)		
I have no pain or discomfort		☐
I have slight pain or discomfort		☐
I have moderate pain or discomfort		☐
I have severe pain or discomfort		☐
I have extreme pain or discomfort		☐
5. Anxiety/ Depression (Please select the most appropriate)		
I am not anxious or depression		☐
I am slight anxious or depression		☐
I am moderate anxious or depression		☐
I am severely anxious or depression		☐
I am extremely anxious or depression		☐

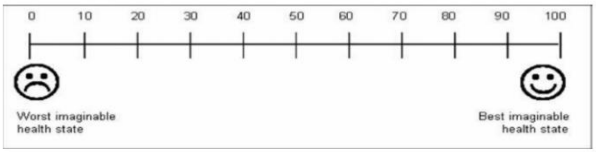
Version December 20th 2018 ~ 21 ~

Figure 34 Thai PCI registry (Follow-up 6-month (continued))

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

How are your health today?, 100 is means best and 0 means worst.
Please mark the cross (X) into the picture below and write the number in the box ☐



Your health today = ☐☐☐

Expenses incurred from hospitalization apart than those charged by the hospital from the last 6 months.

– **Patient**

Total transportation cost ☐☐,☐☐☐baht

Total food cost ☐☐,☐☐☐baht

Total accommodation cost ☐☐,☐☐☐☐baht

Your average income <u>per month</u> ☐☐☐,☐☐☐baht

Time lost from traveling to the hospital/not heading to work for past 6 months ☐☐☐ day

– **Caretaker**

Total transportation cost ☐☐,☐☐☐baht

Total food cost ☐☐,☐☐☐baht

Total accommodation cost ☐☐,☐☐☐baht

Your average income <u>per month</u> ☐☐☐,☐☐☐baht

Total time spent during the patient recovering for past 6 months ☐☐☐ day

Version December 20th 2018 ~ 22 ~

Figure 35 Thai PCI registry (Follow-up 6-month expenses)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐☐

L. FOLLOW-UP (12 Month)	☐ Hospital Visit	☐ Phone Follow up	☐ Medical Record Review
L01: Date of follow-up			☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY(B.E.))
L02: Repeated Hospitalization (due to Cardiovascular problems)	☐ Yes ☐ No	date:	☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY(B.E.)) Primary diagnosis : ____________
L03: Myocardial Infarction :	☐ Yes ☐ No	date:	☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY(B.E.))
L04: Heart Failure :	☐ Yes ☐ No	date:	☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY(B.E.))
L05: Stroke :	☐ Yes ☐ No	date:	☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E).)
→ *If Yes :*	☐ Ischemic	☐ Hemorrhagic	☐ N/A
L06: Repeated Revascularization	☐ Yes ☐ No	date:	☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
– **Unplanned PCI**	☐ Yes ☐ No		
– **Staged PCI**	☐ Yes ☐ No		
L07: Death	☐ Yes ☐ No	date:	☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
– **Sudden Death**	☐ Yes ☐ No		
– **Cardiovascular Death**	☐ Yes ☐ No		
L08: Major bleeding :	☐ Yes ☐ No	date:	☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))
L09: Others: (please specify)		date:	☐☐-☐☐-☐☐☐☐ (DD-MM-YYYY (B.E.))

Version December 20th 2018 ~ 23 ~

Figure 36 Thai PCI registry (Follow-up 12)

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

EQ-5D-5L : Follow up 12 month	☐ Can do it	☐ Cannot do it
**if Cannot do it, please specify the reason **	☐ Death	☐ Incapable
1. Mobility (Please select the most appropriate)		
I have no problems in walking about		☐
I have slight problems in walking about		☐
I have moderate problems in walking about		☐
I have severe problems in walking about		☐
I am unable to walk about		☐
2. Self-care (Please select the most appropriate)		
I have no problems washing or dressing myself		☐
I have slight problems washing or dressing myself		☐
I have moderate problems washing or dressing myself		☐
I have severe problems washing or dressing myself		☐
I am unable to wash or dress myself		☐
3. Usual activities (e.g. work, study, housework, family or leisure activities) (Please select the most appropriate)		
I have no problems doing my usual activities		☐
I have slight problems doing my usual activities		☐
I have moderate problems doing my usual activities		☐
I have severe problems doing my usual activities		☐
I am unable to do my usual activities		☐
4. Pain/ Discomfort (Please select the most appropriate)		
I have no pain or discomfort		☐
I have slight pain or discomfort		☐
I have moderate pain or discomfort		☐
I have severe pain or discomfort		☐
I have extreme pain or discomfort		☐
5. Anxiety/ Depression (Please select the most appropriate)		
I am not anxious or depression		☐
I am slight anxious or depression		☐
I am moderate anxious or depression		☐
I am severely anxious or depression		☐
I am extremely anxious or depression		☐

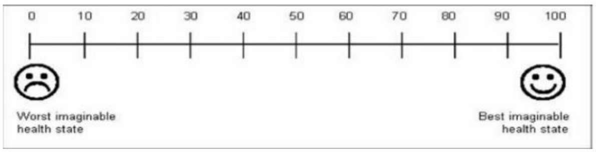
Version December 20th 2018 ~ 24 ~

Figure 37 Thai PCI registry (Follow-up 12 (continuous))

Source: THAI PCI REGISTRY version Dec 20th, 2018

THAI PCI REGISTRY Registry ID: ☐☐-☐☐☐☐

How are your health today?, 100 is means best and 0 means worst.
Please mark the cross (X) into the picture below and write the number in the box ☐



Your health today = ☐☐☐

Expenses incurred from hospitalization apart than those charged by the hospital from the last 6-12 months.

- **Patients**
  - Total transportation cost ☐☐,☐☐☐baht
  - Total food cost ☐☐,☐☐☐baht
  - Total transportation cost ☐☐,☐☐☐baht
  - Your average income per month ☐☐☐,☐☐☐baht
  - Time lost from traveling to the hospital/not heading to work for past 6 months ☐☐☐day
- **Caretaker**
  - Total transportation cost ☐☐,☐☐☐baht
  - Total food cost ☐☐,☐☐☐baht
  - Total transportation cost ☐☐,☐☐☐baht
  - Your average income per month ☐☐☐,☐☐☐baht
- Total time spent during the patient recovering for past 6 months ☐☐☐ day

Version December 20th 2018 ~ 25 ~

Figure 38 Thai PCI registry (Follow-up 12 expenses)

Source: THAI PCI REGISTRY version Dec 20th, 2018

VITA