LOWTeq

KI in der Anästhesie und Intesivmedizin

Dr. Aloys Oberthür Dr. Christoph Weigand

Telefon
+49 221 50 29 46 - 0

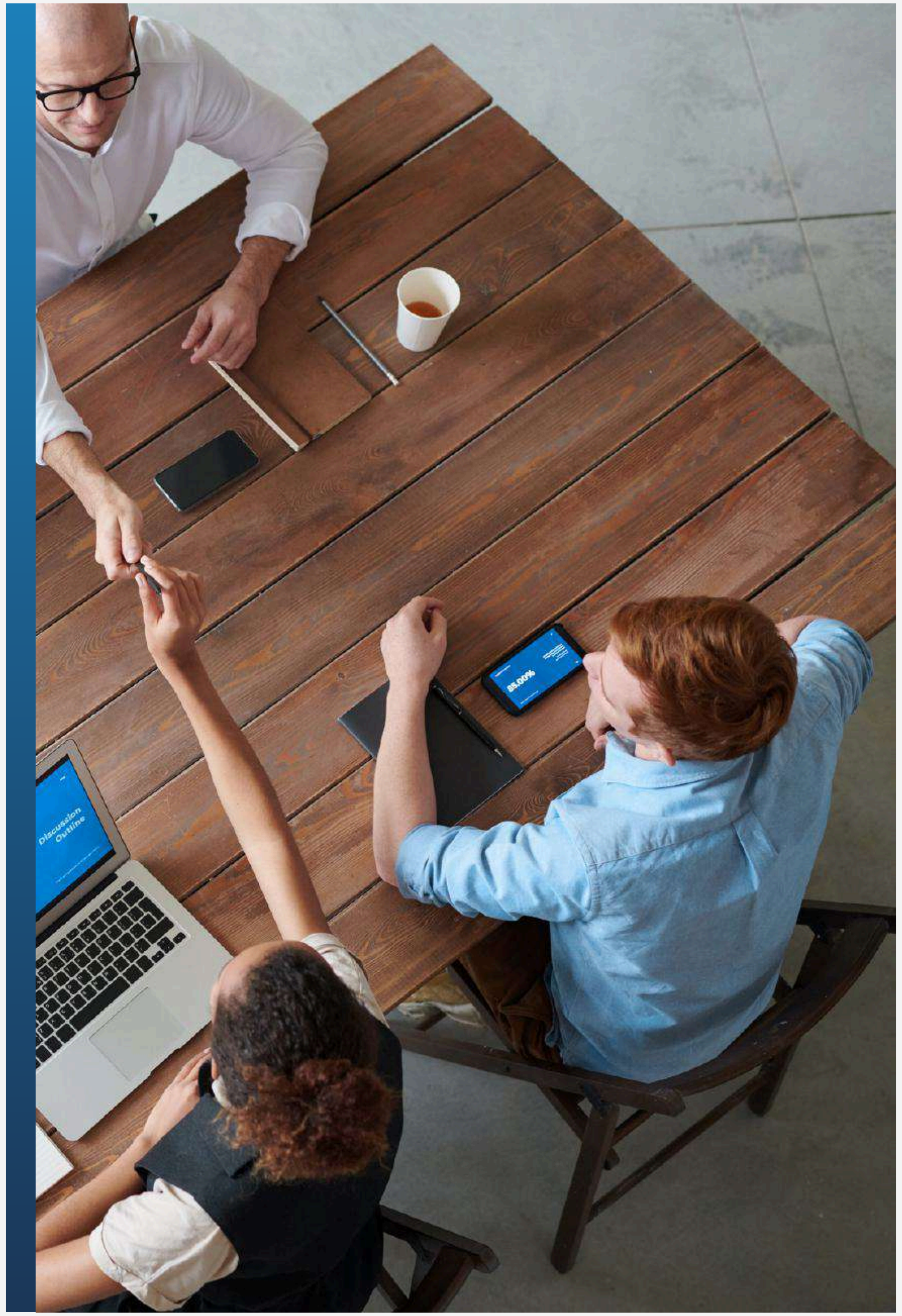
Adresse
LOWTeq GmbH
Widdersdorfer Str. 236 - 240
50825 Köln

Website
www.lowteq.de

LOW Teq

KI betrifft 5 Gruppen

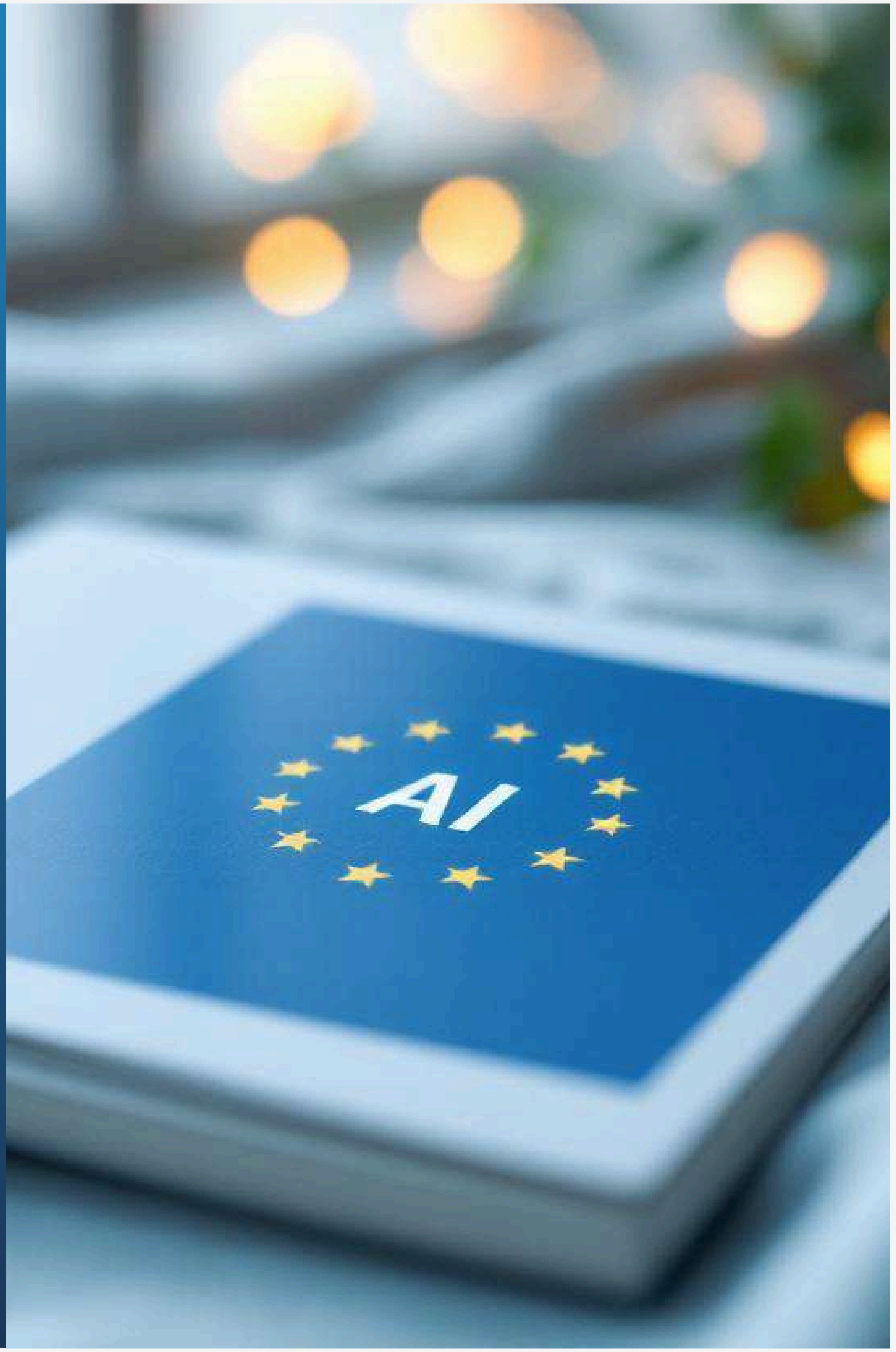
- Anbieter (auch aus Drittländern), die ihre entwickelten KI-Systeme in der EU in Verkehr bringen oder in Betrieb nehmen
- Importeure
- Betreiber
- Distributoren
- Nutzer von KI-Systemen, die sich innerhalb der EU befinden



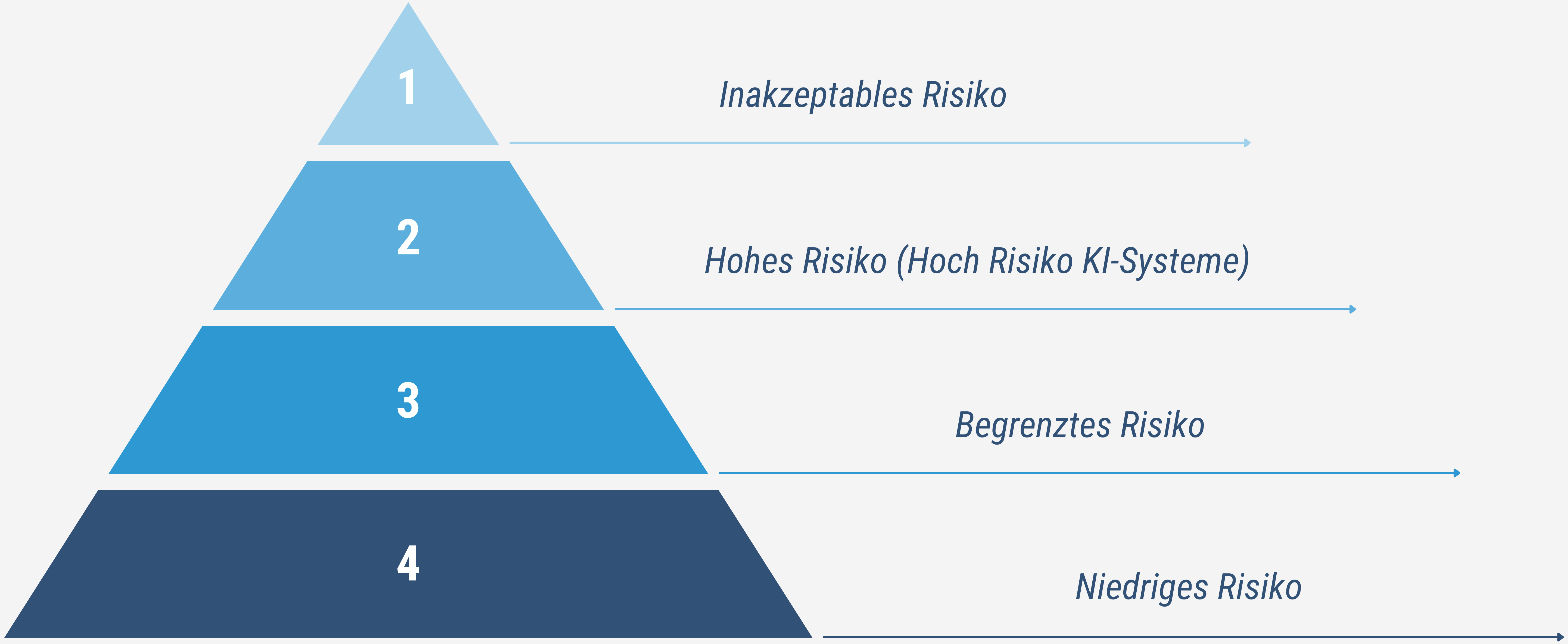
LOW Teq

KI Schlagwörter

- EU Artificial Intelligence Act Regulation on AI
- Die Medical Device Regulation
- Richtlinie Team Notified Bodies



KI Risiko Gruppen



KI Typen

Chatbots
KI beherrscht Umgangssprache

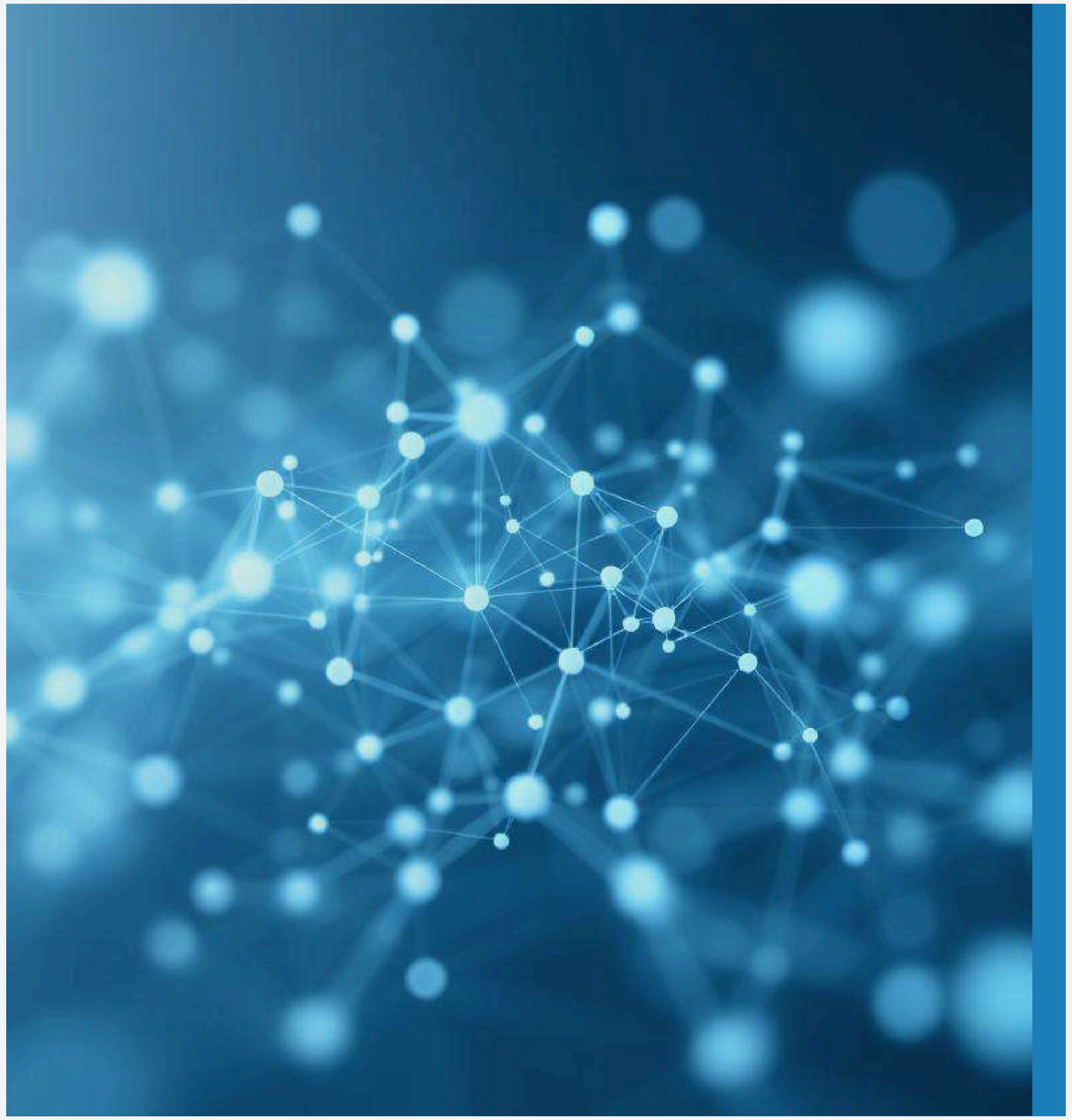
Reasoners
KI kann Probleme so wie ein Mensch lösen

Agents
KI kann über mehrere Tage hinweg Aktionen ausführen

Innovators
KI kann Innovationen hervorbringen

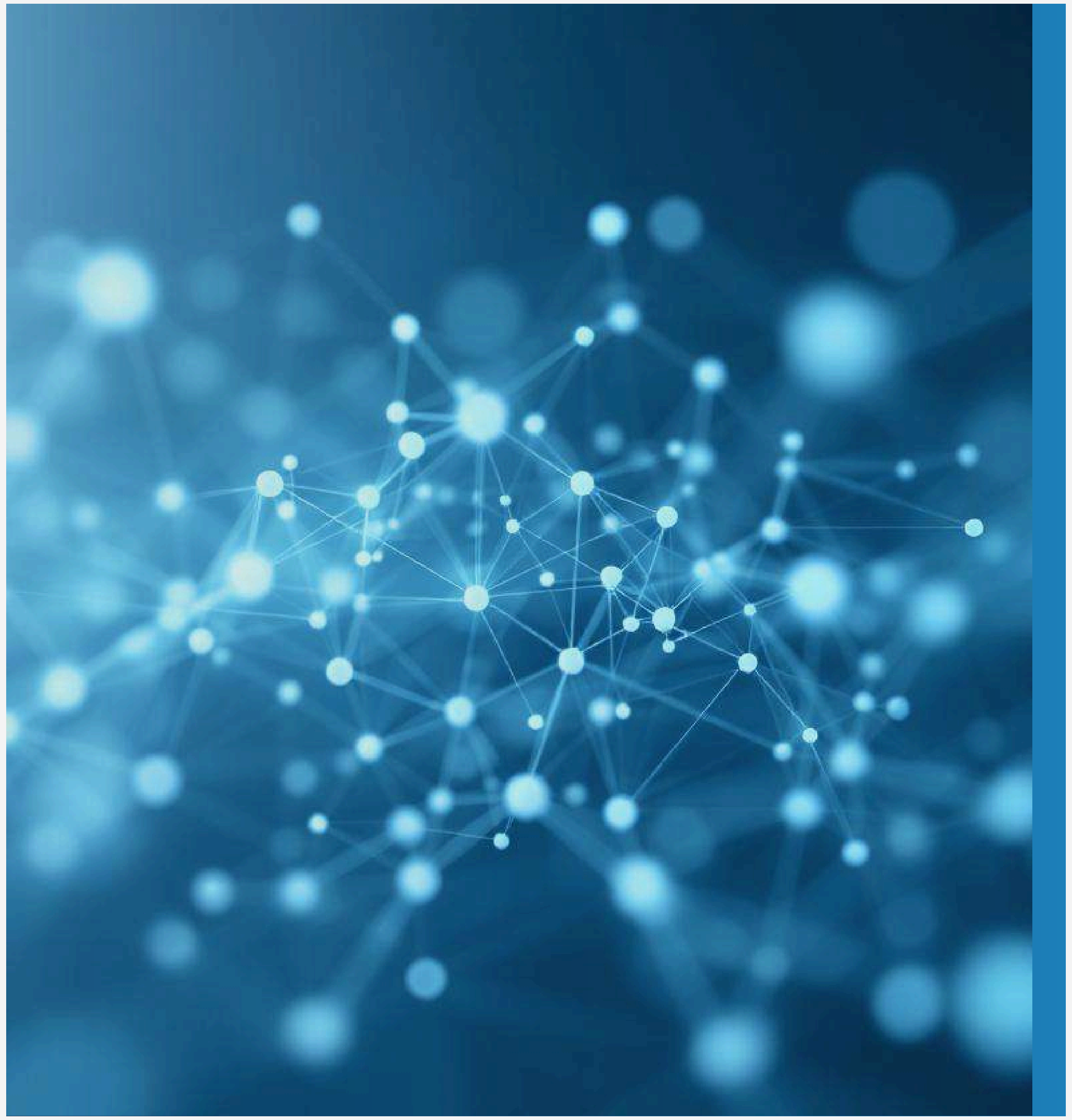
Organizations
KI kann die unterschiedlichen Arbeiten einer ganzen Organisation gleichzeitig ausführen

LOW Teq



KI-Modell(e) Foundation

- *Selbst trainierte KI-Modelle*
- *Fremd trainierte KI-Modelle*



KI-Modell(e) Foundation - *Hardware*

- *Daten/Zeitserien*
- *Gruppieren von X Stück Daten über die Zeit*
    - *Anomalien?*
- *Shift von X Stück Daten nach rechts*
    - *Anomalien?*

Die Modelcard für den Anomaly Detection LSTM Reconstructor

Anomaly Detection Model Card

Introduction

This is a model card for LOWTeq Anomaly Detection LSTM (Long-Short Term Memory) Reconstructor. It contains an overview of the model's purpose and intended use, architecture details, detailed training and testing datasets descriptions and model performance metrics, ensuring transparency and accountability in its development and deployment.

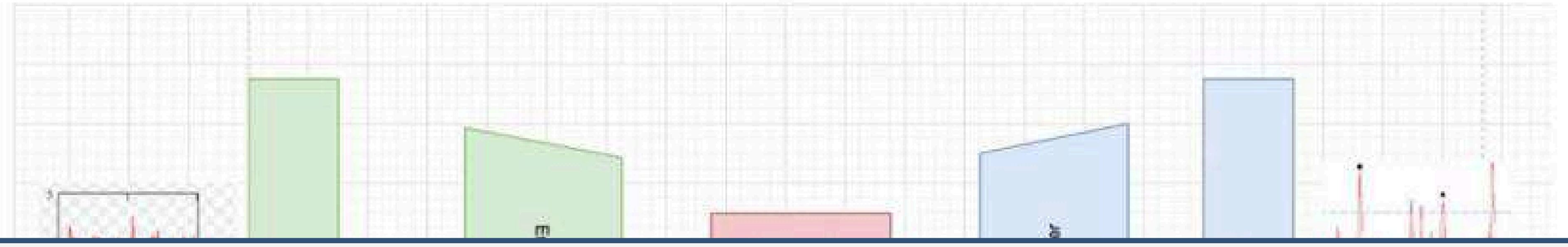
Intended use

The primary use of the model is to detect point or short lasting measurement anomalies within the stream of vital signs data received from medical device manufacturers via HL7 ORU (Health Level 7 Observation Result) messages. These values are subsequently annotated in clinical documentation, empowering users to make informed decisions regarding their retention or removal. Anomalies are data points or groups of data points that exhibit significant deviation from their neighbouring points or clusters and do not conform to the overall trend of the data. Particularly in the ICU (Intensive Care Unit) setting, anomalies in heart rate data often arise from external factors rather than solely reflecting the patient's cardiac activity. These anomalies, which can manifest as sudden spikes or drops in heart rate, are frequently not indicative of the patient's underlying health condition or treatment plan. Common external influences include physical interventions such as patient repositioning, agitation or anxiety, incorrect sensor placement, measurement errors by monitors, or equipment malfunctions. Distinguishing these anomalies from genuine cardiac activity is crucial for accurate monitoring and appropriate intervention aligned with the patient's clinical context. An anomaly detection model is trained specifically to recognise and flag such anomalies, to assist healthcare providers in promptly identifying anomaly values within heart rate data.

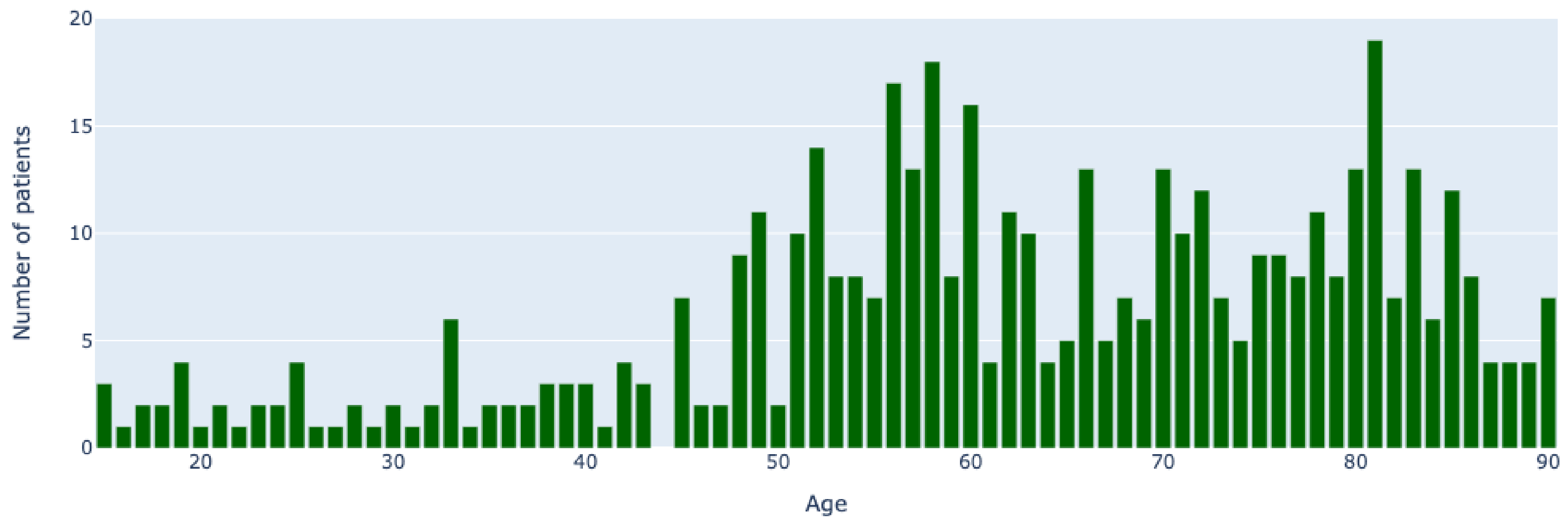
Model description

Description

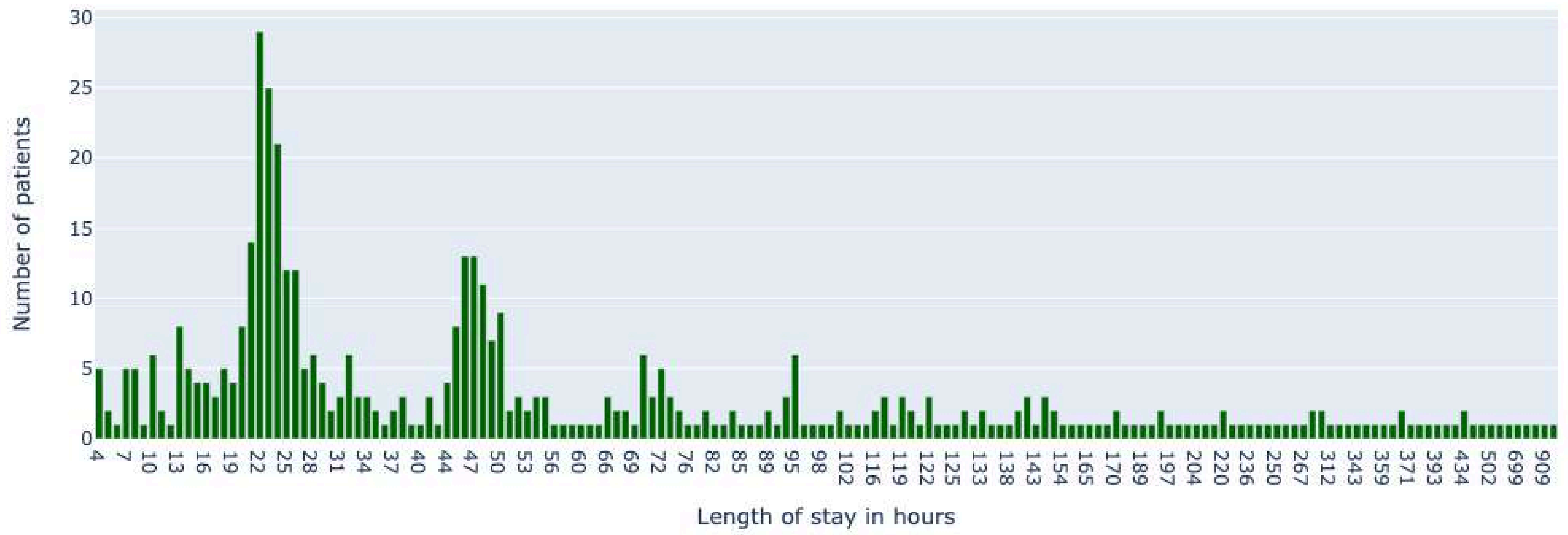
An LSTM autoencoder is a type of neural network architecture used for reconstructing time series data. It consists of two main parts: encoder and decoder. For a given dataset of sequences, an encoder-decoder LSTM is configured to read the input sequence, encode it, decode it, and recreate it. The performance of the model is evaluated based on the model's ability to recreate the input sequence. The autoencoder is trained to minimise the reconstruction error between the input and output sequences, effectively learning to capture the most important features of the data while discarding noise and redundant information. This architecture is particularly effective for tasks such as anomaly detection.



Average age: 62.27 years



Average length of stay: 84.43 hours / 3.52 days



Anomaly Detection Modelcard

- Daten Verteilung
- Bais
- Strukturierte Information
    - Alter
    - Liegedauer

Vergleich der Foundation-Modelle: Auswahl der optimalen Lösung

Wir haben verschiedene Modelle anhand mehrerer Schlüsselfaktoren verglichen, darunter **Architekturbeschreibung**, **Trainingsdatensatz**, **bester Anwendungsfall**, **Vorteile**, **Nachteile**, **rechtliche Überlegungen**, **Hardware-Anforderungen** und **Beispielanwendungen**, um das am besten geeignete Modell für unser Projekt zu bestimmen.

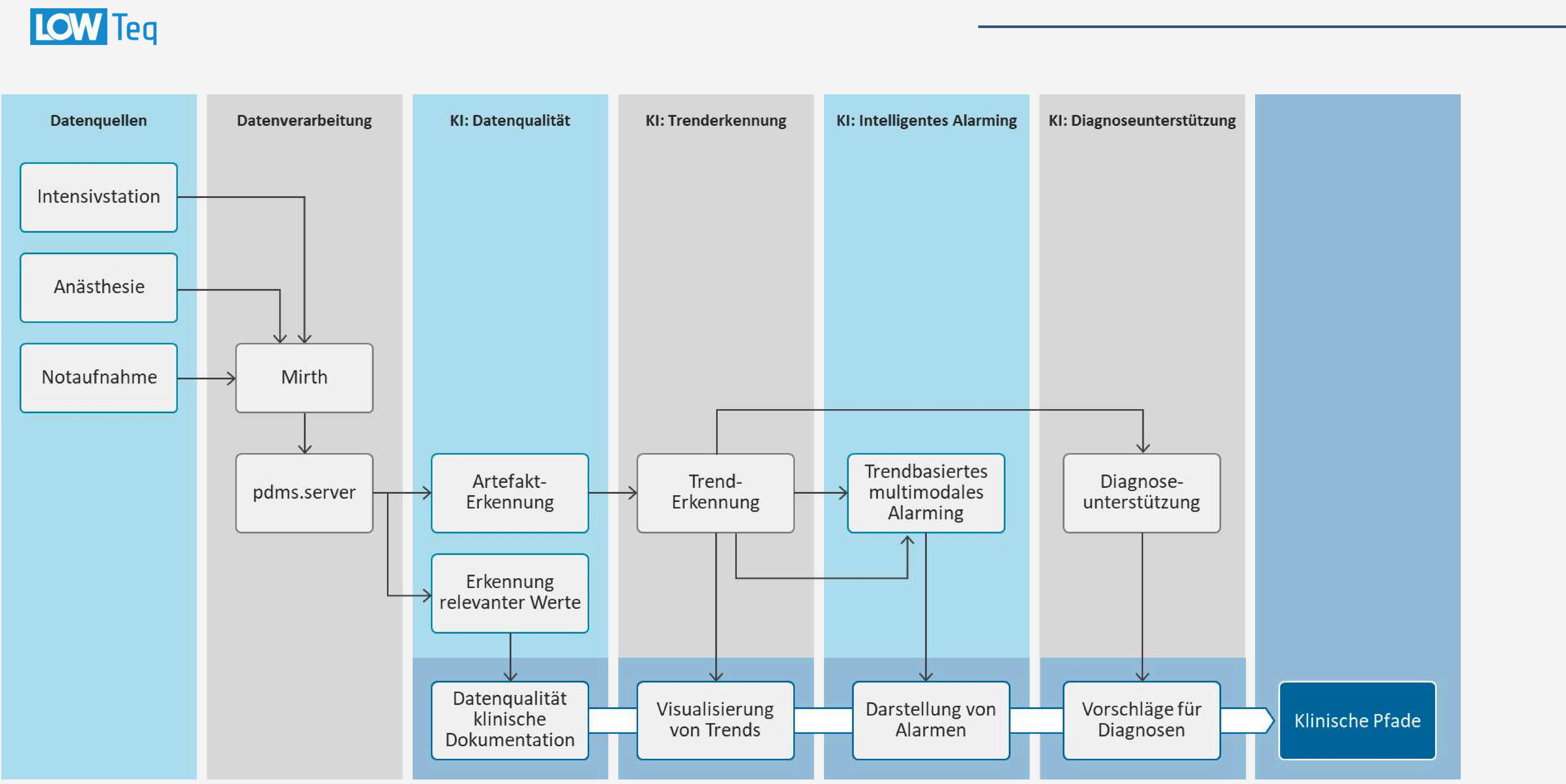
Kurzer Überblick über die verglichenen Modelle

Feature	GluonTS	N-BEATS	Temporal Fusion Transformer (TFT)	TSMixer (PatchTSMixer)	Time-Series Foundation Models (TSFM)	Me LLaMA	TimesFM	Chronos Forecasting	MOMENT	Lag-Llama	Moirai
Architecture Description	Supports multiple DL and probabilistic models	Fully connected neural network with interpretable blocks	Combines LSTM with attention for forecasting	Encoder-decoder architecture	Multiple models including TSMixer, PatchTST, and TinyTimeMixer	LLaMA adapted for medical use cases	Decoder-only Foundation Model	Tokenizes time series for LLM architectures	Combines neural ODEs with transformers for time-series forecasting	LLaMA architecture	Masked encoder-based universal forecasting
Training Dataset	Public datasets like M4, M5, Traffic, Electricity	Various datasets including M4, M3	UCI, Favorita Sales, traffic, electricity datasets, OMI realized library	Weather, traffic, electricity datasets	Weather, traffic, electricity datasets	Pre-trained on medical datasets like MIMIC	Uses public datasets and synthetic data	T5 family, complemented by a synthetic dataset	Collected Time Series Pile, consisting of various public datasets	Uses diverse time series datasets such as energy, transportation, economics	Collected LOTSA dataset
Advantages	Flexible, supports many models and datasets	Interpretable, high performance	Handles multiple data sources, interpretable	High performance, interpretable	Supports zero and few shots forecasting	High accuracy, versatile	High accuracy	Ready for fine tuning	Integrates neural ODEs, highly flexible and accurate	Strong zero-shot generalization	Versatile, universal model
Disadvantages	Requires model selection and tuning	May require significant tuning	Computationally intensive, complex inference	High computational resources for pretraining	High computational resources needed	High computational resources needed	Less interpretable	Slow inference, requires tokenization	Significant computational resources required	High computational cost	Requires tuning and high resources

Regulatorik

- Risikoanalyse
- Klinischer Nutzen
- Funktionsbeschreibung
- Performanz
- Modelldetails

Richtlinien für KI-basierte Medizinprodukte

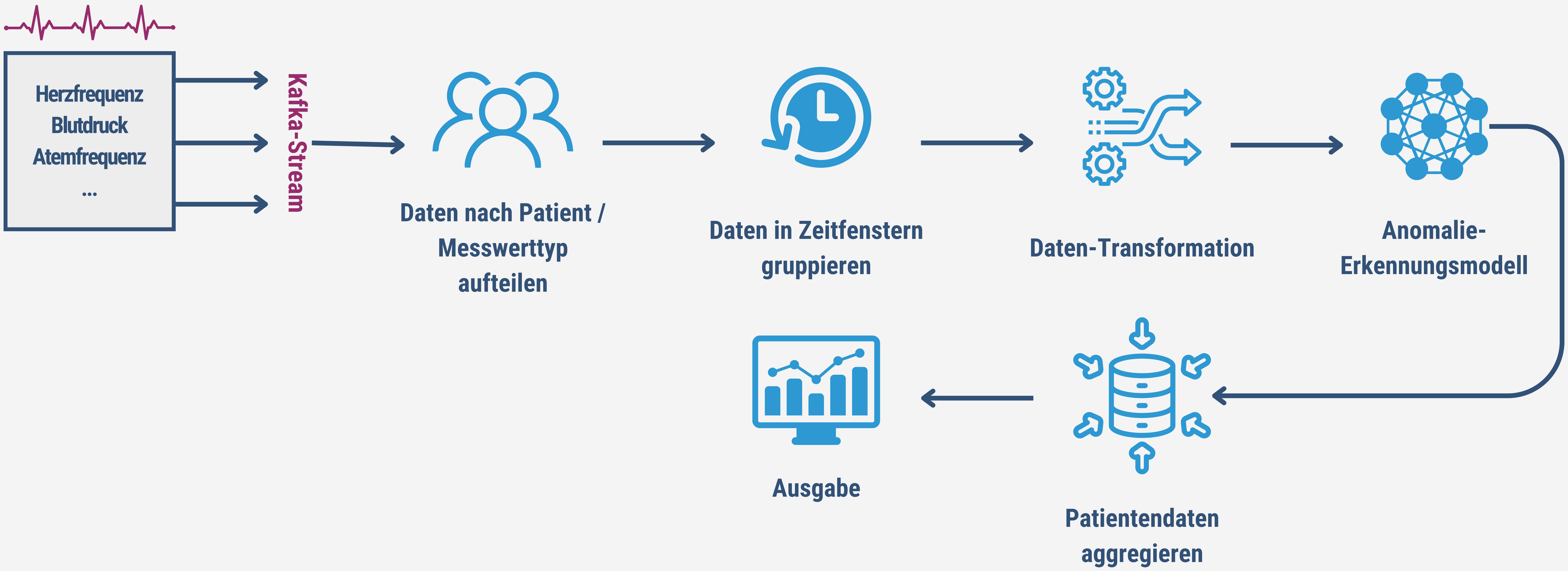

LOW Teq
Datenquellen
Datenverarbeitung
KI: Datenqualität
KI: Trenderkennung
KI: Intelligentes Alarming
KI: Diagnoseunterstützung
Intensivstation
Anästhesie
Notaufnahme
Mirth
pdms.server
Artefakt-Erkennung
Erkennung relevanter Werte
Trend-Erkennung
Trendbasiertes multimodales Alarming
Diagnose-unterstützung
Datenqualität klinische Dokumentation
Visualisierung von Trends
Darstellung von Alarmen
Vorschläge für Diagnosen
Klinische Pfade

Thema 1

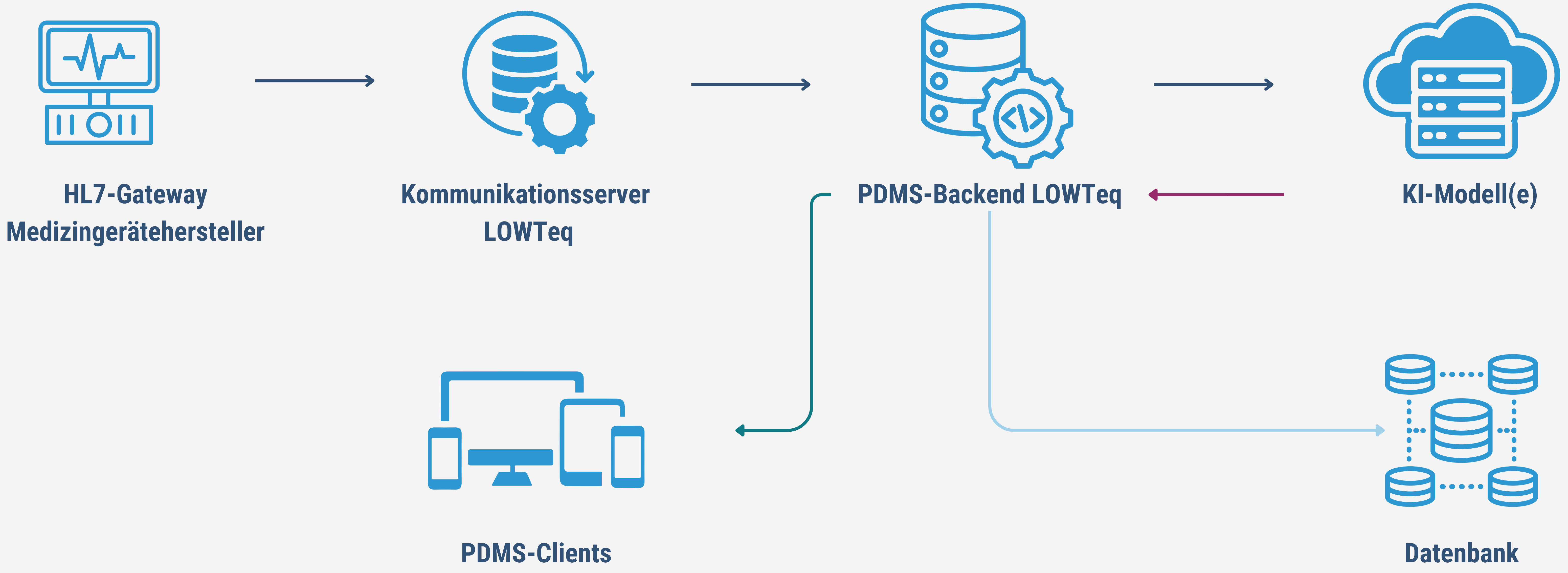
KI zur Erkennung von Messwertartefakten im PDMS

LOWTeq GmbH

Architektur der Lösung: Datenfluss



Architektur der Lösung: Komponentensicht



Klinische Motivation

Häufigkeit von Anomalien auf der Intensivstation

- EKG-Artefakte bis zu 20% (vor allem bei Unruhe)
- Pulsoxymetrie 10%, bis zu 50% (bei schlechter peripherer Durchblutung, Unruhe)
- NIBP häufig, (Unruhe, schlechte Platzierung Cuff)

Bedeutung für die Klinik

- Fehlerhafte / unnötige Alarme (bis zu 70%)
    - relevant, da in Teilen durch Messfehler bedingt
- Bedeutung für Scores
    - relevant, Scores werden insbesondere durch Ausreißer beeinflusst
- Therapieentscheidung
    - eingeschränkt relevant

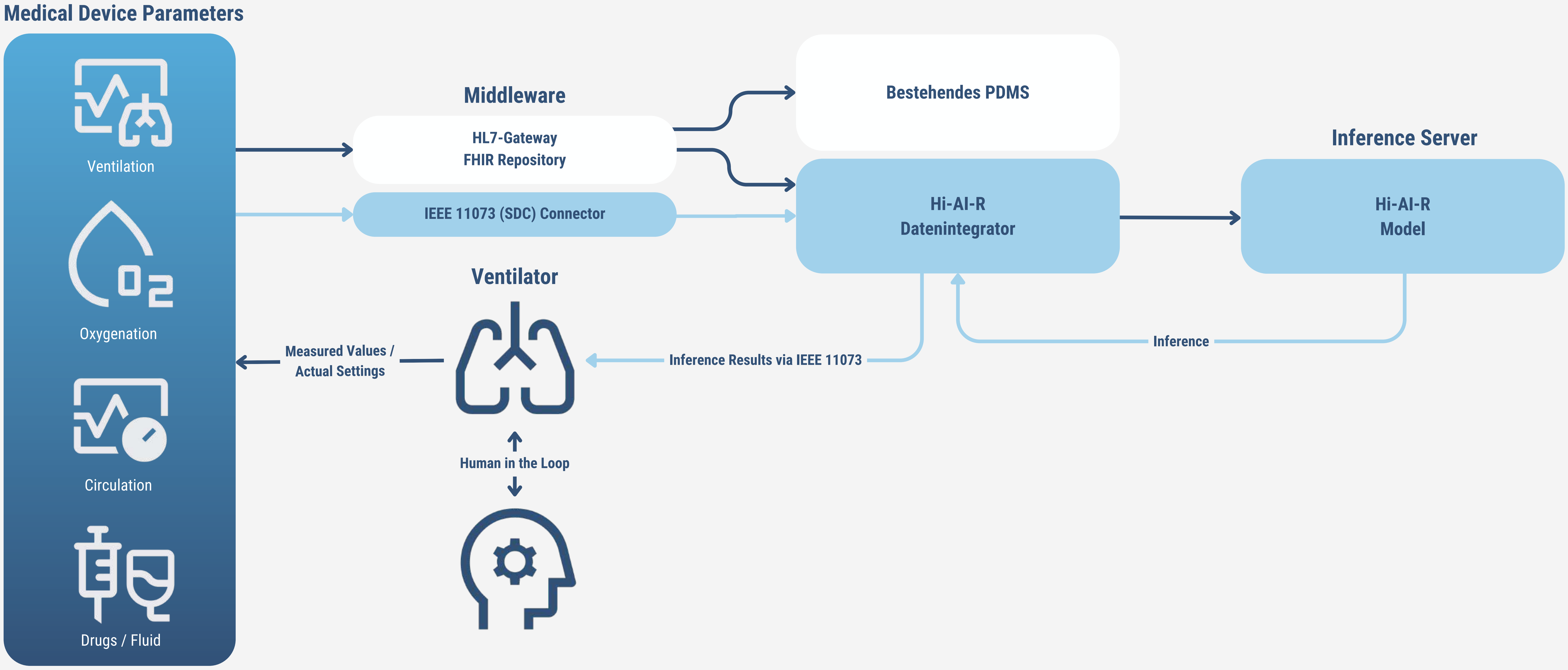
Thema 2
KI zur Optimierung von Beatmungstherapie in der Intensivmedizin

Hierarchisches KI-Assistenzsystem für die Steuerung von Intensivbeatmungsgeräten

The project aims to establish a deep learning mechanism for optimization of ventilator therapy for ICU patients.

Fritz Stephan GmbH / Universitätsklinikum Erlangen / LOWTeq GmbH

Hi-AI-R


Medical Device Parameters
Ventilation
Oxygenation
Circulation
Drugs / Fluid
Middleware
HL7-Gateway
FHIR Repository
IEEE 11073 (SDC) Connector
Bestehendes PDMS
Hi-AI-R
Datenintegrator
Inference Server
Hi-AI-R
Model
Inference
Ventilator
Measured Values /
Actual Settings
Inference Results via IEEE 11073
Human in the Loop

Thema 3
KI zur Vermeidung von ungeplanten Wiederaufnahmen des Patienten nach Entlassung

Forschungsarbeit von Dr. Justus Vogel, Uni St. Gallen - School of Medicine - Chair of Health Economics, Policy, and Management

Gemeinsamer Innosuisse Antrag von Dr. Justus Vogel und Dr. Aloys Oberthür LOWTeq GmbH

Causal clinical decision support for critial care medicine

Predictive Support

The system will identify patients at risk of critical adverse events, such as:

- Anastomotic leaks or wound infections following surgery
- Hospital-acquired pneumonia or sepsis
- Inpatient mortality

Early detection allows clinicians to prioritize at-risk patients for diagnostics and intervention, potentially improving outcomes and reducing complications.

Causal Inference Support

Our system will assist with nuanced treatment decisions by simulating the impact of alternative clinical actions. For example:

- Deciding when to extubate a patient from mechanical ventilation (now vs. later)
- Choosing optimal ICU discharge timing (today vs. tomorrow)

These models help clinicians estimate the likely outcome of different actions (e.g., ICU readmission), supporting personalized and data-driven decisions.

LOW Teq

Ansätze anderer

CORRESPONDENCE

Predicting vital sign deviations during surgery from patient monitoring data: developing and validating single-stream deep learning models

Alina Dubatovka[1], Christoph B. Nöthiger[2], Donat R. Spahn[2], Joachim M. Buhmann[1], Tadzio R. Roche[2,*,†] and David W. Tscholl[2,†]

[1]Department of Computer Science, ETH Zurich, Zurich, Switzerland and [2]Institute of Anaesthesiology, University of Zurich, University Hospital Zurich, Zurich, Switzerland

*Corresponding author. E-mail: Tadzioraoul.roche@usz.ch
†Contributed equally to this work and share last authorship.

Keywords: algorithms; artificial intelligence; biosignals; clinical decision support systems; digital medicine; machine learning; perioperative medicine, vital signs