Assignment 1: FHIR Storyboarding

Predictive Feature Set Exchange for Shock

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Date: 26 October 2025

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1. Problem Selection

Scenario: Emergency Shock Prediction in Intensive Care

Rajesh Kumar, a 52-year-old construction worker from Delhi, is admitted to the ICU at AIIMS following complications from pneumonia. His condition appears stable initially with normal vital signs, but the medical team knows that patients with his profile are at risk for developing circulatory shock within the next 24 hours. The ShockModes predictive model requires complex, multimodal feature sets derived from continuous physiological measurements and clinical interventions to predict shock 24 hours in advance with high accuracy.

Problem: The raw high-frequency time-series data (like Heart Rate, Systolic Blood Pressure, Respiratory Rate) and the necessary derived statistical features (e.g., time-series entropy, Fourier coefficients) must be exchanged efficiently between the ICU's EHR system and the external AI service running the ShockModes model. Standard clinical FHIR resources alone are insufficient for conveying these complex derived features, which serve as input vectors for the machine learning algorithm that can predict abnormal Shock Index (SI $\geq$ 0.7) with 83% sensitivity and 94% specificity.

Goal: Define a FHIR profile that standardizes the packaging and exchange of this critical, multimodal feature set to enable 24-hour advance prediction of circulatory shock in ICU patients like Rajesh.

2. FHIR Resource Selection

The exchange of multimodal features for shock prediction requires resources that capture physiological measurements, therapeutic interventions, and clinical procedures:

FHIR Resource Category	Resource Name	Purpose in Scenario

Clinical	Observation	Primary resource for carrying both raw vital signs (time-series) and derived statistical features (e.g., HR Time Series Entropy, SBP FFT coefficients) needed by the ShockModes model
Clinical	MedicationAdministration	Documents specific therapeutic interventions (e.g., heparin sodium prophylaxis) which serve as critical input features for the prediction model
Clinical	Procedure	Documents invasive procedures (e.g., mechanical ventilation, intubation) that are essential binary features for shock prediction
Administration	Patient	Identifies the subject of the prediction cohort - Rajesh Kumar and his demographic information
Conformance	StructureDefinition	Defines the constraints applied to the Observation resource (the ShockModes Profile)

3. Archetype Profiling (ShockModes Feature Set Profile)

To handle the complexity of time-series data processed by tools like tsfresh (which extracts 3,117 features), we must constrain the core FHIR Observation resource using a Profile.

Profile Name: ShockModesFeatureSetObservation

Mandating Derived Feature Codes:

- Constraint: The Observation.code element must use structured terminology representing derived statistical features rather than simple measurements
- Example Code: Instead of basic LOINC for 'Heart Rate', the code must represent features like RR_TS_ENTROPY or SBP_FFT_coefficient_abs_coeff_40
- Rationale: Enforces semantic interoperability for the specific feature set required by ShockModes

Time-Series Context (effectivePeriod):

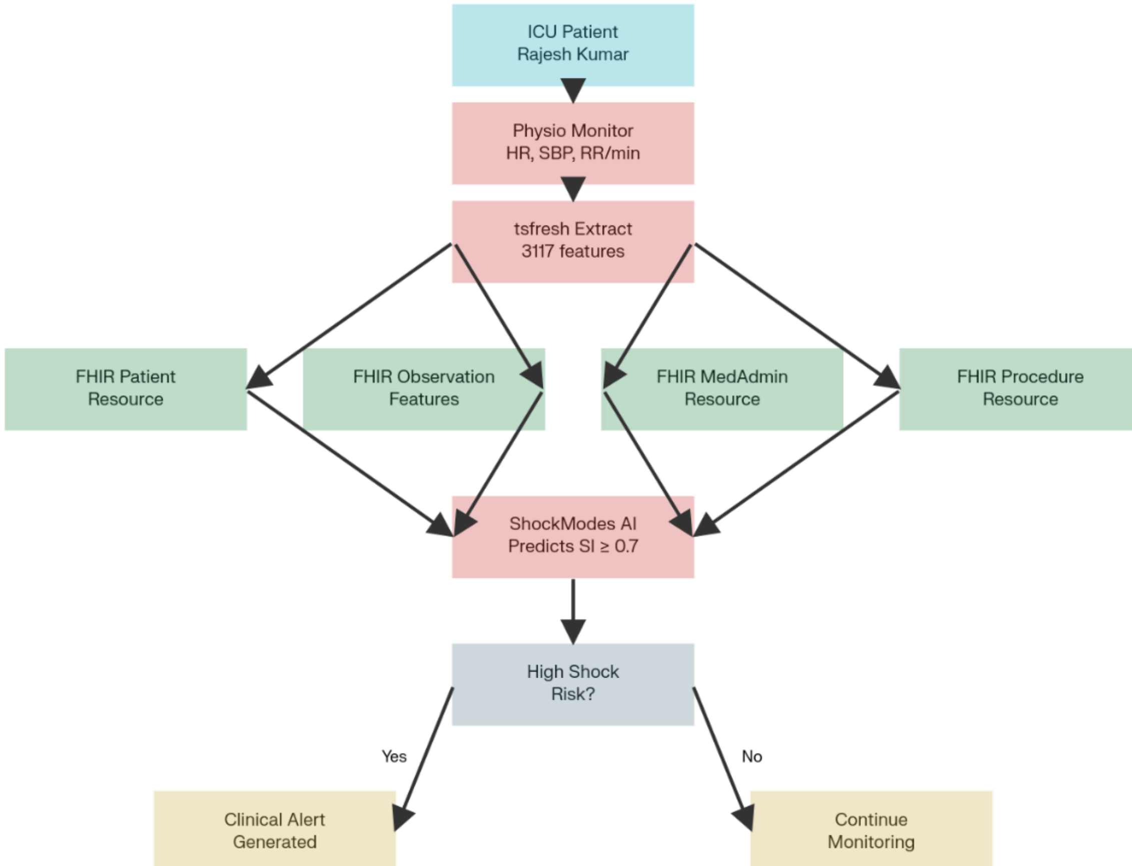
- Constraint: The effectivePeriod must be mandatory, strictly defining the 24-hour time window over which raw physiological data was collected and features computed
- Rationale: Critical for predicting shock events 24 hours in advance with proper temporal context

Value Standardization (valueQuantity):

- Constraint: The valueQuantity element is mandatory and must carry the numerical output of the feature extraction calculation (e.g., entropy scores, Fourier coefficients)
- Rationale: Ensures consistent numerical representation of complex statistical features

Provenance and Source (derivedFrom):

- Constraint: The Observation must link back (via derivedFrom reference) to the raw, underlying high-frequency Observation resources
- Rationale: Supports FAIR principles of data reusability and provides traceability for clinical validation



FHIR Data Exchange Flow for ShockModes Predictive Feature Set

4. FHIR-Compliant JSON Resource Examples

These examples demonstrate customized FHIR resources carrying the high-impact statistical features derived from Rajesh Kumar's vitals, ready for consumption by the ShockModes predictive model.

Patient Resource

json

```
{
  "resourceType": "Patient",
  "id": "rajesh-kumar-icu",
  "name": [
    {
```

```
      "use": "official",
      "family": "Kumar",
      "given": ["Rajesh"]
    }
  ],
  "gender": "male",
  "birthDate": "1972-03-15",
  "address": [
    {
      "use": "home",
      "city": "Delhi",
      "state": "Delhi",
      "country": "IN"
    }
  ],
  "telecom": [
    {
      "system": "phone",
      "value": "+91-9876543210"
    }
  ],
  "contact": [
    {
      "relationship": [{ "coding": [{ "code": "E" }] }],
      "name": { "text": "Priya Kumar" },
      "telecom": [{ "system": "phone", "value": "+91-9876543211" }]
    }
  ]
}
```


ShockModes Feature Observation Resource

json


```
{
  "resourceType": "Observation",
  "id": "rr-entropy-feature-rajesh",
```

```
  "meta": {
    "profile": [

"http://example.org/StructureDefinition/ShockModesFea
tureSetObservation"
    ]
  },
  "status": "final",
  "category": [
    {
      "coding": [
        {
          "system":
"http://terminology.hl7.org/CodeSystem/observation-ca
tegory",
          "code": "survey",
          "display": "Survey"
        }
      ]
    }
  ],
  "code": {
    "coding": [
      {
        "system":
"http://custom-terminology.org/shockmodes-features",
        "code": "RR_TS_ENTROPY",
        "display": "Respiratory Rate Time Series
Entropy"
      }
    ]
  },
  "subject": {
    "reference": "Patient/rajesh-kumar-icu"
  },
  "effectivePeriod": {
    "start": "2025-10-26T08:00:00+05:30",
    "end": "2025-10-27T08:00:00+05:30"
  },
  "valueQuantity": {
```

```json
    "value": 0.987,
    "unit": "unitless",
    "system": "http://unitsofmeasure.org",
    "code": "{score}"
  },
  "derivedFrom": [
    {
      "reference":
"Observation/raw-rr-time-series-rajesh"
    }
  ],
  "note": [
    {
      "text": "Feature extracted using tsfresh
library from 24h respiratory rate monitoring window."
    }
  ]
}
```


MedicationAdministration Resource

json


```json
{
  "resourceType": "MedicationAdministration",
  "id": "heparin-prophylaxis-rajesh",
  "status": "completed",
  "medicationCodeableConcept": {
    "coding": [
      {
        "system":
"http://www.nlm.nih.gov/research/umls/rxnorm",
        "code": "5224",
        "display": "Heparin Sodium"
      }
    ]
  },
  "subject": {
    "reference": "Patient/rajesh-kumar-icu"
```

```
  },
  "effectivePeriod": {
    "start": "2025-10-26T10:00:00+05:30",
    "end": "2025-10-26T10:05:00+05:30"
  },
  "dosage": {
    "text": "5000 units subcutaneous prophylaxis",
    "dose": {
      "value": 5000,
      "unit": "units",
      "system": "http://unitsofmeasure.org",
      "code": "[iU]"
    }
  },
  "note": [
    {
      "text": "Prophylactic heparin administration -
key feature for ShockModes prediction model."
    }
  ]
}
```

Procedure Resource

json

```
{
  "resourceType": "Procedure",
  "id": "mechanical-ventilation-rajesh",
  "status": "in-progress",
  "code": {
    "coding": [
      {
        "system": "http://snomed.info/sct",
        "code": "40617009",
        "display": "Artificial ventilation"
      }
    ]
  },
```

```
  "subject": {
    "reference": "Patient/rajesh-kumar-icu"
  },
  "performedPeriod": {
    "start": "2025-10-26T09:30:00+05:30"
  },
  "note": [
    {
      "text": "Mechanical ventilation initiated due
to respiratory distress - critical binary feature for
shock prediction."
    }
  ]
}
```

Encounter Resource

json

```
{
  "resourceType": "Encounter",
  "id": "icu-admission-rajesh",
  "status": "in-progress",
  "class": {
    "system":
"http://terminology.hl7.org/CodeSystem/v3-ActCode",
    "code": "IMP",
    "display": "inpatient encounter"
  },
  "type": [
    {
      "coding": [
        {
          "system": "http://snomed.info/sct",
          "code": "305351004",
          "display": "Admission to intensive care
unit"
        }
      ]
```

```
    }
  ],
  "subject": {
    "reference": "Patient/rajesh-kumar-icu"
  },
  "period": {
    "start": "2025-10-26T08:00:00+05:30"
  },
  "serviceProvider": {
    "reference": "Organization/aiims-delhi-icu"
  }
}
```

5. Result

The implementation of the ShockModesFeatureSetObservation FHIR Profile provides critical outcomes for predictive healthcare and AI integration:

Enables Predictive AI Exchange: By standardizing the format of derived time-series features (like Respiratory Rate Time Series Entropy extracted using tsfresh), the FHIR structure facilitates the high-frequency input required by the ShockModes model. This standardization enables the model to achieve 83% sensitivity and 94% specificity for shock prediction 24 hours in advance.

Achieves Semantic Interoperability for Features: The use of precise, custom codes in Observation.code ensures that the receiving AI service understands the exact meaning of numerical values (e.g., differentiating raw HR from HR statistical autocorrelation coefficients). This semantic clarity moves beyond basic syntactic exchange to enable true interoperability between clinical systems and AI services.

Improves Clinical Workflow and Patient Safety: By exchanging pre-computed features rather than massive raw data logs, data transmission is optimized while enabling timely predictions. For patients like Rajesh Kumar, this approach allows the warning system to generate alerts 24 hours before shock onset, potentially reducing the 30-40% mortality rates associated with circulatory shock.

Establishes Data Provenance and Clinical Trust: Mandating the derivedFrom element ensures that predictive features can be traced back to their raw source data, supporting clinical validation and the FAIR principles of data reusability. This transparency is essential for gaining clinician trust in AI-driven early warning systems and supporting quality assurance for clinical algorithms.

Supports Multimodal AI Integration: The profile accommodates the complex feature engineering requirements of modern predictive models like ShockModes, which combines 3,117 statistical features from vital signs with clinical intervention data. This comprehensive approach enables more accurate predictions than single-parameter systems like simple shock index monitoring.

6. References

1. HL7 FHIR:
    a. https://www.hl7.org/fhir/
2. Observation Resource:
    a. https://www.hl7.org/fhir/observation.html
3. MedicationAdministration Resource:
    a. https://www.hl7.org/fhir/medicationadministration.html
4. Procedure Resource:
    a. https://build.fhir.org/procedure.html
5. SNOMED CT:
    a. https://browser.ihtsdotools.org/
6. ShockModes Research Paper:
    a. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4396474
7. tsfresh Documentation:
    a. https://tsfresh.readthedocs.io/