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AI-Enabled Electrocardiogram Analysis for Small Japanese Clinics

Market Potential and Implementation

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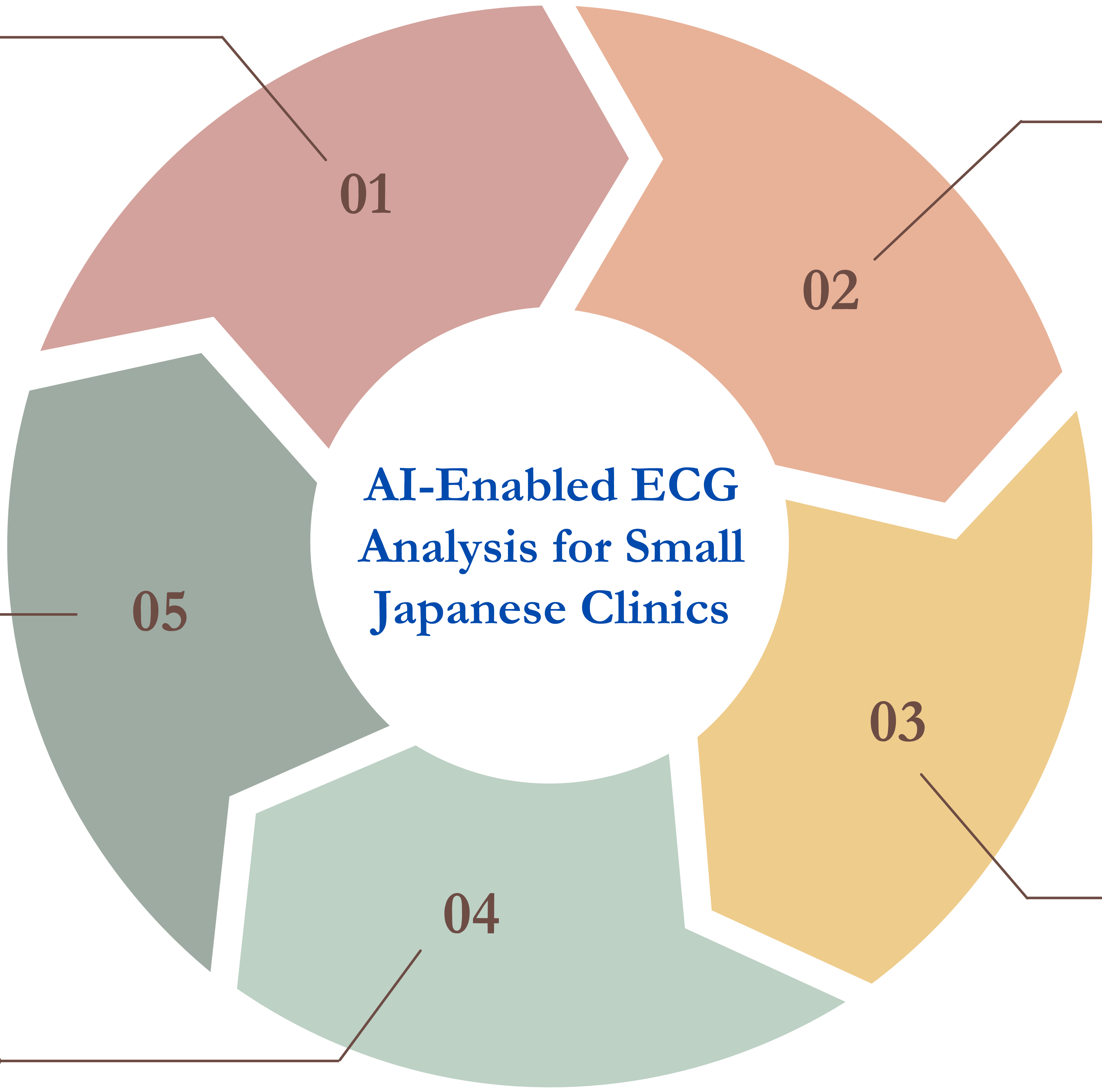
Yamaguchi University, Graduate School of Innovation & Technology Management
Interim Research Report for Specific Topical Research of the year 2024



Motivation - Ikata town case study:

- Rising CVD prevalence
- Limited specialist access in rural areas.
- High error rates in manual ECG interpretation.

Objectives:

- Quantify the impact of visual ECG inspection.
- Develop a prototype for accurate ECG analysis.
- Define market and value proposition.
- Create an implementation plan.

Approach:

- Market analysis & early adopter profiling.
- AI model prototype dev't.
- Implementation plan design.

Key Outcomes:

- 98.46% AI accuracy vs 83.4% human expert.
- Adoption barriers & solutions
- Tailored value proposition for small clinics
- Implementation plan developed.

Next Steps:

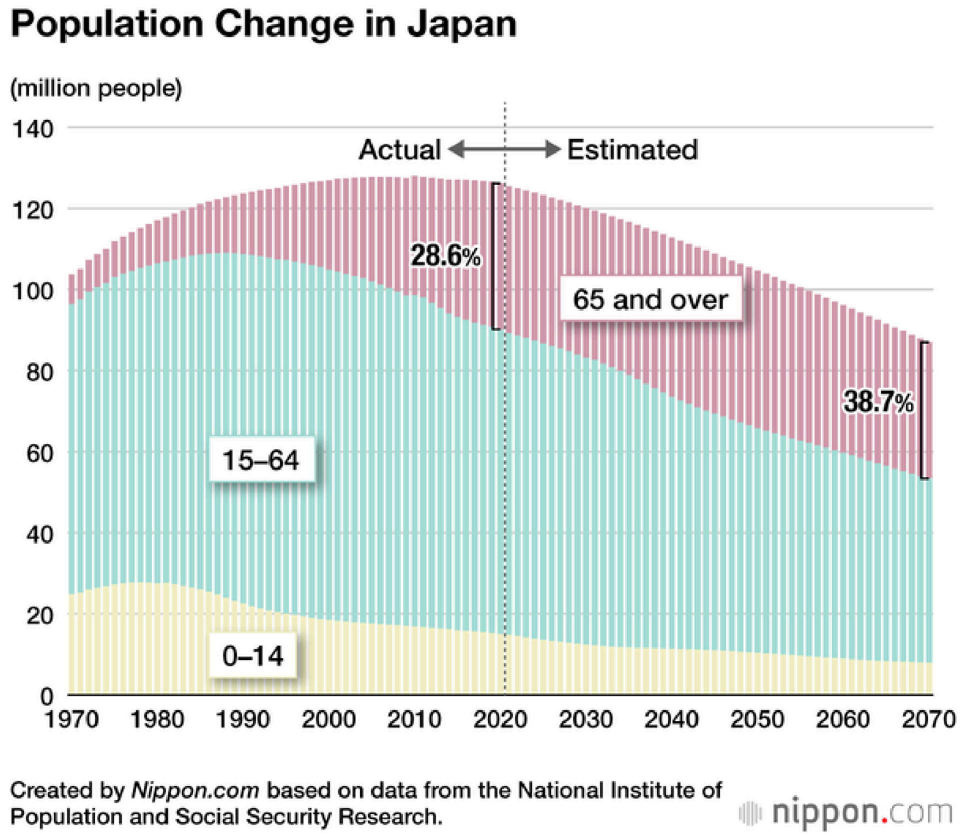
Launch Solution

Agenda

Background & Motivation to the study...

Demographic Context:

- Over 28% aged 65 or older
- ***Rising cardiovascular disease (CVD) prevalence***



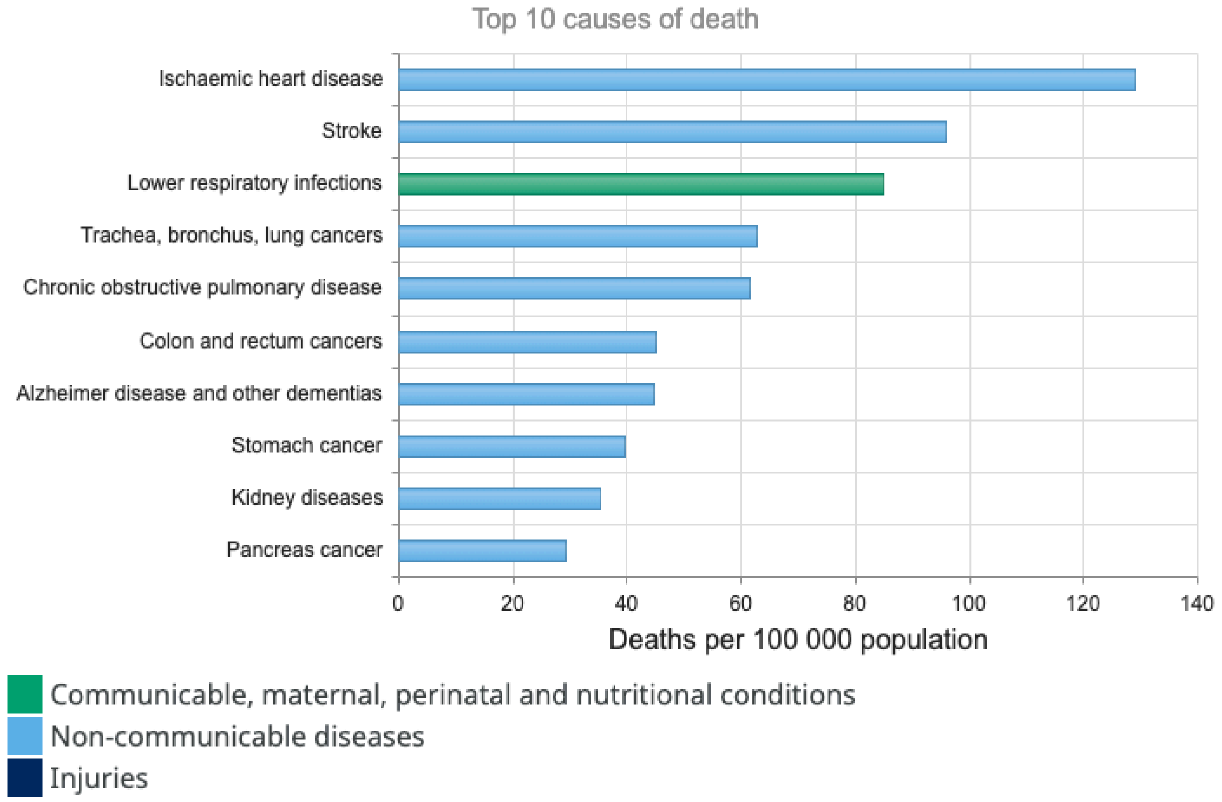
Challenges in Remote Healthcare Delivery:

- ***Shortage of cardiology specialists***, especially in remote areas.
- A ***limited number of doctors*** and clinics serving growing CVD cases.
- General practitioners ***relying on visual ECG inspection***
- ***Limited access to advanced diagnostic tools*** in small clinics.

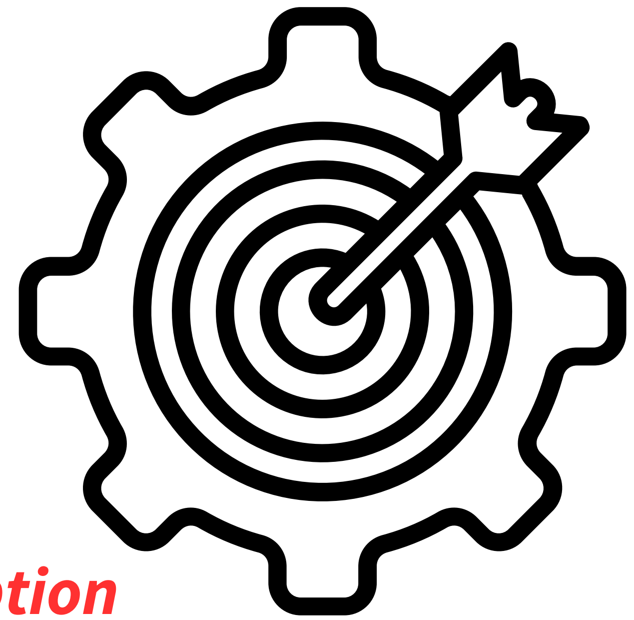
Economic impact:

- Cardiovascular treatment: ***6 trillion yen ($50 billion)*** annually.
- ***1.5 times higher*** than cancer treatment costs.

- **Personal observation from Ikata town:**
  - Patients ***wait weeks*** for specialist visits.
  - Highlighting the urgent need for improved cardiac care access.
- Need for innovative solutions to bridge the urban-rural healthcare gap.

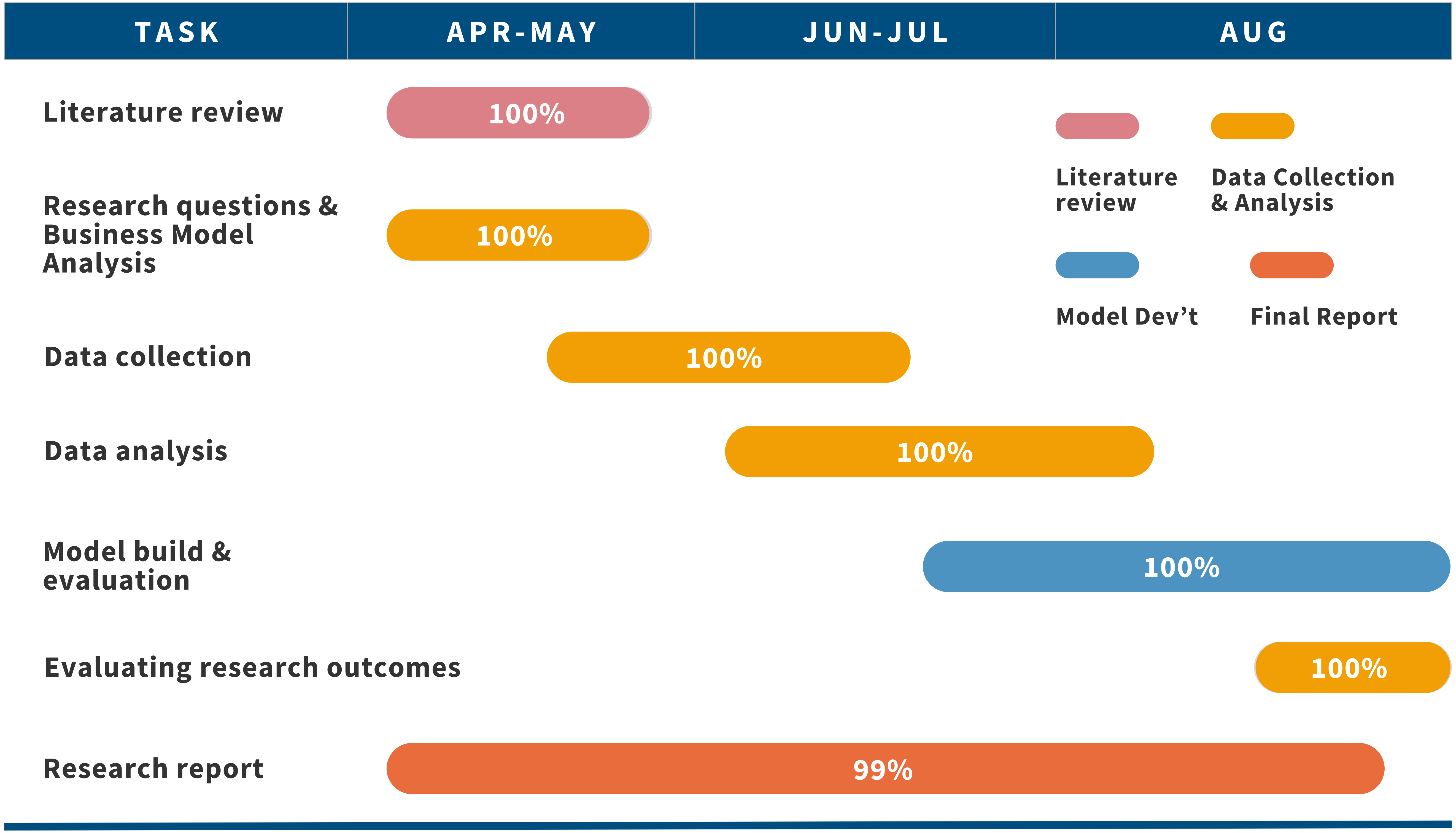


Research Objectives



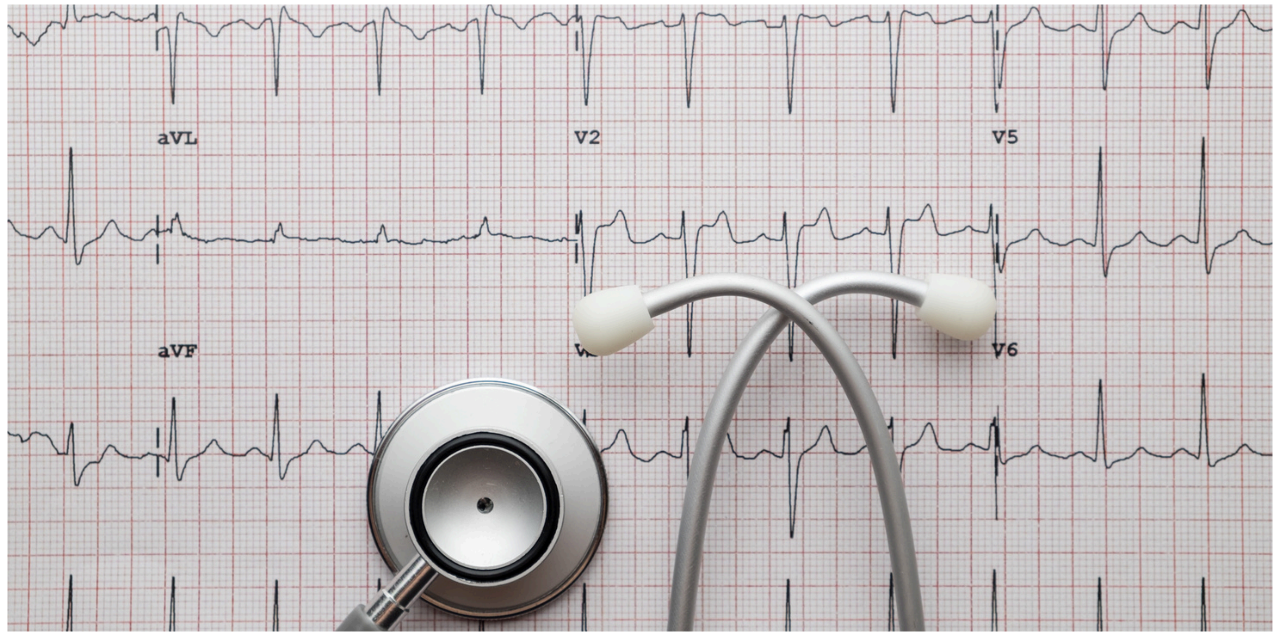
1. Identify the ***impact of visual ECG inspection*** for CVD diagnosis & identify key ***adoption barriers*** to AI-enabled analysis.
2. Develop & evaluate a ***prototype*** deep learning model for ***ECG analysis*** tailored to small clinics, assessing its accuracy & reliability.
3. Define the solution's ***early adopter profile***, ***value proposition***, & ***unique selling points***.
4. Formulate an ***implementation plan*** to overcome identified adoption barriers.

Research schedule & Progress

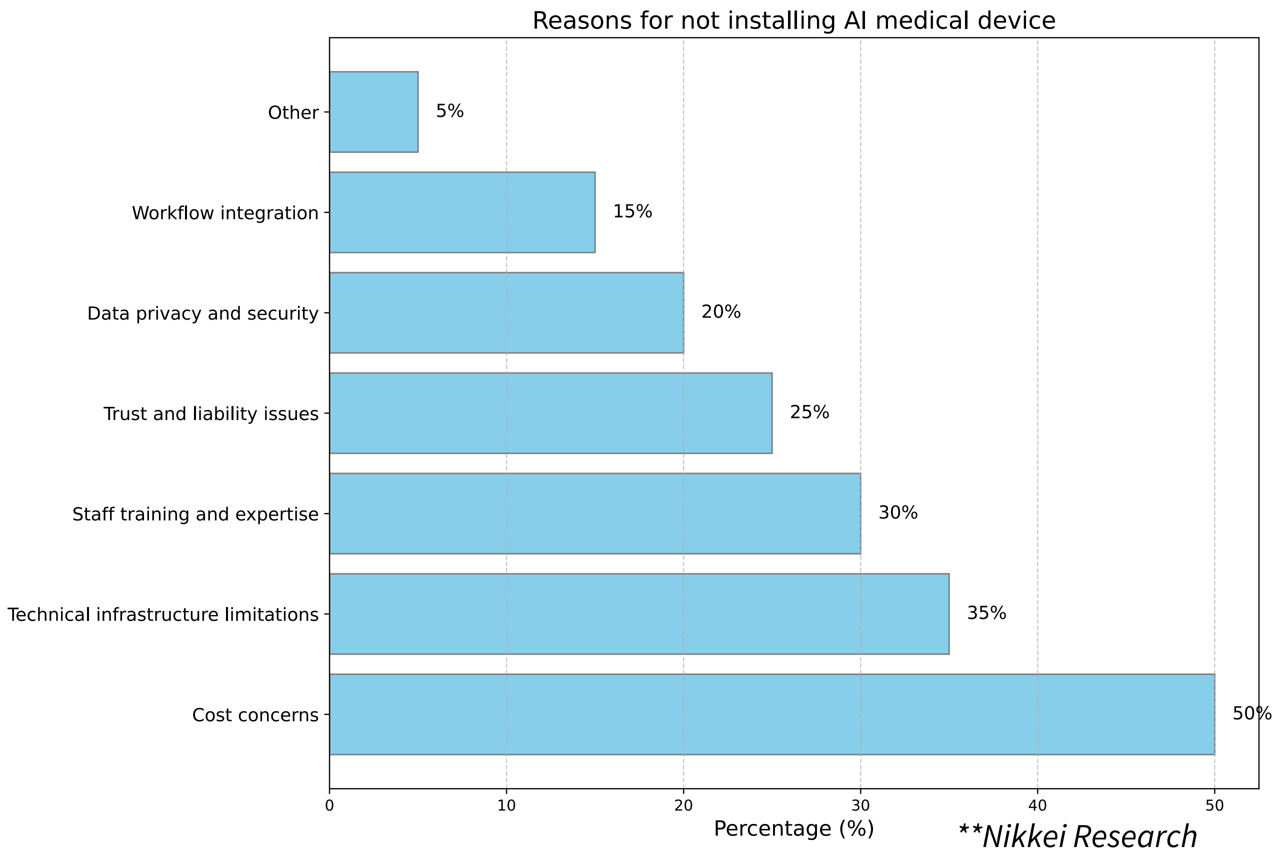


Market Analysis: ECG Interpretation Challenges

- **Accuracy of human ECG interpretation:**
  - Non-cardiologists: ***36-96% accuracy rate***.
  - Cardiologists: ***74.9% - 84% average accuracy***.
  - High error rates in detecting subtle CVD indicators.
- **Consequences of misinterpretation:**
  - Up to ***11% of cases*** lead to inappropriate medical interventions.
  - ***40% of malpractice claims*** involve diagnostic errors, including ECG misinterpretation.
  - ***Wrongful death lawsuits*** due to missed diagnoses of critical conditions.
  - Modern ECG analysis tools are prohibitively ***expensive*** for small clinics.
- **Factors contributing to errors:**
  - ***Extended training*** requirement (***3,500*** supervised ECG reads for proficiency).
  - ***Time pressure*** in ***emergency*** settings.
  - ***Limited access*** to specialists in remote areas.
- **Regional imbalance in specialist concentration:**
  - Specialists prefer metropolitan areas over small cities and towns.
  - Creates significant ***disparities*** in ECG interpretation accuracy.

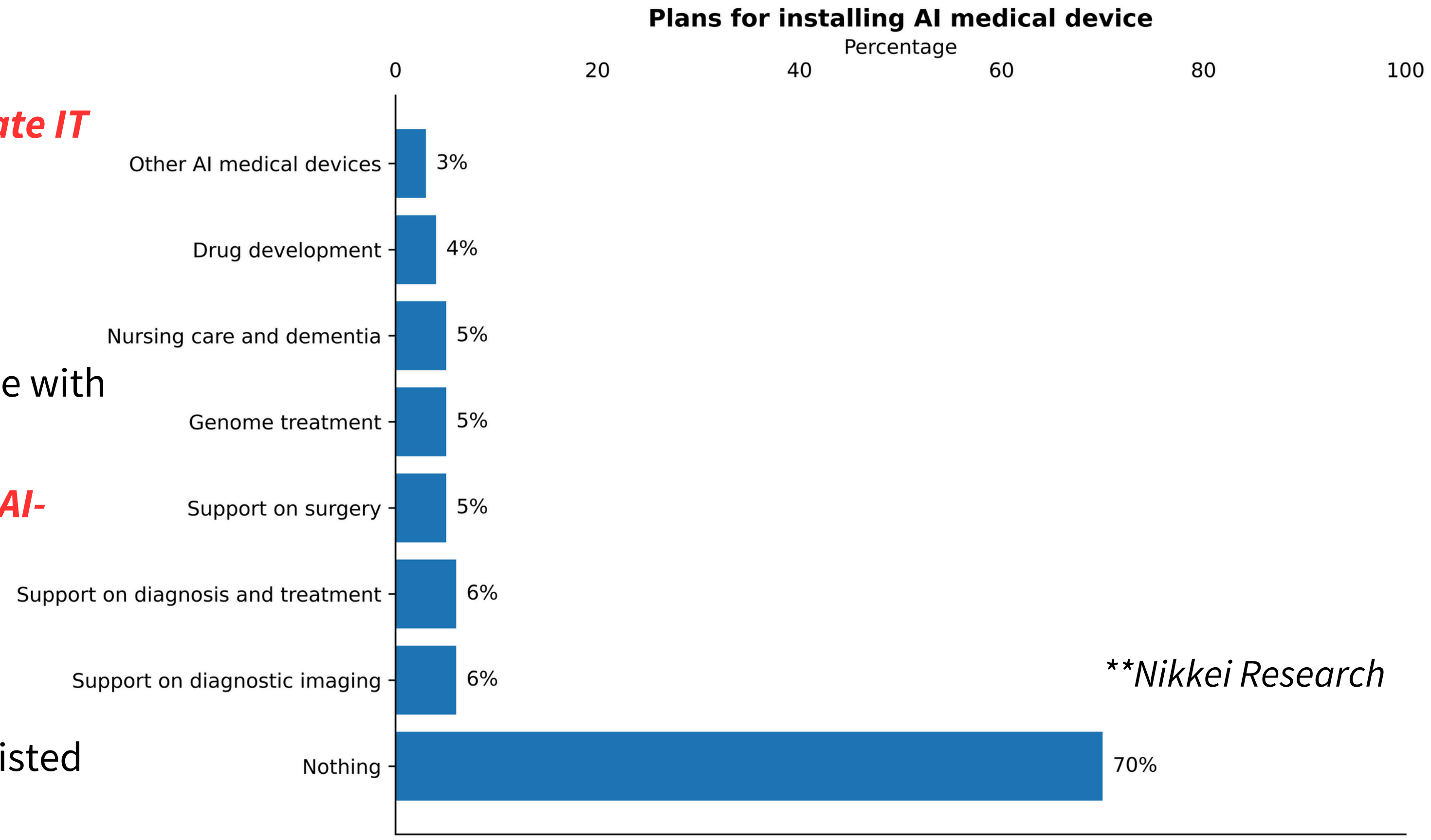


Market Analysis: Adoption Barriers for AI-Enabled ECG Analysis



**Nikkei Research

- **Cost concerns:** ***Initial investment*** in new technology
  - ***Ongoing operational expenses.***
- **Technical infrastructure limitations:** ***Inadequate IT systems*** in small and remote clinics
  - Concerns about ***integration*** with existing equipment.
- **Staff training and expertise:** Limited experience with AI technologies
  - Concerns about operating and ***interpreting AI-assisted tools.***
- **Trust and liability issues:** Skepticism about ***AI reliability*** in critical diagnoses
  - Worries about ***legal responsibility*** for AI-assisted decisions.
- **Data privacy and security:** Patient ***data protection*** concerns
  - Compliance with healthcare data regulations.
- **Workflow integration:** Resistance to changing established clinical routines
  - Concerns about ***disruption*** to current practices.



**Nikkei Research

Technical Development: Data and Preprocessing

Dataset

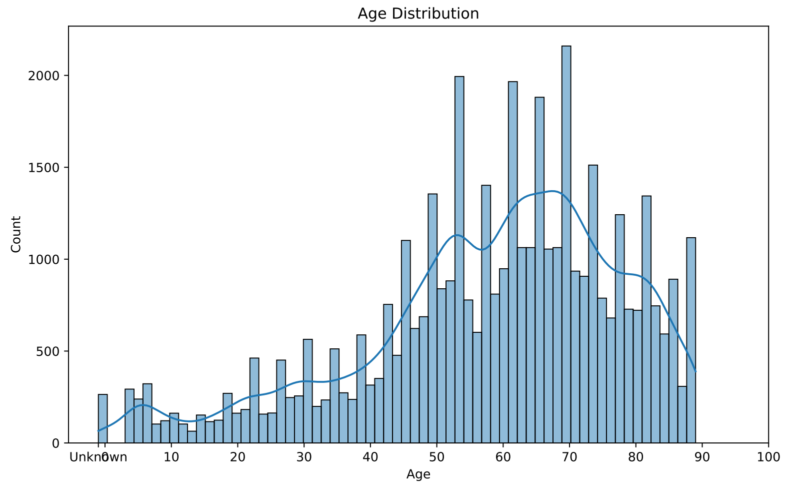
- "A large scale 12-lead electrocardiogram database for arrhythmia study"
- **Size:** 45,152 patient ECGs (10-second readings), Sampling Rate @ 500 Hz
- **Source:** Physionet.org
- **Usage:** ***Creative Commons Attribution 4.0 International License (CC-BY 4.0)***

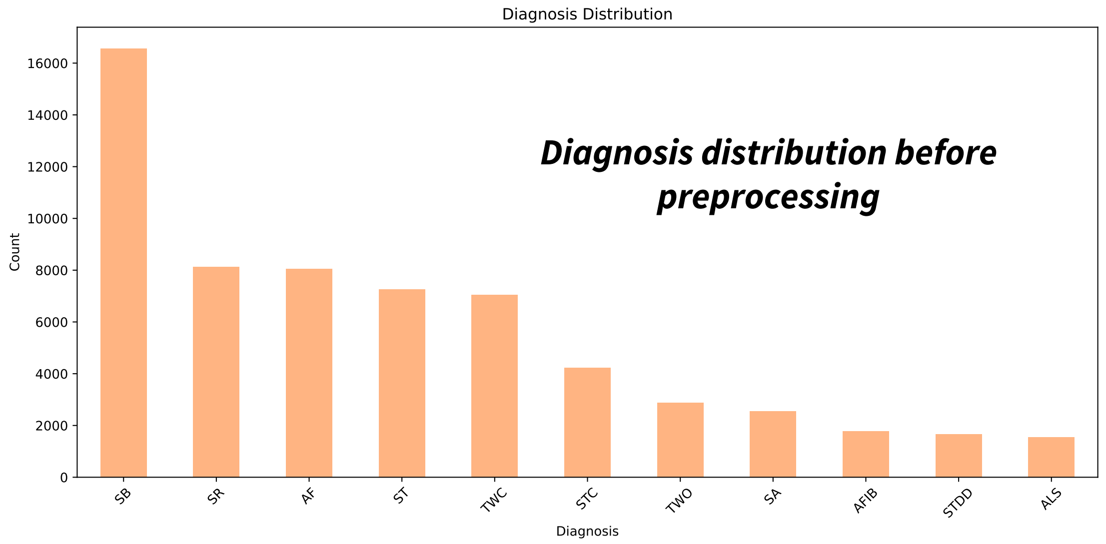
EDA & Preprocessing

- **Age:** Right-skewed, median 60-70 years
- **Gender:** 56.5% male, 43.5% female
- **Diagnosis:** Initially ***imbalanced***, balanced after resampling

Data Handling

- **Resampling:** ***SMOTE & RENN for class balance***
- **Splitting:** ***70%*** training, ***15%*** validation, ***15%*** test





Diagnosis distribution before preprocessing

Training distribution after preprocessing & class balancing

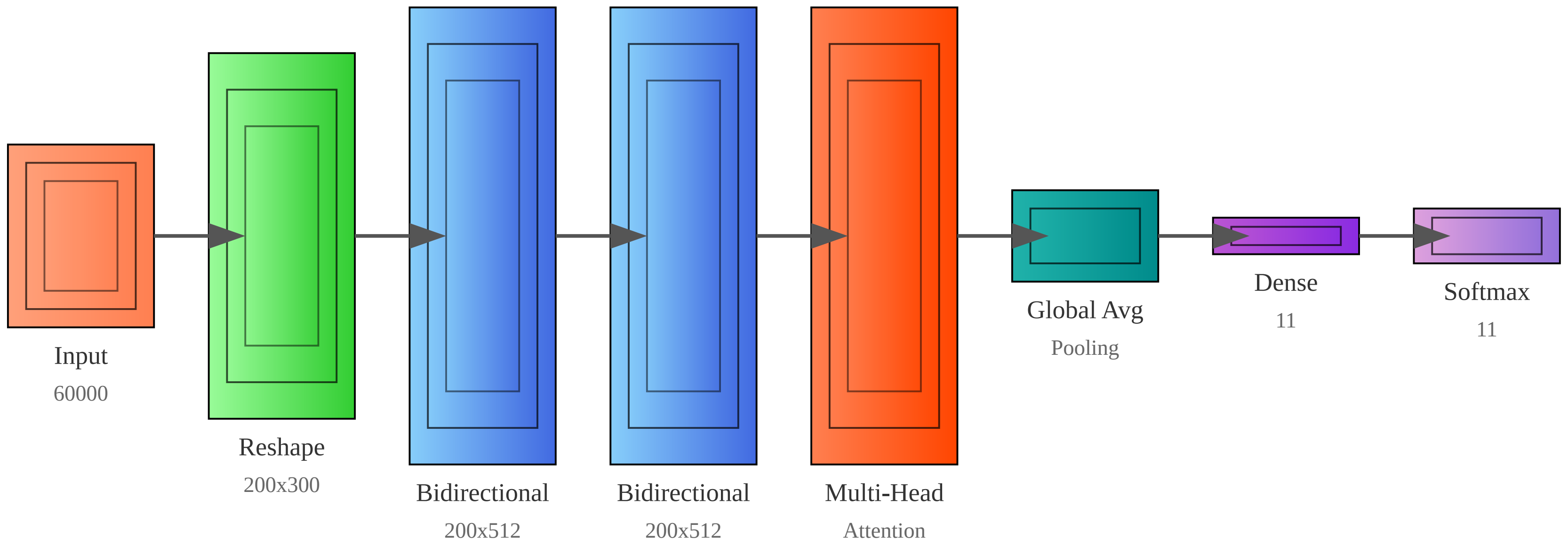
Technical Development: Model Architecture and Hyperparameter Tuning

Model Architecture

- **Lightweight design:** ***5,460,875*** trainable parameters.
- **Key components:**
  - ***2 Bidirectional GRU layers (512 units each).***
  - Multi-head attention layer.
- **Deployment flexibility:**
  - Cloud or edge devices.

Hyperparameter Tuning

- **Method:** ***Hyperband Search Algorithm***
- **Optimal Configuration:**
  - ***512 GRU*** units in ***2 layers***
  - Dropout rate: ***0.2***
  - ***13*** attention heads
  - L2 regularization: ***0.00021***
  - Learning rate: ***0.00014***



Model: "functional_4"

Layer (type)	Output Shape	Param #	Connected to
input_layer_4 (InputLayer)	(None, 60000)	0	-
reshape_4 (Reshape)	(None, 200, 300)	0	input_layer_4[0][0]
bidirectional_8 (Bidirectional)	(None, 200, 512)	857,088	reshape_4[0][0]
batch_normalization_8 (BatchNormalization)	(None, 200, 512)	2,048	bidirectional_8[0][0]
dropout_12 (Dropout)	(None, 200, 512)	0	batch_normalization_8[0][…
bidirectional_9 (Bidirectional)	(None, 200, 512)	1,182,720	dropout_12[0][0]
batch_normalization_9 (BatchNormalization)	(None, 200, 512)	2,048	bidirectional_9[0][0]
dropout_13 (Dropout)	(None, 200, 512)	0	batch_normalization_9[0][…
multi_head_attention_4 (MultiHeadAttention)	(None, 200, 512)	3,413,376	dropout_13[0][0], dropout_13[0][0]
global_average_pooling1d_4 (GlobalAveragePooling1D)	(None, 512)	0	multi_head_attention_4[0]…
dense_4 (Dense)	(None, 11)	5,643	global_average_pooling1d_…

```
Total params: 16,384,675 (62.50 MB)
Trainable params: 5,460,875 (20.83 MB)
Non-trainable params: 2,048 (8.00 KB)
Optimizer params: 10,921,752 (41.66 MB)
```

Technical Development: Performance Metrics

Overall Performance

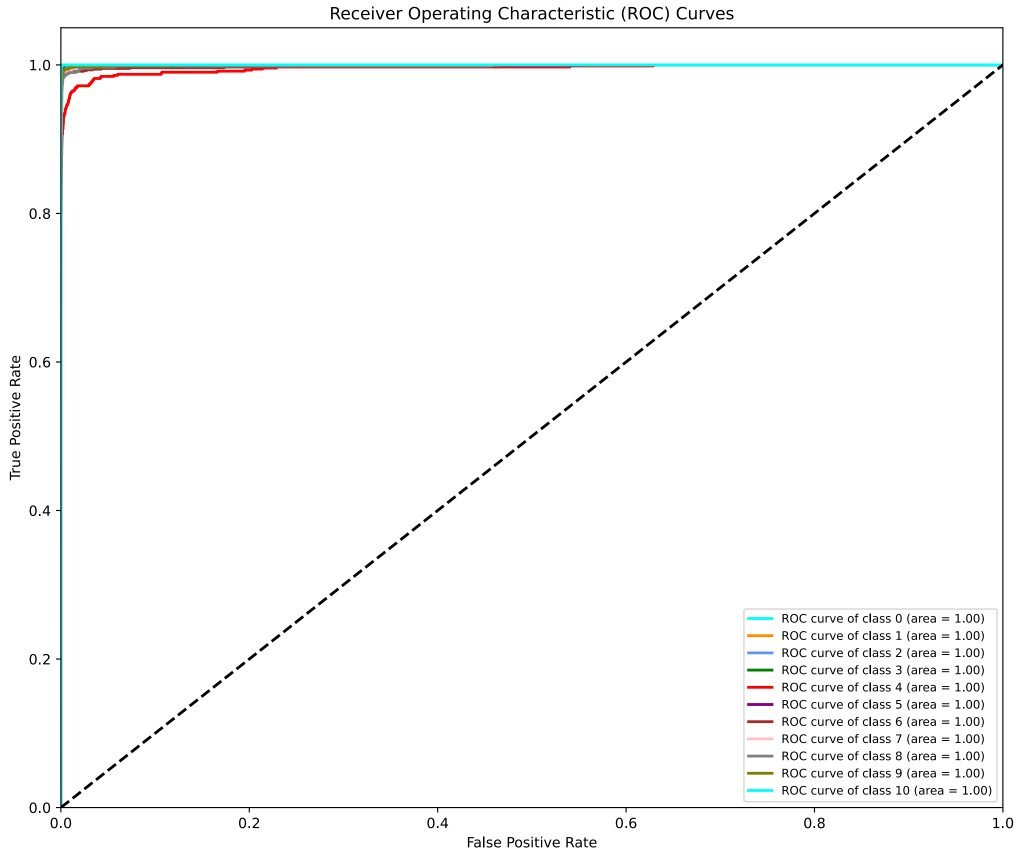
- **Test Accuracy:** *98.46%*
- **Macro-average F1-score:** *0.9819*
- **Weighted-average F1-score:** *0.9845*

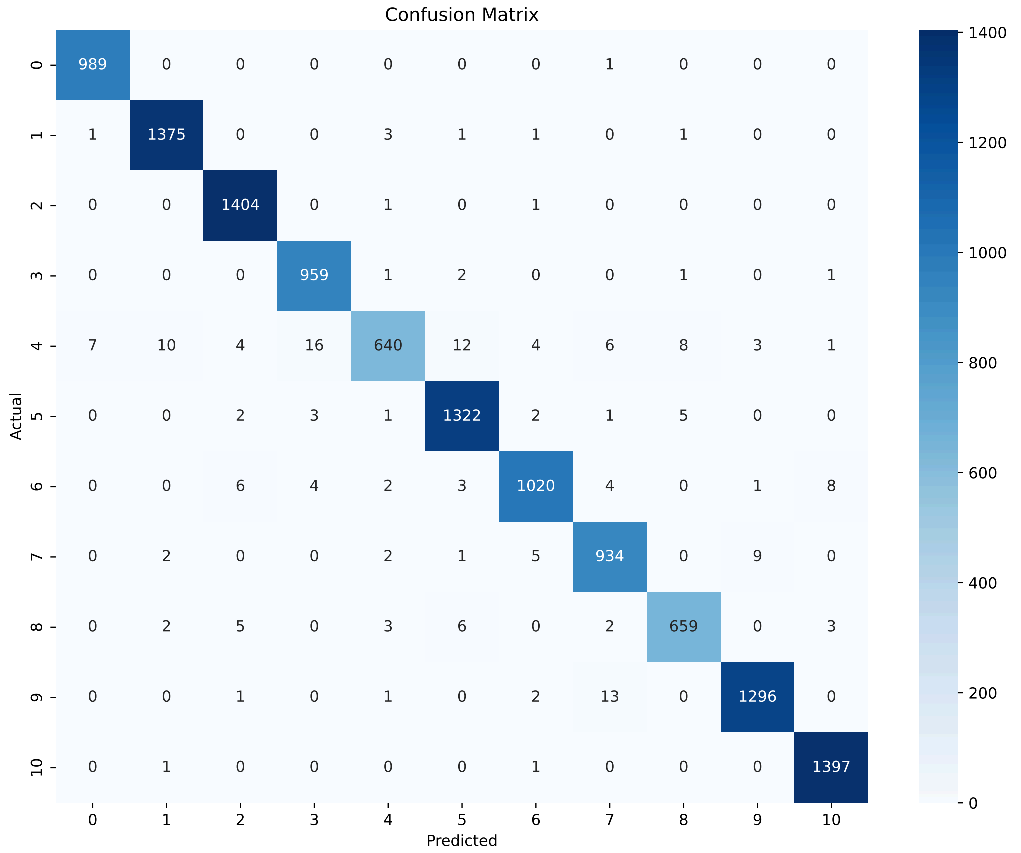
Class-wise Performance

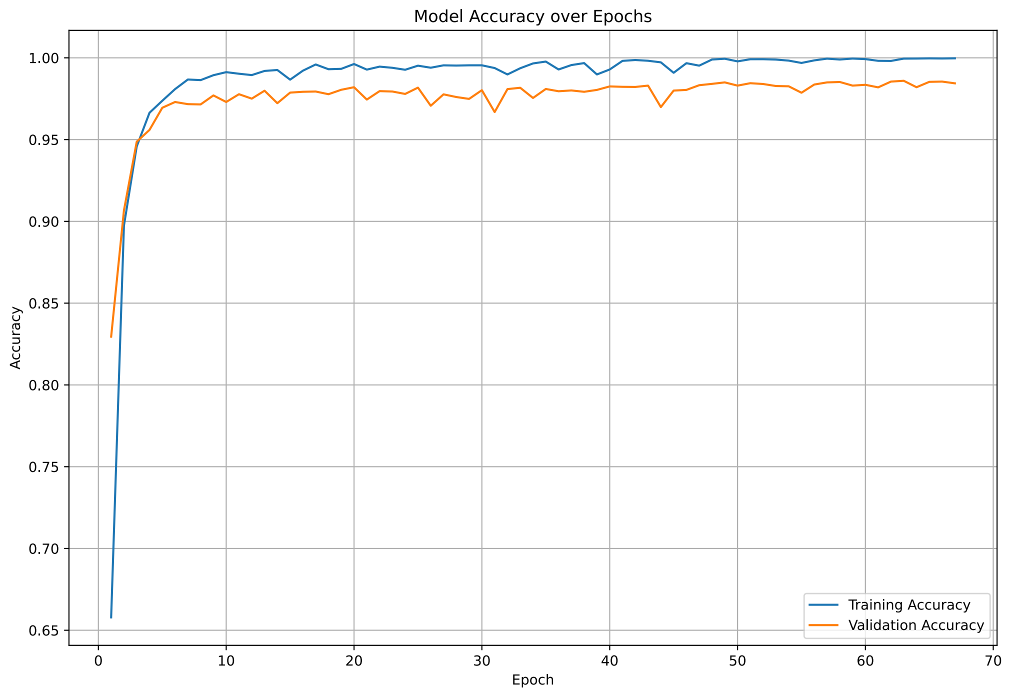
- **Precision range:** *0.972 - 0.992*
- **Recall range:** *0.900 - 0.999*
- **F1-score range:** *0.938 - 0.995*

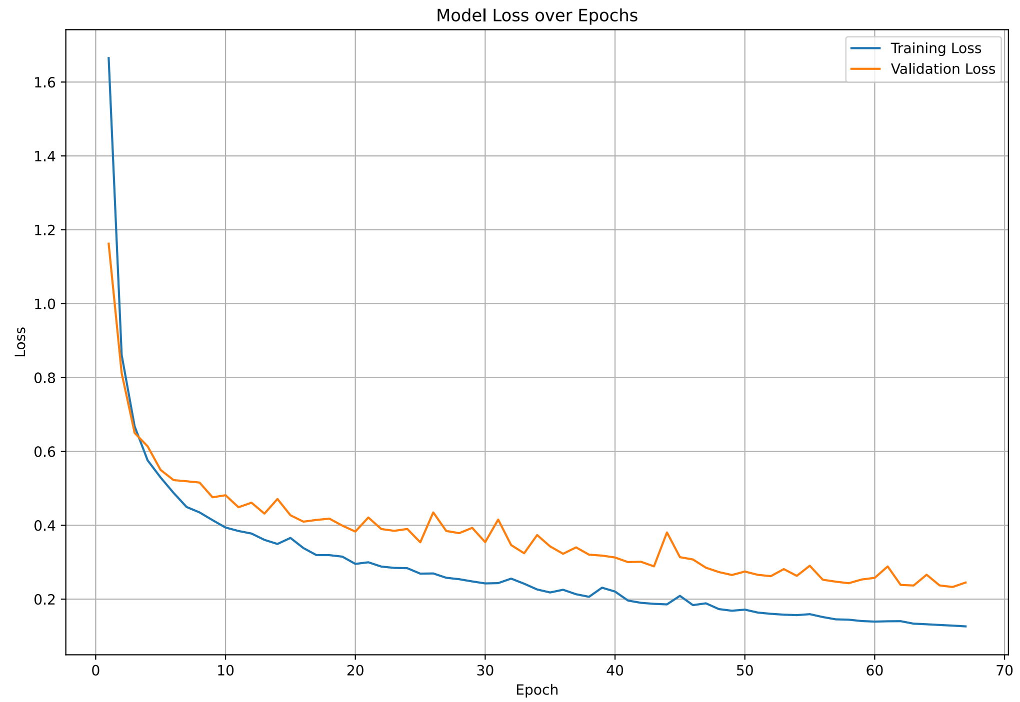
Model Training

- **Total epochs:** *67*
- **Training accuracy:** *99.97%*
- **Validation accuracy:** *98.44%*









Technical Development: Comparison with Human Interpretation

Model Performance

- **Accuracy:** 98.46%
- **Consistent across 11 cardiac conditions.**

Human Expert Performance

- **Mean accuracy:** *~83.4% (based on literature)*
- **Variability in interpretation across different experts.**

Key Advantages of AI Model

- ***Higher consistency across various conditions***
- **Rapid analysis:** seconds vs. minutes
- Potential for 24/7 availability

Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.9920	0.9990	0.9955	990
1	0.9892	0.9949	0.9921	1382
2	0.9873	0.9986	0.9929	1406
3	0.9766	0.9948	0.9856	964
4	0.9786	0.9001	0.9377	711
5	0.9814	0.9895	0.9855	1336
6	0.9846	0.9733	0.9789	1048
7	0.9719	0.9801	0.9760	953
8	0.9777	0.9691	0.9734	680
9	0.9901	0.9871	0.9886	1313
10	0.9908	0.9986	0.9947	1399
accuracy	0.9846	0.9846	0.9846	0.984649
macro avg	0.9837	0.9805	0.9819	12182
weighted avg	0.9846	0.9846	0.9845	12182

Complementary Role

- ***AI as a supportive tool for human clinicians***
- Enhancing diagnostic capabilities, especially in remote settings.

Market Definition & Value Proposition

Early Adopter Profile

- ***Small to medium clinics*** (1-5 physicians) in semi-urban and rural areas
- ***High volume*** of cardiovascular patients (30%+ of consultations)
- ***Limited access to cardiology specialists*** (<8 hours/week)
- Recently ***adopted EHRs***, open to innovation.

Value Proposition

- **Improved diagnostic accuracy:** Potential ***20%+*** reduction in missed diagnoses
- **Time efficiency:** ECG analysis reduced from ***minutes to seconds***
- **Cost-effective expertise:** Specialist-level interpretation without a full-time cardiologist
- **Enhanced patient care:** ***Early detection*** and ***intervention*** for cardiac issues
- **Risk mitigation:** ***Reduced exposure*** to malpractice claims.

Unique Selling Points

- AI-powered yet ***tailored*** to small clinic needs
- Seamless ***integration*** with 95% of common ECG machines
- Cloud and edge deployment options for ***data security and flexibility***
- Continuous learning and updates to stay current with the latest cardiac research.

Implementation Plan to Overcome Adoption Barriers

1. Addressing Cost Concerns:

- Flexible pricing strategy:
  - ***Tiered pricing*** based on clinic size and usage
  - ***Pay-per-use*** option for low-volume users
  - A ***freemium*** model with basic features free, premium features paid.

2. Overcoming Technical Infrastructure Limitations:

- Offer both cloud-based and ***on-premises*** deployment options.

3. Facilitating Staff Training and Expertise Development:

- **Comprehensive *customer education* program: Online resources, regional workshops, ongoing support.**

4. Building Trust and Addressing Liability Concerns:

- Clear communication: AI as a ***supportive tool***, not a replacement for clinical judgment
- Implement ***AI explainability*** features for transparency in decision-making.

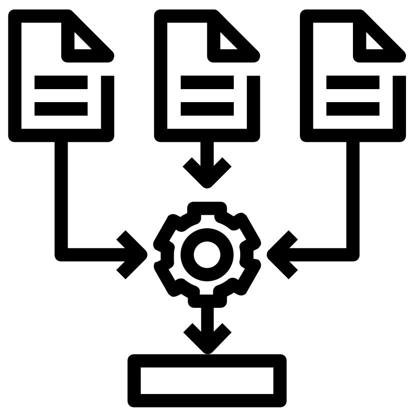
5. Ensuring Seamless Workflow Integration:

- ***Compatibility*** with 95% of ECG machines and formats commonly used in Japanese clinics.

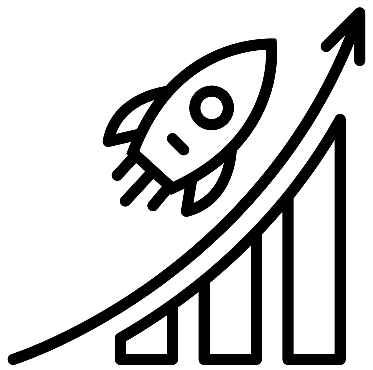
6. Addressing Data Privacy and Security Concerns:

- End-to-end ***encryption*** and ***on-premise inferencing*** options.

Future Development & Next Steps



- **Enhance model with *multimodal clinical data integration***
- **2. Develop *predictive analytics* for *personalized preventive care***
- **3. Launch a startup to bring the *solution to market***



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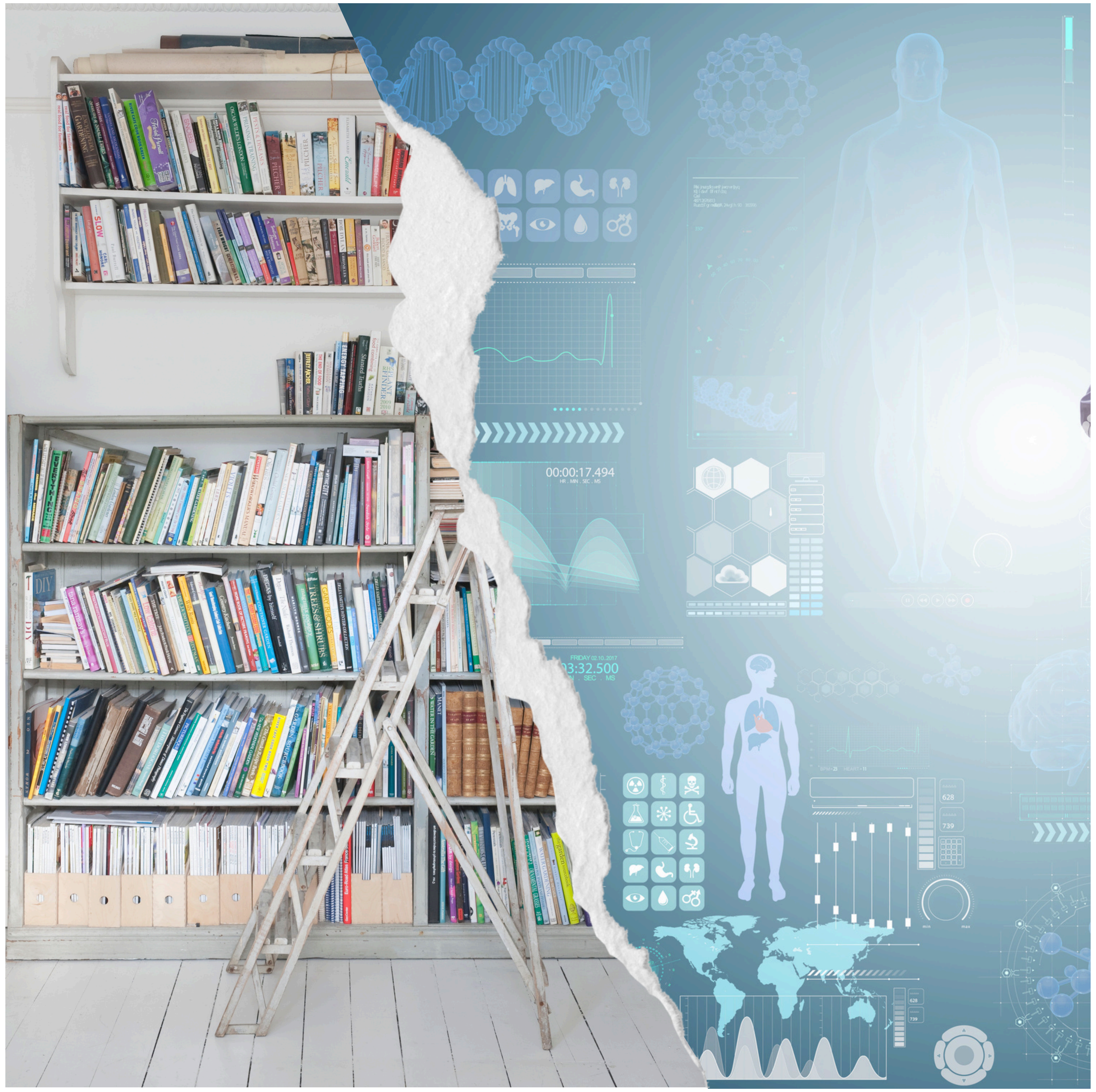

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Thank you!

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