

**Föderierte Forschungsinfrastrukturen für ein lernendes Gesundheitssystem in der
Akut-, Intensiv- und Notfallmedizin**

Von der Medizinischen Fakultät
der Rheinisch-Westfälischen Technischen Hochschule Aachen
zur Erlangung des akademischen Grades eines Doktors der Theoretischen Medizin
genehmigte Dissertation

vorgelegt von

Jonas Bienzeisler, M.Sc.

aus Bremen

Berichter: Universitätsprofessor Dr. med. Rainer Röhrig
Professor Dr. med. Jörg C. Brokmann

Tag der mündlichen Prüfung: 10. November 2025

Diese Dissertation ist auf den Internetseiten der Universitätsbibliothek online verfügbar.

Publikationen, die die Dissertation darstellen

1. **Bienzeisler J**, Triefenbach L, Kombeiz A, Lottes M, Vogel C, Grabenhenrich L, Fischer M, Kocher T, Niekrenz L, Dreher M, Müller C, Röhrig R, Majeed RW; AKTIN and SPoCK Research Group. A Federated and Distributed Data Management Infrastructure to enable public health surveillance from Intensive Care Unit Data. *Stud Health Technol Inform*. 2022 May 25;294:490-494. doi: 10.3233/SHTI220507
2. **Bienzeisler J**, Kombeiz A, Ehrentreich S, Otto R, Schirrmeister W, Pegoraro M, Brammen D, Puladi B, Röhrig R, Majeed RW, AKTIN Research Group. Implementation Report on Pioneering Federated Data Access for the German National Emergency Department Data Registry. *NPJ Digital Medicine* 2025 doi: 10.1038/s41746-025-01481-w
3. **Bienzeisler J**, Becker G, Erdmann B, Kombeiz A, Majeed RW, Röhrig R, Greiner F, Otto R, Otto-Sobotka F, AKTIN Research Group. The Effects of Displaying the Time Targets of the Manchester Triage System to Emergency Department Personnel: Prospective Crossover Study. *J Med Internet Res* 2024;26:e45593 doi: 10.2196/45593

Weitere Publikationen

1. **Bienzeisler J**, Fischer H, Thiemann VS, Röhrig R. Human-Induced Errors in Networked Healthcare Research: Risk Management Under the GDPR. *Stud Health Technol Inform*. 2020 Jun 16;270:1128-1132. doi: 10.3233/SHTI200338. PMID: 32570557.
2. Drynda S, Schindler W, Slagman A, Pollmanns J, Horenkamp-Sonntag D, Schirrmeister W, Otto R, **Bienzeisler J**, Greiner F, Drösler S, Lefering R, Hitzek J, Röhrig R, Swart E, Walcher F. Evaluation of outcome relevance of quality indicators in the emergency department (ENQuIRE): study protocol for a prospective multicentre cohort study. *BMJ Open* 2020;10:e038776. doi: 10.1136/bmjopen-2020-038776.
3. Löbe M, Bialke M, **Bienzeisler J**, Drepper J, Ganslandt T, Haderer S, Kraska D, Lablans M, Sax U, Speer R, Stäubert S, Kaulke K, Board of Trustees of the ToolPool Gesundheitsforschung. ToolPool Gesundheitsforschung - A Repository for Software and Services Focused on Supporting Clinical and Epidemiological Research. *Stud Health Technol Inform* 2022;293:19-27. doi: 10.3233/SHTI220342.
4. Triefenbach L, Otto R, **Bienzeisler J**, Kombeiz A, Ehrentreich S, Röhrig R, Majeed RW, AKTIN Research Group. Establishing a Data Quality Baseline in the AKTIN Emergency Department Data Registry - A Secondary Use Perspective. *Stud Health Technol Inform* 2022;294:209-213. doi: 10.3233/SHTI220439.
5. Slagman A, Pigorsch M, Greiner F, Behringer W, Bernhard M, **Bienzeisler J**, Blaschke S, Burst V, Dechant K, Dommasch M, Ewen S, Gries A, Hans FP, Kanz KG, Klein M, Kumpers P, Napp M, Plata C, Ramshorn-Zimmer A, Risse J, Röhrig R, Somasundaram R, Schunk D, Walcher F, Möckel M. Medical and cardiovascular emergency department visits during the COVID-19 pandemic in 2020: is there a collateral damage? A retrospective routine

data analysis. Clin Res Cardiol 2022;111:1174–1182. doi: 10.1007/s00392-022-02074-3.

6. Brücken D, Unterkofler J, Pauge S, **Bienzeisler J**, Hübel C, Zechbauer S, Rossaint R, Greiner W, Aufenberg B, Röhrig R, Bollheimer LC, Optimal@NRW Research Group, Brokmann JC. Optimal@NRW: optimized acute care of nursing home residents using an intersectoral telemedical cooperation network - study protocol for a stepped-wedge trial. Trials 2022;23(1):814. doi: 10.1186/s13063-022-06613-1.
7. Boender S, Greiner T, Kocher T, Wagner B, Greiner F, **Bienzeisler J**, Diercke M, Grabenhenrich L, AKTIN Research Group, Aigner A, Ullrich A. Changes in emergency department utilisation in Germany before and during different phases of the COVID-19 pandemic, using data from a national surveillance system up to June 2021. BMC Public Health 2023;23:799. doi: 10.1186/s12889-023-15375-7.
8. Seeger I, Klausen AD, Günther U, **Bienzeisler J**, Schnack H, Lubasch JS. Gründe für die Nichtteilnahme an einer Patientenbefragung im Kontext der prähospitalen Notfallversorgung durch Gemeindenotfallsanitäter - eine retrospektive Beobachtungsstudie [Reasons for non-participation in a patient survey in the context of prehospital emergency medical care by community emergency paramedics - A retrospective observational study]. Z Evid Fortbild Qual Gesundheitswes 2024;187:61-68. doi: 10.1016/j.zefq.2024.03.007.
9. Heidemeyer H, Auhagen L, Majeed RW, Pegoraro M, **Bienzeisler J**, Peeva V, Beyel H, Röhrig R, van der Aalst WMP, Puladi B. A Pipeline for the Usage of the Core Data Set of the Medical Informatics Initiative for Process Mining - A Technical Case Report. Stud Health Technol Inform 2024;317:30-39. doi: 10.3233/SHTI240835.
10. Kombeiz A, **Bienzeisler J**, Majeed RW, Röhrig R, AKTIN Research Group. Designing a User-Friendly Data Request Management System for a Growing Health Data Network - A Case Study in the AKTIN Registry. Stud Health Technol Inform 2024;321:69-73. doi: 10.3233/SHTI241065.
11. **Bienzeisler J**, Bax SN, Schunk D, Wrede C, Erdmann B, Walcher F. Notfallversorgung: Die digitale Rettungskette. Deutsches Ärzteblatt 2024;121(12):828-831.

Inhalt

Publikationen, die die Dissertation darstellen	2
A Federated and Distributed Data Management Infrastructure to enable public health surveillance from Intensive Care Unit Data	5
Implementation report on pioneering federated data access for the German National Emergency Department Data Registry	10
The Effects of Displaying the Time Targets of the Manchester Triage System to Emergency Department Personnel: Prospective Crossover Study	26
Appendix	55
Synopsis: Federated research infrastructures for a learning healthcare system in acute, intensive, and emergency care	56
Danksagung	72
Erklärung § 5 Abs. 1 zur Datenaufbewahrung	73
Erklärungen gemäß § 5 Abs. (1) und (2), und § 11 Abs. (3) 12. der Promotionsordnung	74
Curriculum Vitae	78

A Federated and Distributed Data Management Infrastructure to Enable Public Health Surveillance from Intensive Care Unit Data

Jonas BIENZEISLER^{a,1}, Lucas TRIEFENBACH^a, Alexander KOMBEIZ^a,
Matthäus LOTTES^b, Christopher VOGEL^b, Linus GRABENHENRICH^b, Martina
FISCHER^b, Theresa KOCHER^b, Lukas NIEKRENZ^c, Michael DREHER^c, Christoph
MÜLLER^d, Rainer RÖHRIG^a and Raphael W. MAJEED^a on behalf of the AKTIN and
SPoCK Research Group

^a*Institute of Medical Informatics, Medical Faculty of RWTH Aachen, Aachen, Germany*

^b*Department of Methodology and Research Infrastructure, Robert Koch Institute,
Berlin, Germany*

^c*Department of Pulmonology and Intensive Care Medicine, Medical Faculty of RWTH
Aachen, Aachen, Germany*

^d*Data Integration Centre (DIC), University Hospital RWTH Aachen, Aachen, Germany*

Abstract. The Robert Koch Institute (RKI) monitors the actual number of COVID-19 patients requiring intensive care from aggregated data reported by hospitals in Germany. So far, there is no infrastructure to make use of individual patient-level data from intensive care units for public health surveillance. Adopting concepts and components of the already established AKTIN Emergency Department Data registry, we implemented the prototype of a federated and distributed research infrastructure giving the RKI access to patient-level intensive care data.

Keywords. Critical care, routine care research, EHR, database, data privacy

1. Introduction

Intensive Care Units (ICU) are not only a crucial part of the health system but also an essential data source for public health surveillance. For the modeling and prediction of ICU occupancy during the COVID-19 pandemic, German authorities rely on mandatory reporting of COVID-19 cases and aggregated capacity data from hospitals [1]. Such data are collected and analyzed by the Robert-Koch Institute (RKI), the German National Public Health Institute. In the Project SPoCK (*Steuerungs-Prognose von intensivmedizinischen COVID-19-Kapazitäten*), the RKI, cooperating with universities, aims at improving the prediction of intensive care COVID-19 capacities. The automated provision of routine data sources on an individual-patient level is expected to enhance the predictive precision of the models. Furthermore, such data is seen of great value to

¹ Jonas Bienzeisler, Corresponding author; E-mail: jbienzeisler@ukaachen.de

improve *public health surveillance* in general [2]. Internationally, routine data could also be re-used for comparative effectiveness research or evaluation of COVID-19 government interventions. However, assessment of data on individual-patient level from multiple sites is opposed by legal guidelines in the European Union. The General Data Protection Regulation (GDPR) limits the sharing of sensitive data, typically requiring explicit patient consent for data processing. Our objective was to develop and operate a GDPR-compliant research infrastructure for routine data stemming from ICUs, that enables public health surveillance and other applications through the RKI.

1.1. Background

In Germany, data from the intensive care registry² is used to track the number of COVID-19 patients requiring intensive care [1]. Aside from structural characteristics of hospitals that maintain intensive care beds, information on ICU capacities and COVID-19 case numbers are collected in a *central* database. For reimbursement, it is also mandatory for ICUs to collect vital parameters and multiple clinical scores in patient data management systems. In practice, clinical scores are used to assess the current, disease-related patient status for individual risk prediction and necessary resources [3]. The predictive value of these scores has also been demonstrated in patients with COVID-19 admitted to the ICU [4] and could be used in occupancy models for the management of ICU capacities [2].

These data cannot be used so far because centralized storage of individual health data under the GDPR typically requires consent which is not feasible for ICU patients and might cause a selection bias. Privacy-preserving methods are usually used to access and analyze sensitive medical data for research despite data protection regulation. Two strategies are common to make use of data; either algorithms are distributed to the decentralized data and only anonymous results are aggregated [5,6] or only data that can be considered anonymous is aggregated (as in the intensive care registry) [7,8].

The *AKTIN (Alliance for information and communication technology in intensive care and emergency medicine) Emergency Department Data Registry* demonstrates, that such an evaluation is possible using a federated and distributed research infrastructure based on *decentral* data warehouses for anonymous aggregation or distributed computing [7–9]. Employing the concepts and software solutions of the AKTIN Registry, we implemented a data management infrastructure for the evaluation of ICU routine records for health surveillance, the so-called *SPoCK Data-Infrastructure*.

2. Methods

The methods for conceiving the SPoCK Data-Infrastructure are based on the specific requirements for data capture and general requirements for sustainable operation.

2.1. Specific Requirements for data capture

The RKI required fast and actual access to patient-level data from multiple German ICUs for public health surveillance of COVID-19. The central analysis of structured reports

² www.intensivregister.de

by the RKI was mandatory, as the data needs to be analyzed together with pre-existing surveillance models. Thus, standardized processes for retrieval, transmission, and analysis of collected data were necessary. Semantically and syntactically comparable and compatible data were required. Finally, participating ICUs needed the tooling and implementation guidelines to store data and render it accessible for central pooling.

2.2. General Requirements

The handling of the health data is subject to legal and ethical constraints varying from country to country. In the European Union and under the GDPR, consent is mandatory for processing health data, if opening clauses are not in place. Under the premise of proper technical and organizational measures, health data may be processed for reasons of public interest such as health surveillance (Art. 9 (2) (i), GDPR). Integration into national and international research efforts is mandated for sustainable infrastructure projects. The generic concepts of the telematics platform for medical research networks [10] and the German medical informatics initiative [11] determine a national state of the art. Common technologies, terminologies, and data models are obligatory for integration into international research efforts.

3. Results

The general and specific requirements of the data collection match the requirements of the AKTIN Registry [9]. For setting up the SPoCK Data-Infrastructure in a short time, components of the AKTIN Registry were therefore modified to suit the use case. As there were only minor resources for data collection in participating hospitals, we restricted data to routine records collected for billing purposes. We aligned our concepts with recommendations for data protection for medical research networks in Germany [10].

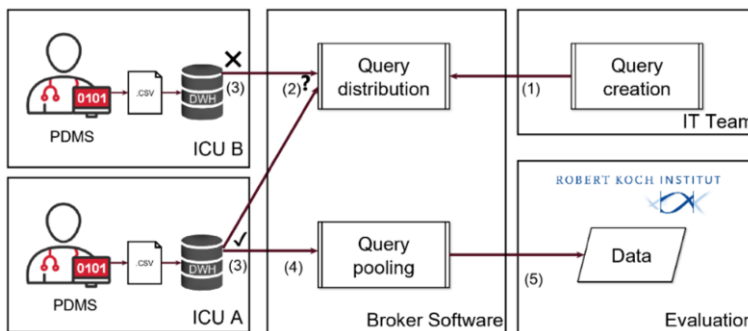


Figure 1: Federated and distributed research infrastructure of the Project. (1) The IT Team creates a query. (2) The query is distributed by the broker software to participating ICUs and can be checked (3) locally. (4) The SPoCK data warehouse (DWH) submits the results of the query to the broker software, anonymized data exports are pooled. (5) Data are delivered to the RKI.

3.1. Concept

We used the pre-existing software solutions of the AKTIN infrastructure for distributed data collection and federated data storage (c.f. Fig. 1). The used components are *not* connected to the AKTIN Registry but form a separate infrastructure. Data are stored in

modified instances of AKTIN data warehouses that employ an individual *SPoCK import script* [7,9]. The import script consists of an *Extract-Transform-Load* (ETL) pipeline employing Logical Observation Identifiers Names (LOINC) and Codes and Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT) for annotation in i2b2. A modified instance of the AKTIN Broker can be used to query data. The data warehouse software is supplied and deployed using Linux-based installation packages.

Using these software components, a data set can be collected continuously and prospectively for the purposes of public health surveillance in a data warehouse. For simplicity, required data are exported in a CSV format from the patient data management system daily and then imported into the data warehouse. Each clinic operates and administrates the data warehouse on a dedicated server. The ownership of data and responsibility lies with the respective clinic. For public health surveillance, the data can be queried centrally via the broker and then evaluated by the RKI. It is the obligation of participating clinics to ensure that queried data are anonymous (c.f. Fig. 2).

3.2. Implementation

Currently, the framework is being piloted in the first clinic after approval of the ethics committee³. Data from 13144 cases were imported into the data warehouse. The first delivery of data to evaluation is intended for the first quarter of 2022. Furthermore, it is planned to roll out the software to two more clinics operating patient data management systems from different vendors.

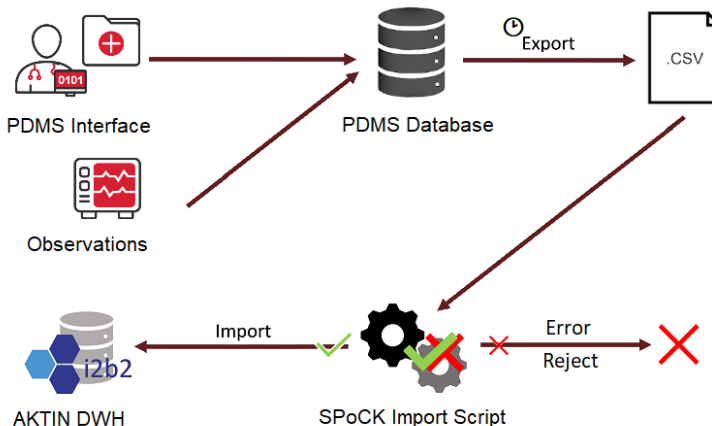


Figure 2: Data collection. Data are exported from patient data management system in CSV format using a repeating Cronjob. Exports are automatically imported into a AKTIN data warehouse (DWH) using the SPoCK import script which consists of an Extract-Transform-Load (ETL) pipeline.

4. Discussion and conclusions

The primary objective of our work was to enable public health surveillance from patient-level ICU data. We designed a research infrastructure that is capable of automatically providing the RKI with such data. We started with data collection and proved feasibility

³ Ethics Committee Medical Faculty of RWTH Aachen University, EK 483/21.

in practice. The infrastructure is in operation. We based the infrastructure on pre-existing software solutions of the AKTIN Registry. The proof was given that the concepts and software components of the AKTIN Registry can be adapted to other scenarios and are ready for use in scenarios besides the emergency department. Further, the AKTIN components carry the potential for the rapid set up of health surveillance protocols. One advantage is that neither patients' informed consents need to be collected nor data needs to be aggregated on client side. As a result, the infrastructure can be scaled more easily to include data from small and large hospitals nationwide. The only prerequisite is automatic data provision and the installation of an AKTIN data warehouse. As long as the same terminologies and data models are used, it is possible to transfer the approach to other countries; import scripts or interfaces must be adapted accordingly.

Due to financial, organizational, and technical limitations, our work is limited to data collected from one ICU. Multiple instances have yet to be connected to a research network to provide data from multiple sites. Currently, data only consists of clinical scores collected for billing purposes. In the future, the data set needs to be extended and standardized to guarantee syntactic and semantic interoperability. Industry standards like HL7 ORC messages or HL7 FHIR resources should be used instead of CSV format to allow data stemming from any data source, nationally and internationally. Data are only collected for public health surveillance and cannot be used for health research. However, the infrastructure could be adapted to allow for potential health research as well.

References

- [1] Schuppert A, Theisen S, Fränkel P, Weber-Carstens S, Karagiannidis C. Bundesweites Belastungsmodell für Intensivstationen durch COVID-19. *Med Klin Intensivmed Notfmed* 2021.
- [2] Azzopardi-Muscat N, Kluge HHP, Asma S, Novillo-Ortiz D. A call to strengthen data in response to COVID-19 and beyond. *J Am Med Inform Assoc* 2021;28:638–39.
- [3] Rapsang AG, Shyam DC. Scoring systems in the intensive care unit: A compendium. *Indian J Crit Care* 2014;18:220–28.
- [4] Taylor EH, Marson EJ, Elhadi M, Macleod KDM, Yu YC, Davids R, et al. Factors associated with mortality in patients with COVID-19 admitted to intensive care: a systematic review and meta-analysis. *Anaesthesia* 2021;76:1224–32.
- [5] Beyan O, Choudhury A, van Soest J, Kohlbacher O, Zimmermann L, Stenzhorn H, et al. Distributed Analytics on Sensitive Medical Data: The Personal Health Train. *Data Intelligence* 2020;2:96–107.
- [6] Kapsner LA, Kampf MO, Seuchter SA, Gruendner J, Gulden C, Mate S, et al. Reduced Rate of Inpatient Hospital Admissions in 18 German University Hospitals During the COVID-19 Lockdown. *Front Public Health* 2020;8:594117.
- [7] Brammen D, Greiner F, Kulla M, Otto R, Schirrmeister W, Thun S, et al. The German Emergency Department Data Registry – real-time data from emergency medicine: Implementation and first results from 15 emergency departments with focus on Federal Joint Committee's guidelines on acuity assessment. *Med Klin Intensivmed Notfmed* 2020.
- [8] Boender TS, Cai W, Schranz M, Kocher T, Wagner B, Ullrich A, et al. Using routine emergency department data for syndromic surveillance of acute respiratory illness before and during the COVID-19 pandemic in Germany, week 10-2017 and 10-2021, Preprint at medrxiv 2021.
- [9] Ahlbrandt J, Brammen D, Majeed RW, Lefering R, Semler SC, Thun S, et al. Balancing the need for big data and patient data privacy--an IT infrastructure for a decentralized emergency care research database. *Stud Health Technol Inform* 2014;205:750–54.
- [10] Pommerening K., Helbing K, Ganslandt T, Drepper J Leitfaden zum Datenschutz in medizinischen Forschungsprojekten: Generische Lösungen der TMF 2.0. Schriftenreihe der TMF – Technologie- und Methodenplattform für die vernetzte medizinische Forschung e.V, Berlin: MWV Medizinisch Wissenschaftliche Verlagsgesellschaft mbH & Co. KG; 2017.
- [11] Semler SC, Wissing F, Heyder R. German Medical Informatics Initiative: A National Approach to Integrating Health Data from Patient Care and Medical Research. *Methods Inf Med* 2018;57:e50-6.



Implementation report on pioneering federated data access for the German National Emergency Department Data Registry



Jonas Bienzeisler¹✉, Alexander Kombeiz¹, Saskia Ehrentreich², Ronny Otto², Wiebke Schirrmeister², Marco Pegoraro³, Dominik Brammen², Behrus Puladi^{1,4}, Rainer Röhrig¹ & Raphael W Majeed^{1,5}

Continuous access to electronic health records will fuel the digital transformation of medicine. For data-sharing initiatives, the challenge lies in ensuring data access aligns with the interests of data holders. Federated data access authorization, where data remains controlled locally, may offer a solution to balance these interests. This paper reports on a digital health implementation of the federated data access authorization system used in the German National Emergency Department Data Registry. Using data from 2017 to 2024, we analyzed the system's effectiveness in managing data access in a nationwide research network of 58 emergency departments. Facilitating access to more than 7.9 million records, 75% of data access queries were authorized within 15 days. The system also supports periodic queries, enabling recurring real-time access. Query volumes grew from 15 to over 23,000 by 2024, with completion rates of 86%. The system may thus serve as a blueprint for data-sharing initiatives worldwide.

A continuous stream of data is essential for the digital transformation of healthcare, but data collection efforts are useless if the data cannot be efficiently accessed^{1–3}. The volume of clinical data stored in health information systems is constantly growing, but the benefits of holding all this data will only be realized through continuous, real-time data sharing, especially within initiatives like the European Health Data Space, which aims to create a unified system for healthcare data sharing in Europe⁴. In a learning healthcare system, technologies like digital twins or artificial intelligence rely on seamless access to electronic health records (EHRs), the patient-centered digital records of medical treatment⁵.

Providing universal access to EHRs for secondary purposes can prove challenging, as stakeholders such as physicians and hospitals may prefer to maintain control over their data^{6–8}. The sharing of EHRs introduces underestimated complexities relating to data ownership, privacy, and consent^{9,10}, termed the privacy-exploitation barrier⁴. Thus, access to big data for secondary purposes is increasingly expected to be facilitated by federated approaches within local healthcare settings, rather than centralized data collections¹¹. Following this concept, research networks make data from

nodes (local data storages, e.g., a hospital lab orders database) findable and accessible, thereby enhancing the use of health data as provisioned by the World Health Organization¹².

The success of global data-sharing initiatives hinges on the development of processes that enable safe, efficient, and reliable data access authorization while respecting data ownership and stakeholder interests. Federated data access authorization could be a scalable solution facilitating purpose-limited data access. In this paper, we report on the digital health implementation of a nationwide federated data access authorization system for the continuous sharing of EHR data from emergency departments (following guidelines and checklists for reporting on digital health implementations¹³).

The system is used by the German National Emergency Department Data Registry (ED registry)¹⁴. It is the largest distributed research network in the world that uses informatics for integrating biology and the bedside data warehousing platform (*i2b2*)¹⁵, with 77 connected ED nodes. Emergency departments (EDs) in Germany offer both pre-hospital and in-hospital acute care services to the public and are integral to private and public

¹Institute of Medical Informatics, Medical Faculty of the RWTH Aachen University, Aachen, Germany. ²Department of Trauma Surgery, Otto von Guericke University, Magdeburg, Germany. ³Chair of Process and Data Science (PADS), Department of Computer Science, RWTH Aachen University, Aachen, Germany. ⁴Department of Oral and Maxillofacial Surgery, University Hospital RWTH Aachen, Aachen, Germany. ⁵Department of Internal Medicine, Universities of Giessen and Marburg Lung Center (UGMLC), German Center for Lung Research (DZL), Giessen, Germany. ✉e-mail: jbienzeisler@ukaachen.de

hospitals. Comparable to most Western healthcare systems, they function as key hubs for urgent ambulatory and life-saving in-hospital treatment. As in other federal systems, there is a variation in healthcare regulation across the federal states of Germany.

The ED registry is based on a distributed and federated research infrastructure (AKTIN infrastructure), initiated and orchestrated by the Alliance for Information and Communication Technology in Intensive Care and Emergency Medicine, abbreviated as AKTIN in German. The infrastructure is operated within the Network University Medicine in Germany and gives access to EHRs from German EDs¹⁴. Records are sourced via an HL7 Clinical Document Architecture (CDA) interface from the emergency department documentation system. These CDA documents are delivered to a local AKTIN data warehouse (DWH)¹⁶ via a RESTful HL7 FHIR binary endpoint in accordance with the FHIR standard specification and then stored.

Each EHR corresponds to the routine documentation of an emergency department encounter episode. The stored documentation adheres to the standardized emergency department medical record¹⁷ of the German Interdisciplinary Association for Intensive Care and Emergency Medicine, which is developed independently of the AKTIN infrastructure in collaboration with HL7 Germany.

The AKTIN infrastructure utilizes the open-source i2b2 data warehousing technology to empower participating EDs to integrate and manage the records exported via the HL7 CDA interface in an AKTIN DWH. The AKTIN infrastructure (Fig. 1) is composed of individual ED nodes, each representing a distinct emergency department unit within the participating hospitals operating an AKTIN DWH. These may include multiple, geographically separate EDs operating as independent organizational units in

larger hospitals. While the emergency department medical record serves as a standardized ontology in all AKTIN DWHs, the selection of variables documented varies across ED nodes.

Within the framework of the AKTIN infrastructure, it is standard practice to forego the collection of informed consent for data sharing. This is possible because EHRs are stored independently within each ED, adhering to general medical confidentiality obligations. The local nodes maintain full control of their own data¹⁸.

Deidentified data can be queried for explicitly defined purposes following an established use and access protocol of the ED registry. A Data Use and Access Committee (DUAC) reviews data requests from scientists and enforces ethical and scientific standards¹⁸. The stored data can be accessed through the AKTIN Broker—a middleware service operated by the AKTIN-IT Group for querying the data stored in the AKTIN DWHs. After federated data access authorization, the queried data are collected and analyzed as a service or under supervision in a trusted research environment—the AKTIN Trusted Data Analytics Center (AKTIN TDAC).

Common ontologies facilitate data access by providing a structured framework for interoperability¹⁹. Universal and ongoing access, however, introduces governmental challenges if the purposes, receiver, and content of data requests (queries) vary^{8,20,21}. In the AKTIN infrastructure, ED nodes must balance the interests of stakeholders when authorizing data access. The participating hospitals operate within a competitive framework. They optimize efficiency and quality in patient care to maintain a competitive advantage and reduce costs²². A competitive setting ensures a cautious approach towards data sharing²³. Furthermore, hospitals may have to navigate personal interests, such as the desire of personnel to utilize data for internal research.

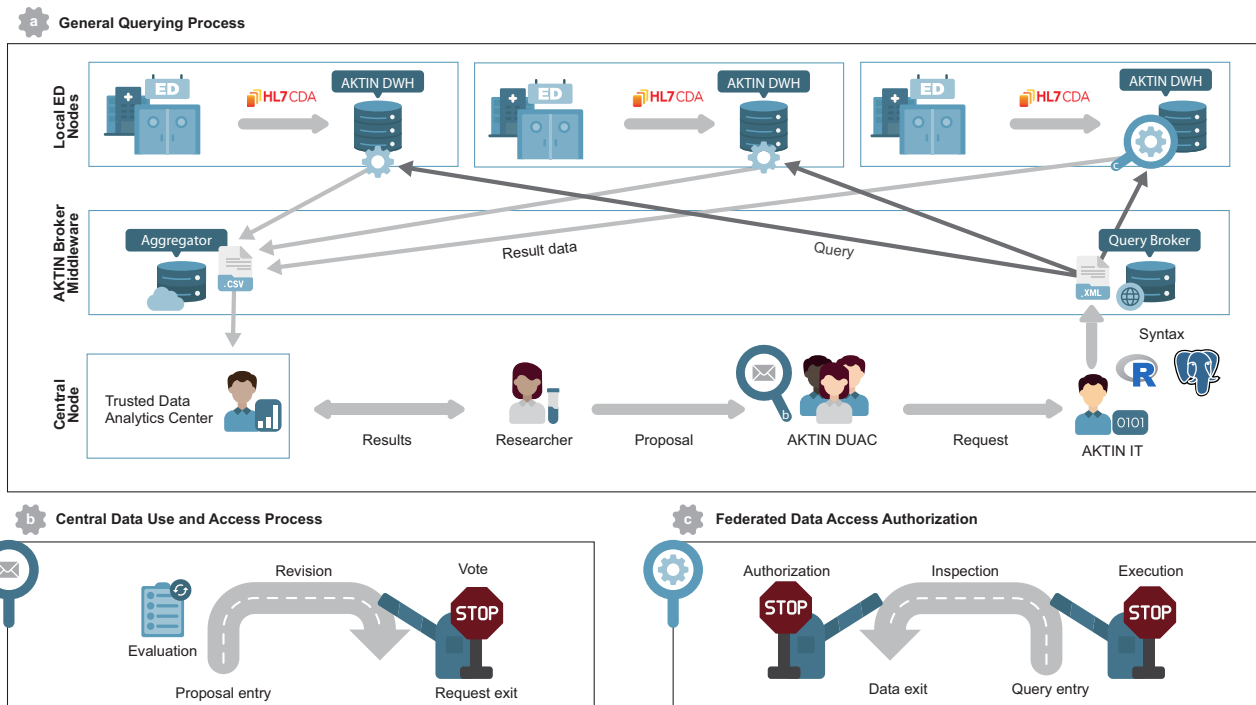


Fig. 1 | AKTIN infrastructure processes¹⁸. **a** Electronic health record data are captured in the participating emergency department nodes within an AKTIN data warehouse. After approval from the Data Use and Access Committee (DUAC), the AKTIN IT group translates proposals into R or SQL syntax. From the syntax, a data query is created which is communicated to the nodes using the AKTIN Broker via xml data structure including additional descriptive- and provenance metadata. The local emergency department (ED) node must authorize data access for each query. **b** The DUAC evaluates proposals and formulates a vote translated into a technical request. **c** A federated data access authorization process is implemented within the

AKTIN DWH software. The AKTIN IT group receives technical requests and then uses the AKTIN Broker middleware to send queries to AKTIN DWHs in the ED nodes. The ED nodes may execute the query, inspect the results in CSV format, and authorize data access. The R logo is used under the terms of the Creative Commons Attribution-ShareAlike 4.0 International license (available from www.r-project.org/logo/). Postgres, PostgreSQL, and the Slonik Logo[®] are trademarks or registered trademarks of the PostgreSQL Community Association of Canada, and are used with their permission (available from www.postgresql.org/about/policies/trademarks).

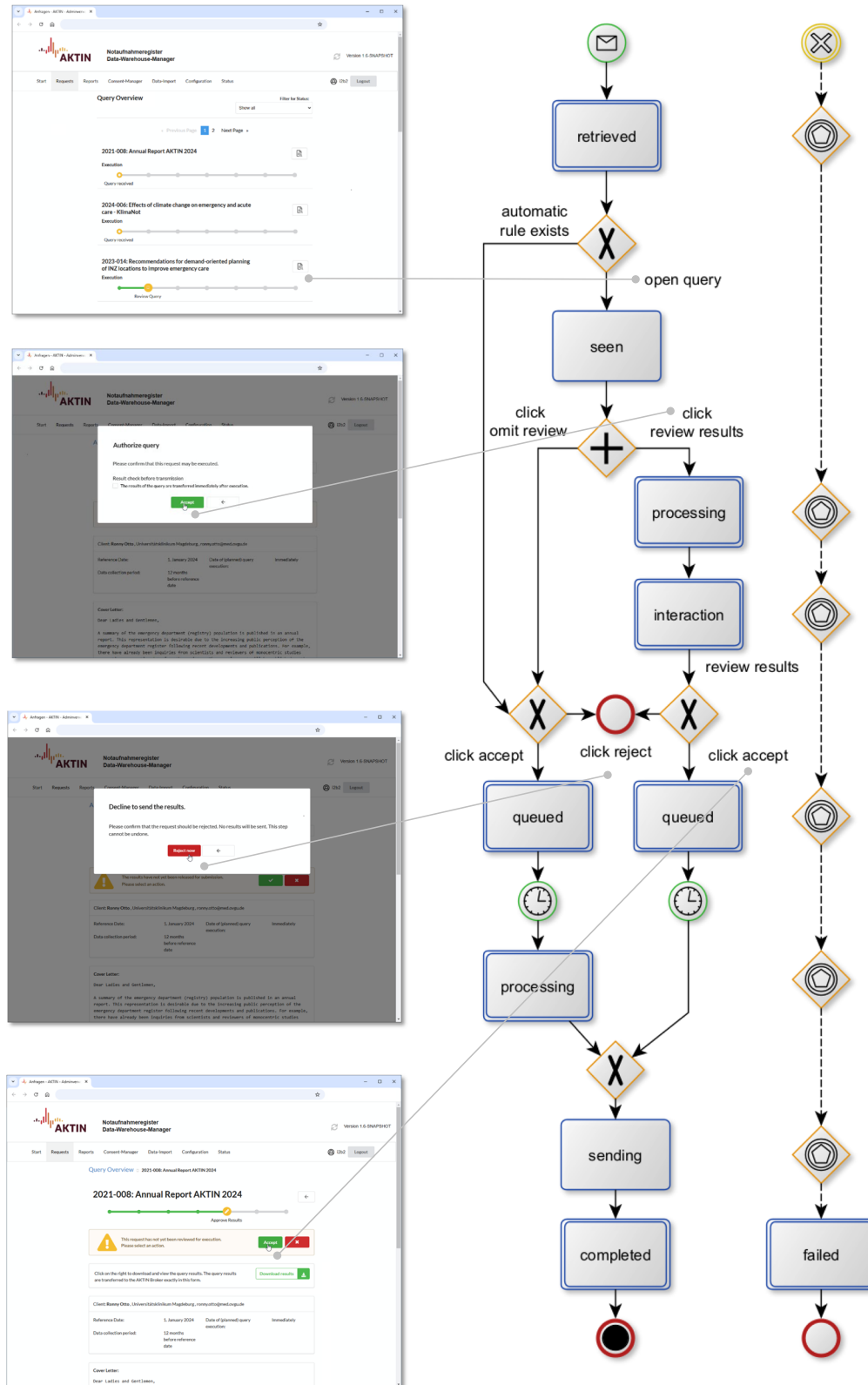


Fig. 2 | Formal workflow description and translated screenshots of local data access authorization of a query in an AKTIN data warehouse manager within a local node of the AKTIN infrastructure. Errors in the federated data access authorization process (left)

result in failed queries (right). Note: this diagram employs a modified version of BPMN, adapted to clarify specific workflow elements unique to the AKTIN infrastructure. This adaptation may not strictly adhere to formal BPMN guidelines.

The decentralization of data governance introduces additional complexity. Each of the 16 German states has its own medical and general data processing regulations combined with the European General Data Protection Regulation (GDPR) provisions. While physicians operate within the

scope of these laws, their responsibilities—particularly regarding the non-disclosure of medical information—are defined by the German criminal code. Data may be shared if opening clauses are in place or data is anonymized. Data protection officers are typically the process owners responsible

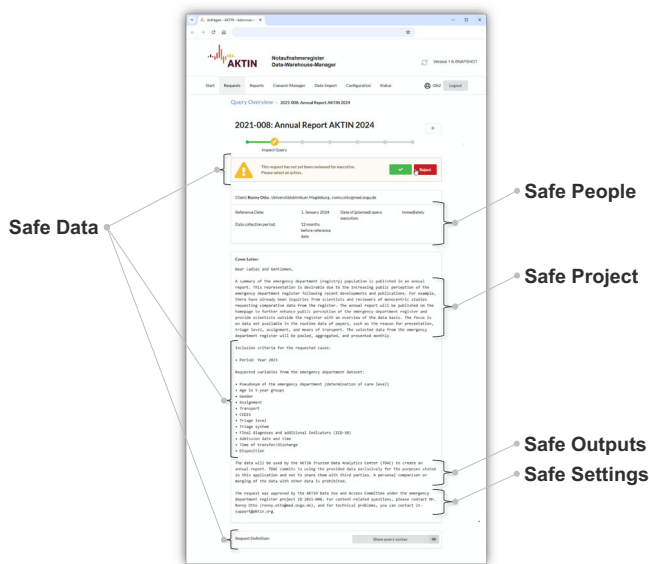


Fig. 3 | Translated visualization of a query within the dedicated data request view in the AKTIN DWH manager. Participating emergency department nodes of the AKTIN infrastructure review the query and individually decide if they want to authorize data access.

for ensuring compliant data-sharing and the determination of applicable regulations.

Because hospitals, data protection officers, and physicians may bear liabilities, they must be equipped to make informed decisions regarding EHR sharing for secondary purposes. Research networks thus require complex frameworks for data access authorization. In the United States, PCORnet[®] facilitates data sharing under HIPAA²⁴, while the German Medical Informatics Initiative employs a two-tiered strategy where central and local committees review proposals for data access²⁵. Technical solutions, like DataShield^{26,27}, MedCo²⁸, and SHRINE²⁹, allow the automatic querying of data. However, they lack mechanisms for a federated review process. Projects like the Norwegian PraksisNet³⁰, and PopMedNet³¹, which were utilized by PCORnet[®] before transitioning to PCORnet[®] Front Door, aim to integrate data access frameworks with local control mechanisms. The efficiency of these systems in facilitating data access has neither been evaluated nor explicitly published. Here, we aim to address the research question of whether a federated data access system can effectively enable the nationwide secondary use of emergency department EHRs.

Results

Our first objective was to design and implement a technical system and the processes required to enable secure and safe access to EHRs originating from a research network of multiple ED nodes in the AKTIN infrastructure. We then verified the operational efficiency and reliability of the technical system as our second objective. To do so, we evaluated key performance indicators (KPIs) in a retrospective cohort study based on system log data from operations between 2017 and 2024 within the AKTIN infrastructure.

In the AKTIN infrastructure, Data requests (Supplementary Fig. 1) commence with a research proposal submitted to the DUAC for review. Upon receiving authorization, the AKTIN IT group converts the proposal into a technical request. The AKTIN IT group publishes the technical request as individual queries to the nodes via the AKTIN Broker. The AKTIN DWH instances in the ED nodes poll for new queries for federated data access authorization (Fig. 1c). After authorization, which can be automatized for repeated periodic queries, the AKTIN Broker collects the results. The AKTIN TDAC retrieves the collated results. Analyses are then conducted as a service or within the trusted research environment of the AKTIN TDAC.

Technical system

Based on our first objective, we implemented a technical system for federated data access authorization (Fig. 1c) within the AKTIN DWH Manager. The web application features a dedicated view for general data request management and for each individual query. Users can review data requests sent out as queries within the data request management view and interact with the central AKTIN Broker.

Query requests are published on the AKTIN Broker, encompassing the requisite query syntax (SQL or R Syntax), essential metadata, execution date, and a cover letter. The query is polled and visualized within an AKTIN DWH node. Users can authorize data access. Finally, the AKTIN DWH synchronizes results with the AKTIN Broker and multiple results are aggregated at the AKTIN Broker. The process is logged and managed within the backend of the AKTIN DWH and communicated to the AKTIN Broker, which logs the process status of each query for provenance. Communication between each node in the network and the AKTIN Broker is secured by using individual API Keys.

The AKTIN Broker application utilizes the original i2b2 web client for query formulation and stores queries for on-demand retrieval by AKTIN DWH nodes. Queries and, if approved, results are efficiently relayed back to the server and can then be rendered on the web frontend of the AKTIN Broker. The Broker is content-agnostic, accommodating various query languages and formats alongside their responses. Different terminologies and logics can be defined in the query through customizable XML transformations.

Within each AKTIN DWH node (Fig. 2), the request transitions through various states, offering the flexibility to approve or reject at multiple junctures. A polled request (retrieved) is displayed in the user interface. A request can then be viewed by a user (seen) and either be rejected or accepted. The request is queued until execution time (processing). Execution errors change the state to fail. After successful processing, results can be exported in CSV format. Users can also choose to review requests. The results are processed first, and an additional user interaction for result dissemination (interaction) is required. Users may also configure periodic requests to auto-execute them—a process *inter alia* used for pandemic surveillance³². After initial data access authorization, subsequent queries with identical syntax are automatically executed.

In the AKTIN DWH Manager, after user authentication, polled queries are displayed in a filterable list within the request management view. Each query triggers an email notification and is presented in a dedicated view (Fig. 3) with an ID, comprehensive meta-information, a human-readable cover letter describing purposes, and the definition of the query syntax. Meta-information consists of the requester’s details (name, affiliation, email), a reference date for the data collection period, and the planned execution. The cover letter’s content is not technically standardized but rather segmented to enhance readability. It begins with the rationale for the request, followed by a detailed account of the research questions and relevant outcomes to evaluate safe data. Inclusion criteria for the data and the requested variables are then enumerated. This is followed by a description of the data processors and the general purpose of data processing to evaluate safe settings. Standardized text elements then outline principles of the ethical use of data and general privacy commitments of the ED registry that ensure safe outputs. The described request can be approved or declined in a pop-up window and then be reviewed again. If the technical request defines a repeated query, initial approval includes a provision for automatic result transmission without subsequent authorization or rejection of future individual queries.

System evaluation

For our second objective, we evaluated the technical system according to KPIs. Within the time of operation, at least 7.9 million EHR datasets were integrated within the AKTIN infrastructure (Supplementary Table 2). The number of active nodes connected to the AKTIN Broker grew from 12 in 2017 to 58 in 2024 (Fig. 4). Two thousand nine hundred sixty requests, comprising 76,267 individual queries, were distributed to the nodes. This included 4053 individual queries and 72,214 periodic queries. We saw a

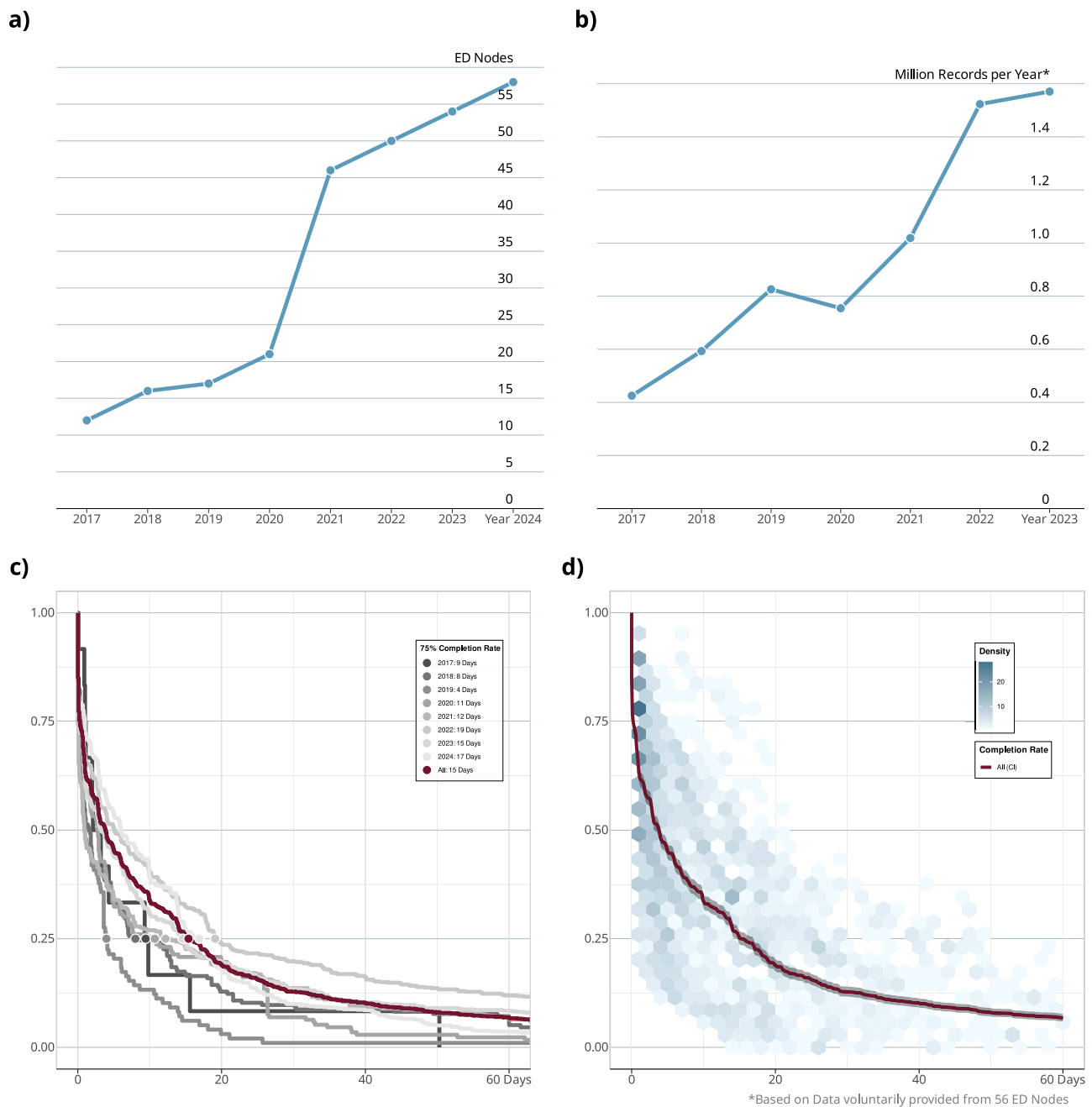


Fig. 4 | Growth of the AKTIN infrastructure and analysis of KPIs. **a** Active ED nodes connected throughout the years illustrate the infrastructure growth since 2017, which **(b)** enables access to 1.6 Million Electronic Health Records in 2023 and 7.9 Million Electronic Health Records in total. Bottom: rate of unanswered queries. Kaplan–Meier survival curves show the proportion of uncompleted individual

queries over days after retrieval by the AKTIN DWH. **c** The behavior of nodes varied slightly across the years; ED nodes replied more swiftly in the first years of the infrastructure. **d** The behavior differs across nodes. The hexagonal density distribution of different Kaplan–Meier curves illustrates the concentration of query completions for all active nodes.

yearly increase in query volumes, from 15 in 2017 to 23,340 queries in 2024. In 2023, each node received a median of 19 individual queries and 386 periodic queries per year.

The completion rate was 79.8% ($n = 3234$) for individual queries, 87.1% ($n = 62,888$) for periodic queries, and overall 86.7% ($n = 66,122$). Failures were infrequent, with individual queries experiencing a slightly higher failure rate of 2.8% ($n = 114$) compared to 1.0% ($n = 722$) for periodic queries. This amounted to a total failure rate of 1.1% ($n = 836$). The number of queries that were opened for review but were not interacted with was recorded at 0.1% ($n = 3$) for individual requests, and even less so for periodic queries at 0% ($n = 16$), culminating in an overall rate of 0.0% ($n = 19$). Retrieved but unanswered queries accounted for 14.2% ($n = 574$) of

individual and 10.6% ($n = 7657$) of periodic queries, resulting in an overall rate of 10.8% ($n = 8231$). Rejected queries constituted 3.0% ($n = 121$) of individual queries and 1.0% ($n = 732$) for periodic queries. We observed a total rejection rate of 1.1% ($n = 853$).

Completion times varied significantly ($P < 0.001$, paired t -test, Supplementary Table 3) between individual and periodic queries. Individual queries took a mean of 17 days (SD: 38) to complete, compared to 9 days (SD: 23) for periodic queries. The median completion time for individual queries was 4 days (range: 0–368 days), and immediate for periodic queries. Because the automatic authorization of periodic queries can be granted to future and past queries, we observed a range from 0 day to 585 days. The time until rejection for individual queries was longer, with a median of

Table 1 | Responsibilities regarding data access authorization within the AKTIN infrastructure

	Central level responsibility	Local level responsibility
Safe projects	DUAC approves data access for specific research proposals.	Local ED nodes ensure that the research projects in which data are used align with local requirements.
Safe people	DUAC authorizes individuals and entities to access data.	Local ED nodes confirm the credentials and permissions of the data requester.
Safe data	DUAC ensures data access meets ethical and privacy standards. AKTIN IT implements queries according to the provisions of the DUAC.	Local ED nodes examine each query to validate its purpose and syntax. Clinical end-users provide context knowledge.
Safe settings	AKTIN TDAC guarantees data processing in secure environments.	The process owner and the hospital evaluate the operational framework within the AKTIN infrastructure.
Safe outputs	AKTIN TDAC oversees the release of aggregated or anonymized data. The DUAC reviews resulting publications.	Local ED nodes approve outputs for publication or further use.

38 days (SD: 89). The processing time exhibited some variability, with individual queries taking a median of 21 s (IQR: 5–85) and periodic queries taking a median of around 12 s (IQR: 5–29 s).

The different nodes showed variations in response patterns to queries (Fig. 4). The response patterns were roughly similar throughout the years. Across all participating ED nodes, 75% of responses came within 15 days of delivery to the node. While most ED nodes responded to queries relatively quickly, some EDs had slower response rates. This is reflected in a prolonged tail and affects the overall mean time until completion.

There were no instances of accidental approvals or rejections. On occasion, individual inquiries were made regarding the authorization process or technical issues. None were made about the content of the queries. The system encountered downtime only once due to a certificate issue. In 2019, the AKTIN Broker server was relocated to a different university without complication.

Our results cover data from EDs across Germany, accounting for at least 1 million EHRs from some 10 million ED cases billed in approximately 1500 emergency departments in Germany in 2021³³. As ED encounter episodes for the same reason of treatment can only be reimbursed once, we estimate the AKTIN infrastructure to encompass around 5% of all ED visits in the country. In some urban regions, the infrastructure has full coverage; one city has three competing public and private hospitals with EDs connected to the infrastructure within a 5-km radius.

All data access is currently free of charge for requesters and ED nodes. However, hospitals seeking active involvement in association bodies, such as the AKTIN DUAC, must become members of the AKTIN non-profit association, which currently incurs an annual fee of 250 €. The AKTIN infrastructure was established within a research project with a budget of €4.1 million. It is currently operated with annual infrastructure funding of €1.5 million provided by the Network University Medicine. 70 participating ED nodes received funding to establish the necessary CDA interfaces and currently receive annual infrastructure funding for their participation (not all of these ED nodes are currently connected to the AKTIN infrastructure and productive). However, 20 ED nodes participate at their own expense. The central components of the AKTIN Infrastructure are operated with a budget of about 500,000€ per year. A full-time software developer and a senior software engineer maintain the technical infrastructure and code base. IT project management and community management are overseen by two project coordinators, while two data scientists focus on data analysis and ensuring data quality. New services are financed through additional research projects and corresponding personnel.

Discussion

Medical research networks avoid central data repositories; Storing data at the source is expected to reinforce data security and privacy compliance, thus empowering data holders. However, integrating data, as well as continuous and universal data querying is a governance challenge for the nodes, hindering broad secondary uses of EHRs³⁴. In terms of our first objective, our results show that federated data access authorization allows the nodes of

a nationwide research network to maintain local control over data, which in turn facilitates data access.

When scaling the AKTIN infrastructure, we found that having transparent operational frameworks allows the nodes to accommodate diverse local standards individually. This flexibility is critical during the local setup of components and when interacting with clinics and process owners, especially local data protection officers. Due to time constraints, data protection offices may delegate clearance of individual data queries to clinical end-users. Transparent governance mechanisms are then required to conduct spot checks. These results align with insights from the UK, highlighting the importance of robust data access pathways and standardized data access forms for population-wide research^{8,20}.

A genuinely federated authorization process, with a power distribution between data providers, use-and-access processes, and data receivers, proved extremely helpful. In some regions, full coverage of ED nodes from competing private and public hospitals was achieved, underlining the level of trust in the framework. The ED registry and the ED nodes can authorize data access individually (Table 1). Our general strategy was to provide technical processes for maximum risk and allow the local nodes to adapt these within their local organizational processes. Including patient perspectives, however, was challenging due to anonymized data and the transient nature of emergency care. Instead, patient organizations are involved in research projects utilizing the AKTIN infrastructure.

The community-driven and interdisciplinary approach of the ED registry was the most effective strategy, facilitating widespread implementation and fast response rates within the technical system. Such an approach also enables the critical incorporation of clinical context knowledge, a prerequisite for any meaningful secondary analyses of EHR data. Data access authorization in clinical settings requires in-depth context knowledge from clinical end-users. The data access processes must not be overly time-consuming or complex. Structuring information to be easily comprehensible to clinical end-users was critical.

The increase in query volumes in the AKTIN infrastructure over the years demonstrates the successful adoption of the framework in various healthcare contexts. While the sample of connected EDs is not representative of the approximately 1500 EDs in Germany, the system still enables nationwide data access in the public and private sectors. Scalability is critical for sustaining the utility of medical research networks within a constantly changing healthcare landscape. We demonstrated that federated data access authorization can address communication barriers, limited access to information, and suboptimal data utilization in emergency medicine. These critical health system challenges are defined by the World Health Organization's Classification of Digital Health Interventions¹². Our implementation emphasizes the importance of robust authorization protocols within a secure trust architecture for overcoming the privacy-exploitation barrier. Our framework could, in principle, be used for data sharing across international borders, as it empowers the local nodes to authorize data access according to the local provisions. Such overarching standards are also present in international research networks operating across different national jurisdictions.

The accessed data is valuable for health services research³⁵, prospective studies³⁶, and artificial intelligence applications³⁷, and was used to establish external quality management between ED through monthly benchmarking reports³⁸. Further, a daily syndromic surveillance report has been introduced by the Robert Koch Institute, the German federal agency responsible for disease control and prevention³⁹. The German Federal Ministry of Health utilizes data for weekly surveillance of ED capacities.

In terms of our second objective, our study shows that federated data access authorization can efficiently manage and handle data requests in research networks on a local level. While there is a high variability in the time until queries are addressed, most nodes answer queries relatively reliably within two weeks. We consider this response time within acceptable parameters, as each query requires an individual decision by the responsible stakeholders at each node. This process cannot be completely automated, as it requires explicit expert knowledge and a careful balancing of interests, which carries associated legal and ethical responsibilities.

Failed queries highlight persistent challenges in sharing healthcare data from EDs. These queries can primarily be attributed to syntax errors within the queries themselves or firewall issues. When data storage is federated, access to data is limited and based on assumptions. These may be invalid. The low rates of failed or retracted queries still indicate high system reliability, the appropriateness of the authorization process, and the clarity of the data request interface. Because anonymous data from system logs could only be used for evaluation, it was not possible to conduct a detailed analysis of query content, reasons for rejection, and usability of user interfaces. Further work is necessary to address the robustness of the technical process at the local and central nodes. A new data request management system is currently being developed⁴⁰. The communication of HL7 FHIR resources will be supported in the future. However, CDA interfaces will be maintained to mitigate implementation costs for existing nodes.

Another limitation of our process is that it does not automatically ensure that the data content distributed to hospitals is secure, requiring manual checks. This dependence places significant trust in the integrity of data handlers, operating under the assumption that no malicious queries will be sent. Additionally, no standardized procedure for assessing and approving IT security measures exists. The IT security approvals in participating clinics are heterogeneous, leading to potential vulnerabilities where data handling protocols differ between nodes. Data breaches may also occur during the manual review of data queries when CSV files are generated, which can easily be shared or the system is incorrectly used. These shortcomings could be addressed on a technical level through privacy-preserving data processing, independent code reviews, or introducing a four-eyes principle.

Scaling data access in nationwide or international research networks requires transparent operational frameworks. Our approach shows that individuals and institutions gain more control over how their data is used by sharing data and joining federated systems. In this way, voluntary participation not only preserves autonomy but also expands the nodes' capacity to shape outcomes. This aligns with the notion that freedom is not the absence of structure, but rather the ability to navigate and affect systems from within.

Our federated data access authorization framework is suitable for data sharing across different jurisdictions, potentially in other research networks worldwide. It enables secure, safe, and fast access to healthcare data from a wide range of healthcare contexts. While the sample of healthcare providers connected to the AKTIN infrastructure may not fully represent EDs in Germany, few systems in use offer continuous, universal, and nationwide access to EHRs. The system's robustness, efficiency, and scalability make it a blueprint for future data-sharing initiatives in healthcare research. Integrating with initiatives like existing medical research networks is possible in principle but may require adaptation.

The system has particular practical relevance in the near future. Initiatives like the European Health Data Space aim to facilitate centralized access to health data across European countries. However, the question remains whether a learning healthcare system truly requires unrestricted

data access, or if we should instead prioritize approaches like ours that emphasize fair data access by allowing data holders to maintain control over their data.

Methods

For the first objective, we designed and implemented a technical system for federated data access authorization based on requirements gathered in 2016 in focus workshops with the initial 16 AKTIN project hospitals and a blueprint summary. For the second objective, we evaluated the efficiency of the system in a retrospective cohort study using KPIs obtained from log data during operation⁴¹.

Blueprint summary

To achieve the first objective, we developed a service-oriented architecture, where centralized services offer specific functionalities (Supplementary Fig. 1). We implemented the architecture based on a broker design pattern and the Five Safes framework, which establishes five key components as a requirement for data access authorization—safe data, safe people, safe projects, safe settings, and safe outputs^{42,43}.

A formal workflow description was developed and implemented within the technical components of the AKTIN infrastructure. We integrated the data access authorization workflow into the graphical user interface of the AKTIN DWH, the AKTIN DWH Manager. The AKTIN DWH backend is built as a Java EE web application, operating on WildFly with an embedded i2b2 instance. On the frontend side, the DWH can be administered through a web application—the DWH Manager—developed in AngularJS. All source code can be accessed on GitHub and is open source (<https://www.github.com/aktin>).

System evaluation

Using KPIs, we retrospectively evaluated the efficiency and reliability of the data access authorization processes⁴¹—objective two. Data for KPIs stemmed from anonymous user interaction data captured by the central AKTIN Broker as proprietary log files during live operation⁴⁴. We extracted log files from the Broker and excluded $n = 19$ inactive or non-productive nodes (in total $n = 77$ nodes) from further analysis. Data included detailed timestamps for each state change of the data authorization workflow communicated with the AKTIN Broker between November 11, 2017, and October 21, 2024. Queries were typically communicated to a subset of relevant nodes; for example, pediatric emergency departments did not receive queries requesting data on adult patients.

To evaluate the systems in use, we differentiated between individual queries and repeated periodic queries (i.e., for daily syndromic surveillance of acute respiratory illness^{39,45} or monthly benchmarking reports³⁸) with automatic rules for authorization. Queries contained technical (i.e., targeted source data validation⁴⁶) and scientific requests (i.e.,⁴⁷ or³⁵). For the KPIs, we monitored the successful and failed queries as a general indicator of efficiency and reliability. Furthermore, we tracked the terminal state of queries, which includes the number of retractions or rejections, as well as withdrawn and unanswered queries, to provide a comprehensive view of the system's usage. To address general efficiency, we evaluated the request volume per year and the time until the completion of queries.

We evaluated hospitals' and data owners' adoption and acceptance of the system on the basis of the number of systems in use and the number of EHRs integrated within the AKTIN DWHs—information we obtained from a voluntary survey for quality assurance practices and which 56 nodes participated.

The ethical committees of all participating institutions approved the operation of the infrastructure in accordance with the WMA Declaration of Helsinki (including the amendments made in Fortaleza and Taipei). The leading vote came from the Ethics Committee of Otto von Guericke University in Magdeburg with 160/15. No ethical review was required for the evaluation of KPIs, as neither personal data was processed nor any intervention was conducted.

Data availability

Data used for the system evaluation are publicly available (<https://doi.org/10.5281/zenodo.14509530>). The AKTIN DUAC terms of operation, the data protection concept, and a list of current research requests are available from www.aktin.org. The standardized emergency department medical record¹⁷ of the German Interdisciplinary Association for Intensive Care and Emergency Medicine is available from <https://aktin.art-decor.pub/>. The Robert Koch Institute, the German federal agency responsible for disease control and prevention publishes a daily syndromic surveillance report available from <https://public.data.rki.de/t/public/views/Notaufnahmesurveillance/DashboardSyndrome>⁴⁸ and the German Federal Ministry of Health publishes Data for weekly surveillance of ED capacities available from <https://infektionsradar.gesund.bund.de/de/gesamt/notaufnahmen>.

Code availability

All source code of the AKTIN infrastructure can be accessed on GitHub and is open source (<https://www.github.com/aktin>). Source code for the system evaluation and exemplary SQL requests are publicly available from GitHub (https://github.com/aktin/publications/tree/main/jbienzeisler/federated_authorization). Analyses were performed using R version 4.3.1.

Received: 30 October 2024; Accepted: 27 January 2025;

Published online: 11 February 2025

References

- Bentzen, H. B. et al. Remove obstacles to sharing health data with researchers outside of the European Union. *Nat. Med.* **27**, 1329–1333 (2021).
- Friedman, C. P., Wong, A. K. & Blumenthal, D. Achieving a nationwide learning health system. *Sci. Transl. Med.* **2**, 57cm29 (2010).
- Wilkinson, M. D. et al. The FAIR guiding principles for scientific data management and stewardship. *Sci. Data* **3**, 160018 (2016).
- Raab, R. et al. Federated electronic health records for the European Health Data Space. *Lancet Digit. Health* **5**, e840–e847 (2023).
- Katsoulakis, E. et al. Digital twins for health: a scoping review. *NPJ Digit. Med.* **7**, 77 (2024).
- Cascini, F. et al. Health data sharing attitudes towards primary and secondary use of data: a systematic review. *EClinicalMedicine* **71**, 102551 (2024).
- Youssef, A. et al. Organizational factors in clinical data sharing for artificial intelligence in health care. *JAMA Network Open* **6**, e2348422 (2023).
- Jefferson, E. et al. The challenges and lessons learned building a new UK infrastructure for finding and accessing population-wide COVID-19 data for research and public health analysis: the CO-CONNECT project. *J. Med. Internet Res.* **26**, e50235 (2024).
- Hulsen, T. ShaRING IS CARING-DATA SHARING INITIATIVES IN HEALTHCare. *Int. J. Environ. Res. Public Health* **17**, 3046 (2020).
- Dron, L. et al. Data capture and sharing in the COVID-19 pandemic: a cause for concern. *Lancet Digit. Health* **4**, e748–e756 (2022).
- Hallock, H. et al. Federated networks for distributed analysis of health data. *Front. Public Health* **9**, 712569 (2021).
- World Health Organization. *Classification of Digital Interventions, Services and Applications in Health: A Shared Language to Describe the Uses of Digital Technology for Health* 2nd edn, (WHO 2023).
- Perrin Franck, C. et al. iCHECK-DH: guidelines and checklist for the reporting on digital health implementations. *J. Med. Internet Res.* **25**, e46694 (2023).
- Brammen, D. et al. AKTIN - The German Emergency Department Data Registry - real-time data from emergency medicine : Implementation and first results from 15 emergency departments with focus on Federal Joint Committee's guidelines on acuity assessment. *Med. Klin. Intensivmed Notfmed* **117**, 24–33 (2022).
- Murphy, S. N. et al. Serving the enterprise and beyond with informatics for integrating biology and the bedside (i2b2). *J. Am. Med. Inform. Assoc.* **17**, 124–130 (2010).
- Dolin, R. H. et al. The HL7 clinical document architecture. *J. Am. Med. Inform. Assoc.* **8**, 552–569 (2001).
- Kulla, M. et al. Nationaler datensatz “Notaufnahme”: entwicklung, struktur und konsentierung durch die deutsche interdisziplinäre vereinigung für intensivmedizin und notfallmedizin. *Anaesthesist* **63**, 243–252 (2014).
- Ahlbrandt, J. et al. Balancing the need for big data and patient data privacy-an IT infrastructure for a decentralized emergency care research database. *Stud. Health Technol. Inform.* **205**, 750–754 (2014).
- Rosenau, L., Behrend, P., Wiedekopf, J., Gruendner, J. & Ingenefer, J. Uncovering harmonization potential in health care data through iterative refinement of fast healthcare interoperability resources profiles based on retrospective discrepancy analysis: case study. *JMIR Med. Inform.* **12**, e57005 (2024).
- Torabi, F. et al. A common framework for health data governance standards. *Nat. Med.* **30**, 26–29 (2024).
- Leeming, G. & Thew, S. DataWell: public involvement in the development of a federated platform for shared patient records in Greater Manchester, U.K. *Stud. Health Technol. Inform.* **244**, 48–52 (2017).
- Mukamel, D. B., Zwanziger, J. & Bamezai, A. Hospital competition, resource allocation and quality of care. *BMC Health Serv. Res.* **2**, 10 (2002).
- Grossman, J. M., Bodenheimer, T. S. & McKenzie, K. Hospital-physician portals: the role of competition in driving clinical data exchange. *Health Aff.* **25**, 1629–1636 (2006).
- Corley, D. A., Feigelson, H. S., Lieu, T. A. & McGlynn, E. A. Building Data Infrastructure to evaluate and improve quality: PCORnet. *J. Oncol. Pract.* **11**, 204–206 (2015).
- Semler, S. C., Wissing, F. & Heyder, R. German medical informatics initiative. *Methods Inf. Med.* **57**, e50–e56 (2018).
- Gruendner, J., Prokosch, H.-U., Schindler, S., Lenz, S. & Binder, H. A Queue-poll extension and DataSHIELD: standardised, monitored, indirect and secure access to sensitive data. *Stud. Health Technol. Inform.* **258**, 115–119 (2019).
- Gaye, A. et al. DataSHIELD: taking the analysis to the data, not the data to the analysis. *Int. J. Epidemiol.* **43**, 1929–1944 (2014).
- Raisaro, J. L. et al. MedCo: enabling secure and privacy-preserving exploration of distributed clinical and genomic data. *IEEE/ACM Trans. Comput. Biol. Bioinforma.* **16**, 1328–1341 (2019).
- Weber, G. M. et al. The shared health research information network (SHRINE): a prototype federated query tool for clinical data repositories. *J. Am. Med. Inform. Assoc.* **16**, 624–630 (2009).
- Kristoffersen, E. S. et al. The Norwegian PraksisNett: a nationwide practice-based research network with a novel IT infrastructure. *Scand. J. Prim. Health Care* **40**, 217–226 (2022).
- Davies, M. et al. Software-Enabled Distributed Network Governance: The PopMedNet Experience. *EGEMS (Wash DC)* **4**, 1213 (2016).
- Schranz, M. et al. Changes in emergency department utilisation in Germany before and during different phases of the COVID-19 pandemic, using data from a national surveillance system up to June 2021. *BMC Public Health* **23**, 799 (2023).
- 9,8 Millionen Behandlungen in Notfallambulanzen im Jahr 2021. Zahl der Woche* (Wiesbaden, 2022).
- Bogaert, P., Verschuuren, M., van Oyen, H. & van Oers, H. Identifying common enablers and barriers in European health information systems. *Health Policy* **125**, 1517–1526 (2021).
- Otto, R. et al. Length of stay as quality indicator in emergency departments: analysis of determinants in the German Emergency

- Department Data Registry (AKTIN registry). *Intern. Emerg. Med.* **17**, 1199–1209 (2022).
36. Drynda, S. et al. Evaluation of outcome relevance of quality indicators in the emergency department (ENQUIRE): study protocol for a prospective multicentre cohort study. *BMJ Open* **10**, e038776 (2020).
 37. Ritter, Z. et al. Using explainable artificial intelligence models (ML) to predict suspected diagnoses as clinical decision support. *Stud. Health Technol. Inform.* **294**, 573–574 (2022).
 38. Otto, R. et al. Implementation of emergency department performance benchmarking using R and LaTeX. *Stud. Health Technol. Inform.* **267**, 238–246 (2019).
 39. Boender, T. S. et al. Using routine emergency department data for syndromic surveillance of acute respiratory illness, Germany, week 10 2017 until week 10 2021. *Euro Surveill* **27**, 2100865 (2022).
 40. Kombeiz, A., Bienzeisler, J., Majeed, R. W., Röhrig, R. & Aktin, R. G. Designing a user-friendly data request management system for a growing health data network—a case study in the AKTIN registry. *Stud. Health Technol. Inform.* **321**, 69–73 (2024).
 41. Munoz-Gama, J. et al. Process mining for healthcare: Characteristics and challenges. *J Biomed Inform.* **127**, 103994 (2022).
 42. Stal, M. The Broker Architectural Framework. In *Workshop on Concurrent, Parallel and Distributed Patterns of Objects Oriented Programming* **95**, 1–19 (1995).
 43. Felix Ritchie. Five Safes: designing data access for research, 2016.
 44. Bienzeisler, J. Anonymized query log dataset for the AKTIN infrastructure. Zenodo <https://doi.org/10.5281/zenodo.14509530> (2024).
 45. Grabenhenrich Mph, L. et al. Gewinnung von echtzeitdaten aus der medizinischen versorgung zur handlungssteuerung in public health. *Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz* **64**, 412–417 (2021).
 46. Triefenbach, L. et al. Establishing a data quality baseline in the AKTIN emergency department data registry—a secondary use perspective. *Stud. Health Technol. Inform.* **294**, 209–213 (2022).
 47. Slagman, A. et al. Medical emergencies during the COVID-19 pandemic. *Dtsch. Arztebl. Int.* **117**, 545–552 (2020).
 48. Robert Koch-Institut & AKTIN-Notaufnahmeregister. Daten der notaufnahmesurveillance. Zenodo <https://doi.org/10.5281/zenodo.14584734> (2025).

Acknowledgements

This manuscript is submitted on behalf of the AKTIN Research Group, whose essential contributions have been invaluable to this research. The authors also wish to thank Catherine Maxwell for her professional assistance in editing, which greatly enhanced the manuscript's clarity.

Author contributions

Conceptualization: J.B., R.R., and R.W.M. Methodology: J.B., R.W.M., and D.B. Software: J.B., A.K., and R.W.M. Validation: R.W.M., B.P., and D.B. Formal analysis: J.B., R.O., B.P., M.P., and D.B. Investigation: J.B., R.R., W.S., and R.W.M. Resources: R.R. Data curation: J.B., A.K., and R.W.M. Writing—original draft preparation: J.B. Writing—review and editing: J.B., A.K., S.E., R.O., B.P., M.P., D.B., W.S. R.R., and R.W.M. Visualization: J.B., A.K., and R.W.M. Supervision: B.P., D.B., R.R., and R.W.M. Project administration: J.B., S.E., W.S., D.B., and R.W.M. Funding acquisition: J.B., R.W.M., W.S., D.B., and R.R. All authors have read and agreed to the published version of the manuscript.

Funding

Open Access funding enabled and organized by Projekt DEAL.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s41746-025-01481-w>.

Correspondence and requests for materials should be addressed to Jonas Bienzeisler.

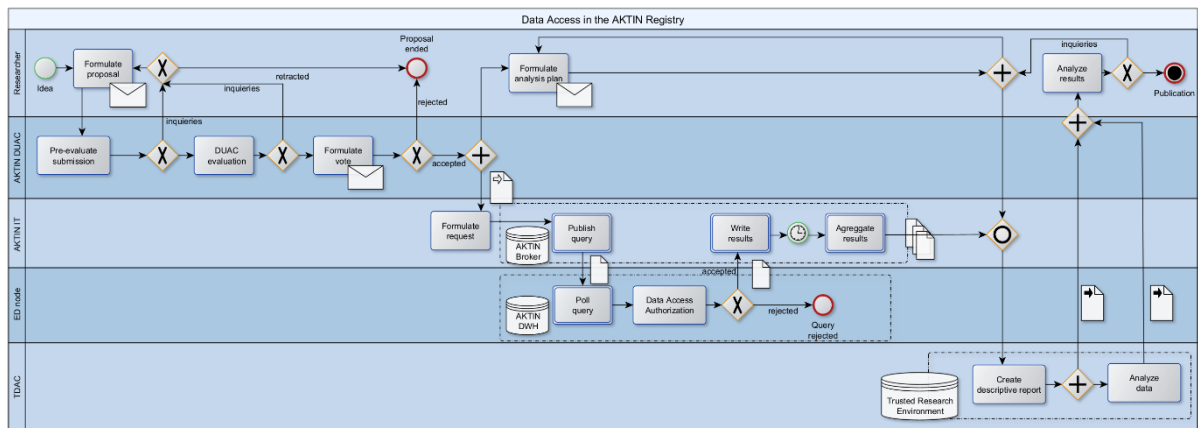
Reprints and permissions information is available at <http://www.nature.com/reprints>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

© The Author(s) 2025

1 Supplementary Information



2

3 *Supplementary Figure 1: Data Access in the AKTIN Emergency Department Data Registry: Data can be requested according*
 4 *to an established data access protocol upon approval from the AKTIN Data Use and Access Committee (DUAC). Using the*
 5 *AKTIN Broker, datasets are queried from local nodes—the AKTIN Data Warehouse—where each query must be individually*
 6 *reviewed. Data can be analyzed in the trusted research environment maintained by the AKTIN Trusted Data Analysis Center.*
 7 *Note: This diagram employs a modified version of BPMN, adapted to clarify specific workflow elements unique to the AKTIN*
 8 *infrastructure. This adaptation may not strictly adhere to formal BPMN guidelines.*

9

10 *Supplementary Table 1: System Requirements*

ID	Requirement Description	User Story	Stakeholder	Notes
1	Data sovereignty and local control	As a data owner, I want to maintain control over data access to ensure compliance with local regulations and individual decision-making processes.	Hospital	Reduces the risk of strategic vulnerability to competitors and data breaches for hospitals.
2	Federated data access authorization	As a data owner, I want a qualified authorization and evaluation of each data access request.	Hospital	Balances risks (data breaches) with benefits (improved data governance, transparency, research).
3	Varying stakeholder roles in data access	As a process owner, I want to have a transparent overview of who authorized data requests to ensure accountability.	Process Owner	Supports streamlined data governance and transparency, addressing liability concerns.
4	Secure and transparent operational framework	As a process owner, I need a secure system that ensures data integrity, data provenance, and procedural visibility to comply with regulations.	Process Owner	Essential for data integrity, reducing privacy breaches and misuse of data.
5	Qualified review of local data and queries	As a process owner, I want to be able to review and validate data queries to ensure they align with local standards before sharing results.	Process Owner	Reduces potential liability for data breaches.
6	Simplified authorization process for end-users	As a user, I want a straightforward interface to authorize data access requests quickly to manage my workload effectively.	User	Mitigates increased workload for users.
7	Optional automatic rules for recurring authorizations	As a user, I want to set up rules to automate repetitive data access authorizations to reduce manual effort.	User	Mitigates increased workload for users.
8	Email notifications for authorization events	As a user, I want to receive notifications when data access requests require my action to stay informed without constantly checking the system.	User	Ensures that users can focus on critical tasks, reducing administrative burden.
9	Data export in accessible formats	As a user, I need the ability to export query results in formats like CSV for further analysis and reporting.	User	Allow users to evaluate data queries
10	Workflow state transitions for data requests	As a user, I want to see the state of data requests at each step to monitor progress and address any issues that arise.	User	Improves accountability for process owners and mitigates the risk of data mismanagement.

11	Error handling in data authorization	As a user, I want clear feedback in case of errors during the data authorization process to quickly identify and resolve issues.	User	Reduces errors in data handling, ensuring a more reliable process for all stakeholders.
12	Continuous access to data stored in AKTIN DWHs for predefined purposes	To operate the AKTIN infrastructure, we need continuous access to data stored in AKTIN DWHs	AKTIN Infrastructure	Essential for maintaining the functionality and objectives of the AKTIN infrastructure.
13	Five Safes	To operate the AKTIN infrastructure, we need to provide the participating nodes with the necessary information to authorize data access	AKTIN Infrastructure	Provide information according to the five safes framework
14	Asynchronous data transmission across nodes	To operate the AKTIN infrastructure, we need the system to support asynchronous data transmission to handle data integration from multiple sources seamlessly.	AKTIN Infrastructure	Enables access to continuous data from different hospitals.
15	Support for multiple data formats	To operate the AKTIN infrastructure, we need the system to accommodate various data formats to ensure compatibility with the locally used and i2b2-based AKTIN DWH.	AKTIN Infrastructure	Enhances the adaptability of data integration across nodes.
16	Long-term data usability with open-source solutions	To operate the AKTIN infrastructure, we need to use open-source solutions to ensure the sustainability and longevity of the data management system.	AKTIN Infrastructure	Allows for sustainable operation and long-term data usability

11

12

13
1415 *Supplementary Table 2: Query Volume per Year and number of ED cases integrated within the AKTIN infrastructure.*

Year	N ED Nodes	N Total ED Cases	N Requests	N Queries	N Individual Queries	N Periodic Queries
2017*	12	425,229	2	15	15	0
2018	16	593,097	25	225	209	16
2019	17	825,815	60	529	111	418
2020	21	754,537	424	5,719	217	5,502
2021	46	1,018,809	668	10,827	463	10,364
2022	50	1,523,266	586	14,630	862	13,768
2023	54	1,570,503	629	20,982	1,045	19,937
2024*	58	1,271,382	566	23,340	1,131	22,209
Total	58	7,982,638	2,960	76,267	4,054	72,214

16 **Data captured for 2017 and 2024 did not cover the entire year.*

17

18

19 *Supplementary Table 3: Analysis of Key Performance Indicators derived from log files of the AKTIN Broker. Individual queries*
 20 *and periodically repeated queries are differentiated. For individual queries, data access has to be authorized individually. For*
 21 *periodic queries, emergency departments may omit future authorization and grant automatic data access authorization for*
 22 *future and past queries.*

	Individual Query (N=4,053)	Periodic Query (N=72,214)	Total (N=76,267)
Last communicated status
completed	3,234 (79.8%)	62,888 (87.1%)	66,122 (86.7%)
failed	114 (2.8%)	722 (1.0%)	836 (1.1%)
interaction	3 (0.1%)	16 (0.0%)	19 (0.0%)
processing	2 (0.0%)	97 (0.1%)	99 (0.1%)
queued	5 (0.1%)	102 (0.1%)	107 (0.1%)
rejected	121 (3.0%)	732 (1.0%)	853 (1.1%)
retrieved	574 (14.2%)	7,657 (10.6%)	8,231 (10.8%)
Days until completed
Mean (SD)	16.5 (38.2)	8.6 (23.5)	9.0 (24.5)
Median (Range)	3.8 (0.0, 510.2)	3.6 (0.0, 481.0)	3.6 (0.0, 510.2)
Q1, Q3	0.3, 15.4	0.7, 6.6	0.7, 7.3
IQR	15.1	5.9	6.6
Days until rejected
Mean (SD)	74.1 (88.7)	21.4 (53.2)	23.6 (56.1)
Median (Range)	38.1 (0.0, 367.8)	-0.0 (-0.0, 584.7)	-0.0 (-0.0, 584.7)
Q1, Q3	12.2, 105.0	-0.0, 0.1	-0.0, 12.0
IQR	92.8	0.1	12.0

23

24

25

26 *Supplementary Table 4: Checklist of iCHECK-DH guidelines*

Item	Section	Description	Line in Manuscript
1	TITLE	Identification as an implementation report, and description of the implementation in the title and/or keywords	Title
2	ABSTRACT	Provide a summary of key elements, including implementation strategy, intervention, and KPIs/Outputs	29-38
3	INTRODUCTION	Context: Describe geographical areas, organizations, target populations, and implementation context	61-67
4		Problem statement: Description of the healthcare or public health problem addressed by the implementation	107-119
5		Similar Interventions: Mention inspiration and added value compared to other implementations	120-130
6	METHODS	Aims and Objectives: Describe main objectives, outcomes, and KPIs	336-339
7		Blueprint summary: Design, key features of the intervention, and implementation strategy	341-347
8		Technical Design: Reasons for tool development, description of functionality, technology type, and integration	345-350
9		Target: Characteristics of the targeted group, site, or system	352-355
10		Data: Data governance, data protection measures, patient consent, and data hosting	353-358
11		Interoperability: Interfaces, standards used, and rationale for choice	353-356
12		Participating entities: Description of organizations, partners, funders, and ownership	336-339

13		Budget Planning: Planned budget, costs, funding, and budget duration	236-238
14		Sustainability: Business model, sustainability model, and exit strategies	236-247
15	RESULTS	Coverage: Implementation coverage (international, national, regional) and relative importance	231-235
16		Outcomes: Primary and other outcome(s) of the implementation	193-226
17		Lessons learned: Success factors, challenges, budget adherence, and recommendations	249-276
18		Unintended consequences: Description of any unintended consequences, harms, or negative side-effects	227-230
19	DISCUSSION	Conclusion: Summary of the conclusions and future implications	277-232
20	GENERAL	General: Statement(s) on regulatory approvals, ethical considerations, and conflicts of interest	372-404

27

28

Original Paper

The Effects of Displaying the Time Targets of the Manchester Triage System to Emergency Department Personnel: Prospective Crossover Study

Jonas Bienzeisler¹, MSc; Guido Becker², MSc; Bernadett Erdmann³, Dr med; Alexander Kombeiz¹, MSc; Raphael W Majeed^{1,4}, MSc, Dr biol hom; Rainer Röhrig¹, Dr med; Felix Greiner^{5,6}, MSc; Ronny Otto⁶, BSc; Fabian Otto-Sobotka⁷, Dipl Math, Dr rer nat; AKTIN Research Group⁸

¹Institute of Medical Informatics, Medical Faculty, RWTH Aachen University, Aachen, Germany

²Dedalus HealthCare, Bonn, Germany

³Klinikum Wolfsburg, Wolfsburg, Germany

⁴Department of Internal Medicine, Universities of Giessen and Marburg Lung Center (UGMLC), German Center for Lung Research (DZL), Giessen, Germany

⁵Institute for Occupational and Maritime Medicine (ZfAM), University Medical Center Hamburg-Eppendorf (UKE), Hamburg, Germany

⁶Department of Trauma Surgery, Otto von Guericke University, Magdeburg, Germany

⁷Division of Epidemiology and Biometry, Faculty of Medicine and Health Sciences, Carl von Ossietzky University Oldenburg, Oldenburg, Germany

⁸see Acknowledgements

Corresponding Author:

Jonas Bienzeisler, MSc

Institute of Medical Informatics

Medical Faculty

RWTH Aachen University

Pauwelsstraße 30

Aachen, 52074

Germany

Phone: 49 24180 ext 88870

Email: jbienzeisler@ukaachen.de

Abstract

Background: The use of triage systems such as the Manchester Triage System (MTS) is a standard procedure to determine the sequence of treatment in emergency departments (EDs). When using the MTS, time targets for treatment are determined. These are commonly displayed in the ED information system (EDIS) to ED staff. Using measurements as targets has been associated with a decline in meeting those targets.

Objective: This study investigated the impact of displaying time targets for treatment to physicians on processing times in the ED.

Methods: We analyzed the effects of displaying time targets to ED staff on waiting times in a prospective crossover study, during the introduction of a new EDIS in a large regional hospital in Germany. The old information system version used a module that showed the time target determined by the MTS, while the new system version used a priority list instead. Evaluation was based on 35,167 routinely collected electronic health records from the preintervention period and 10,655 records from the postintervention period. Electronic health records were extracted from the EDIS, and data were analyzed using descriptive statistics and generalized additive models. We evaluated the effects of the intervention on waiting times and the odds of achieving timely treatment according to the time targets set by the MTS.

Results: The average ED length of stay and waiting times increased when the EDIS that did not display time targets was used (average time from admission to treatment: preintervention phase=median 15, IQR 6-39 min; postintervention phase=median 11, IQR 5-23 min). However, severe cases with high acuity (as indicated by the triage score) benefited from lower waiting times (0.15 times as high as in the preintervention period for MTS1, only 0.49 as high for MTS2). Furthermore, these patients were less likely to receive delayed treatment, and we observed reduced odds of late treatment when crowding occurred.

Conclusions: Our results suggest that it is beneficial to use a priority list instead of displaying time targets to ED personnel. These time targets may lead to false incentives. Our work highlights that working better is not the same as working faster.

(*J Med Internet Res* 2024;26:e45593) doi: [10.2196/45593](https://doi.org/10.2196/45593)

KEYWORDS

EHR; emergency medicine; AKTIN, process management; crowding; triage system; electronic health record; health care; treatment; emergency department

Introduction

The use of triage systems, such as the Manchester Triage System (MTS) and the Emergency Severity Index (ESI), is a standard procedure to determine the sequence of treatment in emergency departments (EDs) [1-4]. The MTS and ESI are used for determining time targets for physician contact. These time targets are usually displayed to ED staff by the ED information system (EDIS). However, it is not known how this affects ED processing times. This study investigates the impact of displaying these time targets for treatment to physicians within the ED on processing times.

Such sociotechnical systems directly impact health care delivery. The data they produce can be used to improve efficiency and effectiveness in a learning health care system [5]. Efficient treatment is necessary because EDs around the world are experiencing an increase in the number of patients they have to treat. Therefore, EDs must determine who to treat to avoid negative outcomes due to inadequate inpatient capacity.

Crowding is an everyday challenge for EDs that is commonly quantified by extreme patient occupancy (patients present in the ED), extended length of stay (LOS) in the ED, and waiting time between triage and treatment [6,7]. Crowding occurs if the demand for emergency care surpasses the available resources within the ED [7,8]. Triage systems are thus necessary to manage the treatment sequence and optimize patient flow [1-4].

These systems are used to quickly assign a triage score to patients arriving at the ED, which defines the priority of treatment. The scores are mostly based on the acuity of the patient's illness and aim at identifying the risk of negative patient outcomes and ensuring timely and adequate treatment [3]. It is mandatory for German EDs to put patients through a triage process or treat them directly. The majority of EDs in Germany use 5-tier triage systems, the most commonly used being the MTS and the ESI [1]. Using these, the acuity of all patients is categorized through a 5-tiered scale, resulting in 5 levels of urgency typically known to personnel by the associated color (Table 1).

Table 1. Definition of the German version of the Manchester Triage System (MTS)

Level	Triage score	Color	Acuity	Time target (minutes)
1	MTS1	Red	Immediate	0
2	MTS2	Orange	Very urgent	10
3	MTS3	Yellow	Urgent	30
4	MTS4	Green	Standard	90
5	MTS5	Blue	Nonurgent	120

With the MTS, a time target is determined by a certified nurse with flowchart diagrams. This target is the latest time that is acceptable until a physician consults the patient. In Germany, these times are between 0 (Level 1, MTS1) and 120 minutes (Level 5, MTS5), contrary to the international version, which sets a limit of 240 minutes (Level 5, MTS5) [1,9]. For example, a patient with an MTS score of MTS2 should be attended by a physician within 10 minutes in Germany. A retriage is possible at any time; however, it becomes mandatory if the proposed time target is not reached.

The triage process and subsequent treatment are usually implemented within the EDIS, supporting clinical documentation, patient tracking, and order management. The triage system and the implementation of the triage system in the EDIS thus represent potential target areas for reducing waiting times, improving patient flow, and, as a result, ED efficiency [10,11].

The triage system and its implementation in the EDIS directly impact the provision of care, waiting times, LOS, and overall patient flow (Figure 1) [1,9-12]. Formally structured and established triage systems have higher validity than informally structured systems, but overall performance varies considerably [13,14]. Using a Dutch version of the MTS in a before-and-after study, Storm-Versloot et al [15] could not see any effects of triaging patients on waiting times but in fact observed increased average waiting times (average time from admission to treatment=15 min) and increased average treatment times (average time from admission to treatment=14 min). However, urgent cases (Level 2) received treatment faster on average (average time from admission to treatment=4 min), and patient satisfaction with respect to waiting times was higher, especially among low-urgency patients who typically crowd the ED. Using computational experiments, van Bockstal and Maenhout [16] similarly associated triage with increased waiting times for patients with less severe injuries and decreased waiting times for acute patients. They also found that there was a beneficial

effect on triage system resource consumption. Vegting et al [17], on the other hand, reported a general increase in the LOS of noncritically ill patients due to triage, attributing it to the fragmentation of the provision of care. However, triage and waiting times are not only important quality management factors but also significantly impact patient satisfaction. Multiple studies suggest that patients care a lot about the time they spend in the ED and receiving information on the length of their projected waiting time, which demonstrates that patient satisfaction correlates strongly with waiting time [18,19]. Aside from these observational studies, ED routine records have been used to predict waiting times using, for example, machine learning [20] and statistical approaches [21,22].

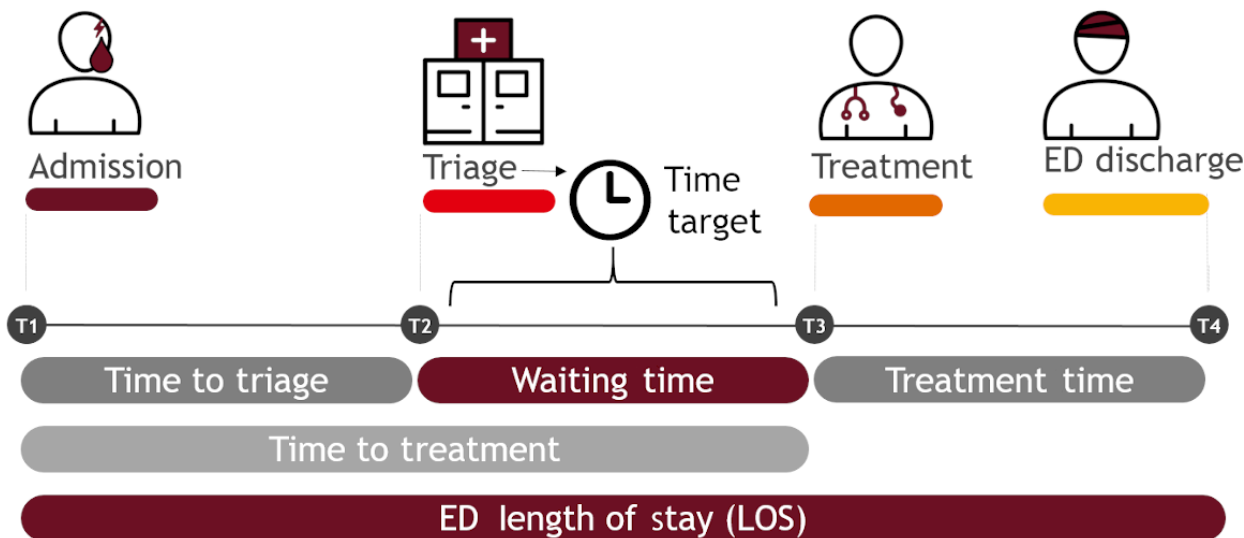
The time it takes to receive treatment is thus understood to be a crucial metric for assessing quality within the ED. Policy makers have also recognized the importance of ED waiting times, but some of the approaches taken to improve them are controversial. In the United Kingdom, for example, the waiting time target that has been set for EDs is 4 hours [23]. It is well known that using measurements as targets is associated with a decline in meeting those targets [24]. This association, known as Goodhart’s law [25] and originating from economics, has often been discussed in the context of health care systems, with some experts believing that setting time targets leads to false incentives within the health care system [20,24,26].

Aside from such legislative requirements, time targets have clinical relevance in managing incoming patient flow within the ED. To track waiting patients, EDISs that implement the MTS usually display the time target determined by the triage score. Such sensory cues add to the cognitive load of attending personnel [27,28]. Further, time pressure may have negative effects on physicians’ performance [29,30].

Therefore, the objective of this study was to analyze the effect on waiting times of displaying treatment time targets provided by the MTS score in the EDIS.

We hypothesized that displaying these targets could alter treatment and waiting times, thus influencing patient flow and crowding. We expected, in accordance with Goodhart’s law, that the practice of displaying time targets for patient treatment, inadvertently contributes to inefficient patient management within EDs. We proposed that the display of these time targets creates a false incentive structure for ED physician personnel. It could potentially lead them to prioritize meeting these targets over other critical aspects of patient care. This focus on time targets might result in suboptimal treatment decisions, potentially exacerbating patient wait times and lowering throughput, contrary to the intended purpose of these targets.

Figure 1. Data collection and variable definition. The evaluation of the intervention was based on routine documentation stemming from an emergency department (ED) information system. Timestamps describing internal patient flow were derived from routine medical records. The main target parameters were time to triage (first contact with a triaging nurse), waiting time from triage until treatment by the physician (first contact with the attending physician), and ED length of stay.



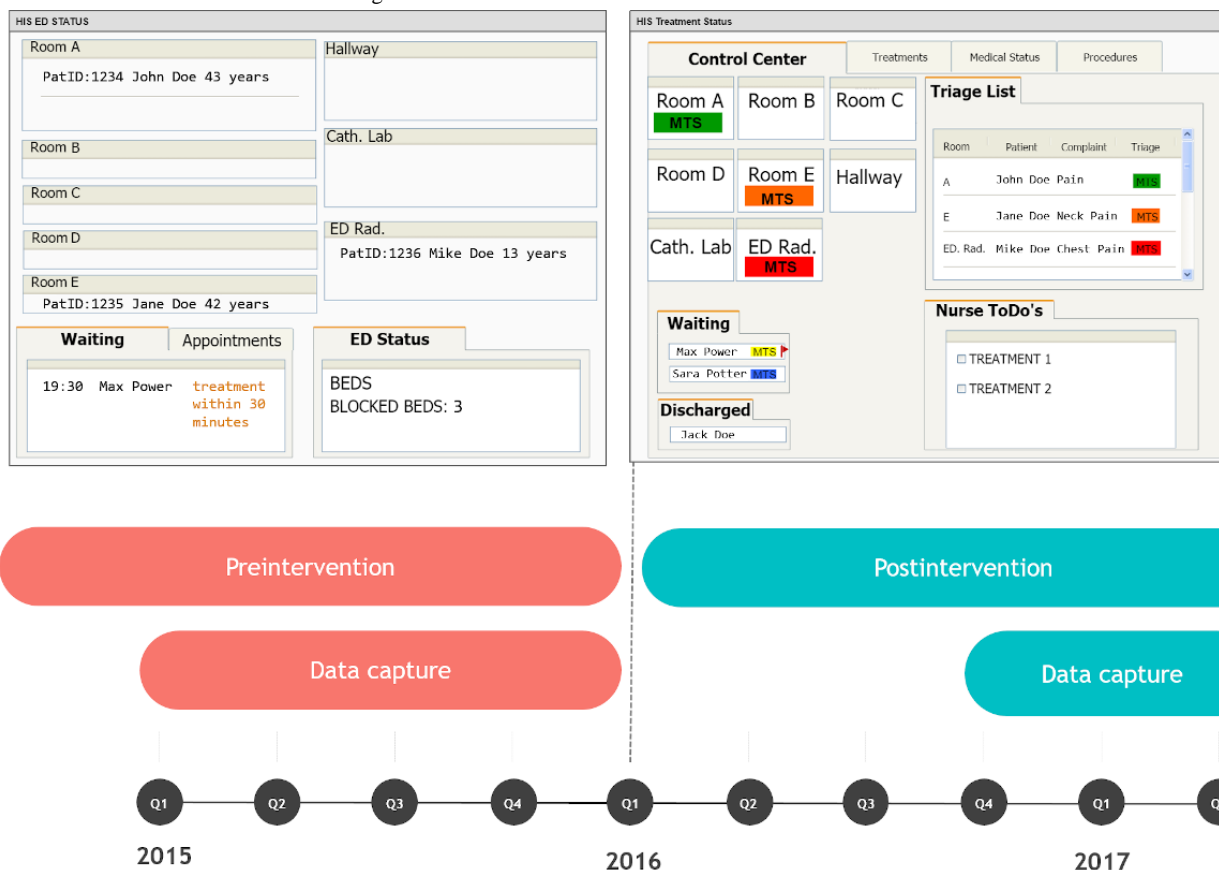
Methods

Overview

Based on routine documentation, we conducted a prospective crossover study of all adult patients treated before

(preintervention) and after (postintervention) an update of the EDIS module used in the ED. The new version no longer displayed MTS time targets but a priority list (Figure 2). Patients thus received treatment with and without displaying the treatment time targets provided by the MTS score.

Figure 2. Study design and mock-ups of the emergency department information system (EDIS). In a prospective cross-over study, we evaluated the effect of displaying treatment time targets provided by the Manchester Triage System (MTS) score to emergency department personnel. Preintervention and postintervention took place before and after the update of an EDIS. The EDIS showed the time target determined by the MTS preintervention (triage time in the mock-up). Postintervention, a priority list (triage list in mock-up) was displayed instead of a time target. A red flag was displayed next to the color-coded MTS score when the time target was reached.



Study Context

We conducted the study within the ED of the Klinikum Wolfsburg in Germany, a central public hospital with around 70,000 patients per year. It is the only hospital to have an ED within a 17-km radius. It has a certified trauma center and processes 35,000 patients in the ED every year.

The standard procedure for patients arriving at the ED (in both phases) involved administrative registration, followed by a triage conducted by a nurse, retriage if necessary, treatment by a physician following a certain waiting time, and finally discharge. In urgent cases (eg, admission by ambulance), triage is bypassed if there are sufficient resources.

No training on triage practices was conducted during the study period. Staff did receive technical training from the software vendor before the implementation of the new module. The staffing levels, both for nursing and medical personnel, remained unchanged throughout the study. The medical staffing in the ED was fixed to a schedule. Following a fixed plan for day and night shifts, a team of 13.7 full-time equivalent positions for physicians directly associated with the ED and 29.2 full-time equivalent positions for nursing staff were maintained. The staffing model was applied on all weekdays, weekends, and public holidays. There were no notable changes in equipment during the study.

The EDIS used in the ED is a module of the monolithic hospital information system ORBIS (Dedalus Healthcare). The EDIS documentation method adhered to the ED medical record of the German Interdisciplinary Association for Intensive Care and Emergency Medicine. The captured routine documentation data are accessible through the alliance for information and communication technology in intensive care and emergency medicine (abbreviated in German as AKTIN) Emergency Department Data Registry operated by AKTIN in Germany [31,32].

Study Design

During the preintervention phase (January 1, 2014, to December 31, 2014), nurses carried out triage and documentation anonymously using paper-based MTS presentation flowcharts and documented data in a view only accessible to the nurses. Nursing care was documented externally. Time points of patient contact and triage score were displayed to physicians and nurses in a user interface (UI) developed in house. The UI used consisted of a list-based view of rooms and patients. Triage and time targets were visible to all personnel in a room overview. Patients were selected for treatment according to the displayed list. Physicians could open an ED medical record by clicking on triaged patients.

In the postintervention phase (October 13, 2015, to January 31, 2016), the Cockpit Notaufnahme EDIS module provided by

Dedalus Healthcare was used, which no longer displayed the MTS time target.

In the postintervention phase, data were collected after a transition period between the intervention phases to mitigate potential biases (Figure 2). During this interval, the adaptations to the new intervention were allowed to stabilize. Apart from using electronic rather than paper flowcharts for determining the MTS, the changes were purely cosmetic. Standard procedures for incoming patients remained the same. The new UI displayed patients, nurses, and physicians in a list according to the urgency of treatment without time targets. A room-based overview of patients was included in the new UI, which served as an overview for all personnel. Patients could be selected and assigned to rooms through drag and drop. A signal was displayed when time targets were exceeded.

Data Acquisition

Overview

We extracted process times at the end of the postintervention phase. Data were collected routinely by the EDIS, anonymized within the clinic, and provided through the infrastructure of the AKTIN Emergency Department Data Registry [31,32].

The main target parameters were the time until triage, waiting time from triage until treatment by the physician, and ED LOS (Figure 1). As a secondary outcome, we calculated a binary classification of late treatment as defined by the assigned triage score, which we interpreted as a proxy for ED efficiency (eg, “1” if waiting time was longer than 10 minutes for patients assigned the triage score MTS2).

Data Exclusion

Documentation errors may lead to implausible or missing timestamps. We considered a physician contact before the initial assessment nonevaluable and excluded nonpositive processing times as well as data with missing admission or triage timestamps. We classified LOS and waiting time that lie above 3 SDs ($>3\sigma$) from the mean (μ) of patients with the lowest acuity (MTS5), rounded to the next complete hour, as outliers. Any processing time between admission, triage, and treatment above 300 minutes or a LOS higher than 600 minutes resulted in exclusion. Further, we omitted data from the transition period.

Data Analysis

Overview

Timestamps were generated automatically by the EDIS when a nurse registered a patient, when a nurse opened the triage view and documented the triage score, when the physician opened the ED record, and when the patient was marked as discharged by the physician (Figure 1). We deduced direct physician contact from the occurrence of missing triage timestamps in combination with physician contact timestamps. In addition, we included data on the count of patients present at the time of physician contact (T3; Figure 1) using a counter that we set to “1” for the first patient in the data set. From the admission timestamp, we extracted the annual season, hour of the day, and whether the admission occurred on a working day (as opposed to a

nonworking day). We corrected erroneous data with the clinic’s help and excluded implausible timestamps from further analysis (ie, timestamp treatment before timestamp administration). We performed all calculations using the statistical software R (version 3.6.1; R Core Team).

Primary Analysis

We extracted the entries from the EDIS into a standardized data entry form. The descriptive main analysis included the median and IQR for metric variables and the computation of absolute and relative frequencies for categorical variables. At the end of the intervention phase, we sought evaluative feedback regarding the intervention’s impact and effectiveness from the head of the ED and ED personnel.

Secondary Analysis

The secondary analysis consisted of generalized additive regression models. Response variables were waiting time until treatment in minutes and the binary occurrence of delayed treatment. The preselected set of covariates were the number of patients present within the ED at the time of physician contact, MTS score, study phase, working day, annual season, and hour of day. We assumed a gamma distribution with a log-link for positive waiting times (model 1) and used logistic regression for delayed treatment (model 2). The covariate hour of the day was included on a cyclic P-spline basis. The number of patients within the ED was modeled with a regular P-spline basis and 2-way interactions of MTS score and study phase, as well as patients present and study phase. The effects on waiting time are reported as multiplicative effects $\exp(\beta)$ with 95% CIs. The logistic regression results are reported as odds ratios (ORs), with 95% CIs. The nonlinear effects estimated by splines are reported graphically.

Ethical Considerations

The study was approved by an ethics committee before the update of the EDIS module (Medical Ethical Committee Uni Oldenburg, Vote-No: 2016-05, Chair F Griesinger). Results are reported according to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines [33].

Results

Overview

In total, we extracted 48,822 data sets from the EDIS: 35,167 in the preintervention phase and 10,655 in the postintervention phase. Excluding 636 data sets with implausible timestamps from further analysis, we analyzed 45,186 data sets (Figure S1 in Multimedia Appendix 1). In general, the distribution of assigned triage scores differed between the preintervention and postintervention phases (Table 2). We noticed an upcoding postintervention an increase in the assignment of more urgent triage levels. However, most triaged patients were still assigned an MTS3 or MTS4 score in both phases. Very few patients in postintervention and none in preintervention were given the most urgent MTS score of MTS1. Thus, in the analyses, we focused on patients assigned a triage score of MTS 2-5.

Table 2. Comparative analysis of preintervention and postintervention study sample characteristics. Categorical variables are presented as frequencies (percentages) and were analyzed using chi-square tests. Continuous variables are presented as means with SDs and reported along with their medians and IQRs. We assumed the number of patients present per day and at physician contact to be normally distributed and compared them using independent sample 2-tailed *t* tests (two tailed). Nonnormally distributed waiting times were compared using Mann-Whitney *U* tests.

Characteristics	Preintervention phase (n=34,727)	Postintervention phase (n=10,459)	Total (N=45,186)	<i>P</i> value
Year, n (%)				<.001
2014	34,727 (100)	0 (0)	34,727 (76.9)	
2015	0 (0)	7556 (72.2)	7556 (16.7)	
2016	0 (0)	2903 (27.8)	2903 (6.4)	
Weekday, n (%)				.89
Working day	23,399 (67.4)	7040 (67.3)	30,439 (67.4)	
Nonworking day	11,328 (32.6)	3419 (32.7)	14,747 (32.6)	
Season of the year, n (%)				<.001
Fall	8698 (25)	4527 (43.3)	13,225 (29.3)	
Spring	8872 (25.5)	0 (0)	8872 (19.6)	
Summer	9003 (25.9)	0 (0)	9003 (19.9)	
Winter	8154 (23.5)	5932 (56.7)	14,086 (31.2)	
MTS^a score, n (%)				<.001
LWBS ^b	0 (0)	38 (0.4)	38 (0.1)	
MTS1	0 (0)	15 (0.1)	15 (0)	
MTS2	220 (0.6)	186 (1.8)	406 (0.9)	
MTS3	4369 (12.6)	2004 (19.2)	6373 (14.1)	
MTS4	10,828 (31.2)	5049 (48.3)	15,877 (35.1)	
MTS5	3059 (8.8)	589 (5.6)	3648 (8.1)	
Direct contact	16,251 (46.8)	2578 (24.6)	18,829 (41.7)	
Adherence to MTS time target, n (%)				<.001
On-time	13,381 (72.4)	5190 (68.6)	18,571 (71.3)	
Late	5094 (27.6)	2376 (31.4)	7470 (28.7)	
Patients per day				.16
Missing data, n	0	0	0	
Mean (SD)	95.142 (10.618)	93.384 (13.732)	94.730 (11.435)	
Median (range)	95.000 (64.000-127.000)	93.000 (1.000-117.000)	95.000 (1.000-127.000)	
IQR	88.000-102.000	86.000-102.000	88.000-102.000	
Patients present at physician contact				<.001
Missing data, n	0	0	0	
Mean (SD)	12.479 (5.908)	15.108 (6.938)	13.073 (6.253)	
Median (range)	12.000 (0.000-33.000)	15.000 (1.000-41.000)	13.000 (0.000-41.000)	
IQR	8.000-16.000	10.000-20.000	8.000-17.000	
Waiting time in minutes				<.001
Missing data, n	16,252	2893	19,145	
Mean (SD)	55.831 (52.088)	58.898 (54.944)	56.722 (52.951)	
Median (range)	39.000 (0.000-294.000)	41.000 (0.000-291.000)	39.000 (0.000-294.000)	
IQR	17.000-80.000	17.000-85.000	17.000-81.000	

^aMTS: Manchester Triage System.

^bLWBS: left without being seen.

Primary Analysis

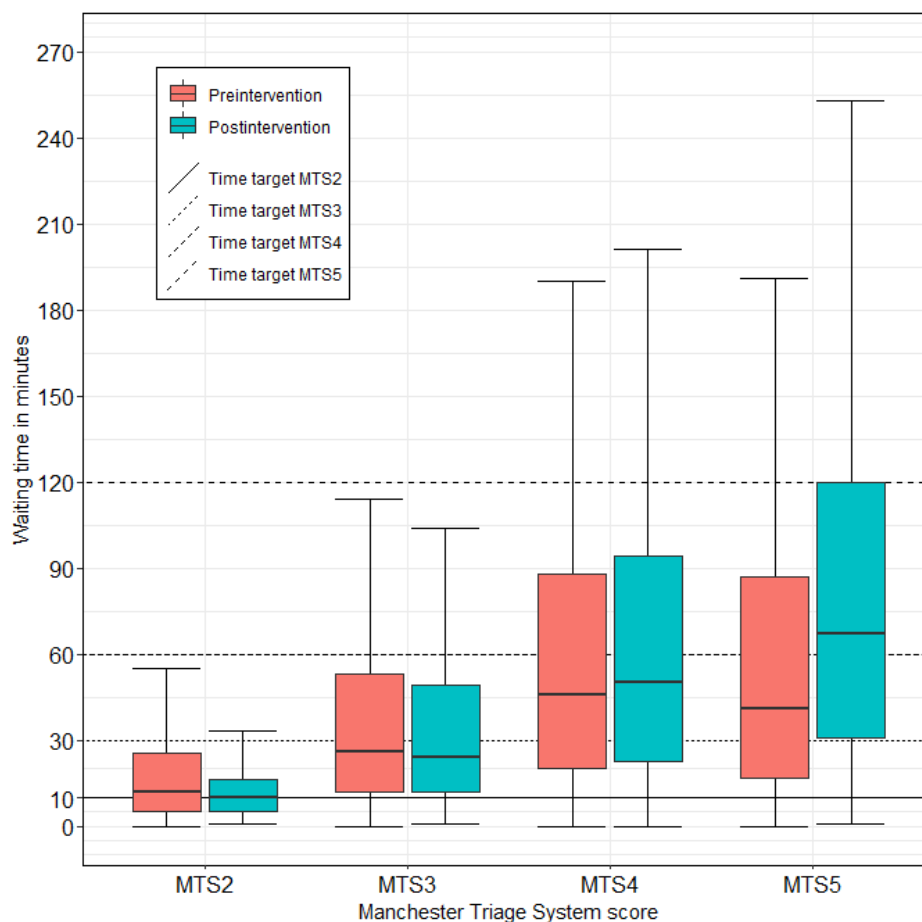
Depending on the severity of the injury, it took different times until a nurse assigned a patient a triage score. The less serious the complaint, the greater the MTS score, and the longer it took until the triage score was assessed. In the postintervention phase, patients with an MTS3 and MTS4 were triaged slightly faster than in the preintervention phase; those with an MTS5 were triaged slower (Tables S1-S5 in [Multimedia Appendix 1](#)).

The percentage of patients who received immediate treatment by a physician instead of first being triaged was higher in the preintervention phase (16,251/34,727, 46.8%) than in the postintervention phase (2578/10,459, 24.6%). Incoming patients that a physician attended to immediately received treatment faster in the postintervention phase (time from admission to

treatment: preintervention phase=median 15, IQR 6-39 min; postintervention phase=median 11, IQR 5-23 min). In postintervention phase only, a small group of patients (n=38) left the ED after triage but before seeing a physician. Generally, we found that the time from patient registration until triage was slightly reduced postintervention, although still somewhat comparable.

The presence of patients had a greater impact, leading to increased waiting times at the triage stage, especially for low-urgency patients ([Figure 3](#)). In the preintervention phase, there was a rise in the time needed until triage, when more than 30 patients were present within the ED. However, we saw no such effect the postintervention phase. Daily patient numbers were comparable in the pre- and postintervention phases.

Figure 3. Waiting times from triage to treatment by assigned triage score and study phase. The old emergency department information system (EDIS) version (preintervention, green) displayed the time target determined by the Manchester Triage System (MTS), while the new EDIS version (postintervention, red) did not. The average waiting times from triage until physician contact varied for MTS5 (pre: 41 min, IQR 17-87; post: 67 min, IQR 31-121 min), MTS4 (pre: 46 min, IQR 20-88; post: 50 min, IQR: 23-95 min), MTS3 (pre: 26 min, IQR 12-53; post: 24 min, IQR 11-49 min), MTS2 (pre: 12 min, IQR 5-26 min; post: 10 min, IQR 5-16 min), and MTS1 (post: 4 min, IQR 2-14 min).



Crowding, as measured in patients present on average per visit, was higher in the postintervention phase (median 12, IQR 8-16) than in the preintervention phase (median 15, IQR 10-20). Accordingly, we observed an increased LOS in the postintervention phase. On average, patients stayed 29 minutes longer in the ED (preintervention phase=median 119, IQR

66-189 min; postintervention phase=median 148, IQR 88-226 min). Less severe cases with MTS4 and MTS5—the majority of cases—waited longer (Tables S1-S5 in [Multimedia Appendix 1](#)).

The waiting time from triage until physician contact increased on average as well (preintervention phase=median 39, IQR

17-80 min; postintervention phase=median 41, IQR 17-85 min), and the time target provided by the MTS was missed in a greater percentage of triaged cases postintervention ($\Delta n = 3,8\%$). The rate of timely treatment changed in the same fashion. Delayed treatment and retriage were more common in the postintervention phase than in the preintervention phase. This effect was mainly due to patients with triage scores of MTS4 and MTS5. For severely injured patients with MTS2 and MTS3, we observed a lower number of treatment instances occurring outside of the target scope. However, although these process times and statistics suggest impeded throughput, practicing physicians reported improved patient flow. Furthermore, the head of the ED reported perceiving an improvement in patient flow and treatment quality.

Secondary Analysis

In the secondary analysis of positive waiting times (model 1, Table S6 in [Multimedia Appendix 1](#)), we found that waiting times increased on average by a factor of 1.27 (CI) in the postintervention phase. ED crowding amplified this effect. However, the estimated interaction effects showed that waiting times postintervention were only 0.15 times as high as in the preintervention phase for MTS1, only 0.49 as high for MTS2, and only 0.68 as high for MTS3. These results can be multiplied by the main effects: that waiting times for MTS1 were, on average, only a third of the waiting times for MTS5, and waiting times for MTS2 were 0.68 of MTS5 waiting times. The effects of weekends and annual seasons in the model were negligible. On an average day, waiting times increased at around 6 AM and from 6 PM to midnight.

We observed some similarities when modeling delayed treatment (model 2; Table S7 in [Multimedia Appendix 1](#)). The odds of late treatment increased by 2.32 (CI) in the postintervention phase but were reduced by a factor of 0.32 for MTS2, by 0.44 for MTS3, and by 0.6 for MTS4. These results stand in positive contrast to the overall odds of delayed treatment of 8.79 for MTS2 compared to MTS5, 4.93 for MTS3, and 1.86 for MTS4. The effects of seasons and weekends are negligible. Similar to positive waiting times, certain hours of the day led to increased odds of delayed treatment—at around 6 AM and from 6 PM to 11 PM.

Discussion

Overview

The introduction of the new software module that did not show the time target for treatment but instead used a priority list resulted in prolonged waiting times for patients with lower acuity (MTS4 and MTS5) but reduced the odds of late treatment for patients with higher acuity (MTS2 and MTS3). Similar to what Storm-Versloot et al [15] observed, patient flow was thus found to be optimized in the second phase of the trial. Critical patients with higher urgency levels received more timely treatment and waited less time, an effect commonly associated with triage systems. When considering all patients, the LOS and waiting times increased. A longer LOS for all patients eventually leads to crowding and can be used to quantify crowding along with ED occupancy [7]. Indeed, we observed a slightly higher number of patients within the ED at the

physician contact stage postintervention. Paradoxically, the head of the ED and the practicing physicians—professionals who are well aware of crowding and the daily implications of inadequate inpatient capacity—were delighted with the new software, refusing to change back to the old system for further investigation. While these remarks are anecdotal, multivariate regression models confirmed the perception that waiting times for critical patients had reduced. Furthermore, the probability of delayed treatment was also reduced.

The waiting time from triage to treatment was optimized, but the time until triage increased, while overcrowding did not affect the latter. The introduction of the new system led to a more sophisticated triage. Severe cases were treated more effectively, as perceived by the ED staff ([Figure 4](#)). Efficient treatment is also reflected in the number of patients sent straight to ED care instead of being triaged [34]; in the postintervention phase, more patients were triaged. We were able to quantify a positive effect of triage with regard to receiving timely treatment when the number of patients waiting increased ([Figure 5](#)). As one might expect, triage has little impact on patient processing when ED occupancy is low, and the ED is thus not crowded.

The findings support the idea that setting and displaying targets—in this case, displaying the time target for the respective MTS—may lead to false incentives. Time constraints may impact the thoroughness of care and the engagement in patient-centered decision-making [35]. We speculate that the knowledge of a time frame leads physicians to a less focused use of resources—particularly for medium urgent cases waiting. Previous work suggests that cues can inadvertently shape clinical priorities and decision-making [27,28]. This may lead to a phenomenon known as target behavior, where the focus of physicians shifts toward meeting set benchmarks rather than optimizing patient care based on clinical needs.

The removal of explicit time targets in this study likely altered the cognitive framework within which physicians operate, redirecting their focus from adhering to arbitrary time constraints to assessing and addressing patient needs more holistically, free from the distortions introduced by time pressures. We moved from strict time targets to a patient-centric model of postintervention.

Moreover, the change in the EDIS could have also disrupted habitual response patterns to visible time cues, necessitating a recalibration of treatment prioritization strategies that no longer relied on time targets as a primary directive [36]. This shift could have been further influenced by any briefings or guidance provided to physicians alongside the software change, which might have emphasized a more patient-centric approach to triage and treatment.

One could be tempted to generalize and conclude that waiting limits introduced by policymakers might lead to similar false incentives in much the same way. ED LOS may thus be insufficient as a quality indicator for ED care on its own and instead must be understood as a process metric, especially concerning ED crowding. These conclusions are speculative but similar to what we have previously observed in a larger sample [37].

Figure 4. Odds of late treatment by triage score and study phase for a fixed time (winter at 6 AM on a weekday) and patients present (n=13) with a standard normal deviation ($\alpha=5\%$). The time target for timely treatment is determined by the Manchester Triage System (MTS) score and was displayed to physicians at all times only in the old emergency department information system (EDIS) version (preintervention). Odds were calculated using a generalized additive regression model, assuming a logistic regression for delayed treatment. The odds of late treatment increased by 2.32 (CI) when using the new EDIS version (postintervention), which did not show the time target to physicians. However, the odds of late treatment were reduced by a factor of 0.32 for MTS2, 0.44 for MTS3, and 0.6 for MTS4.

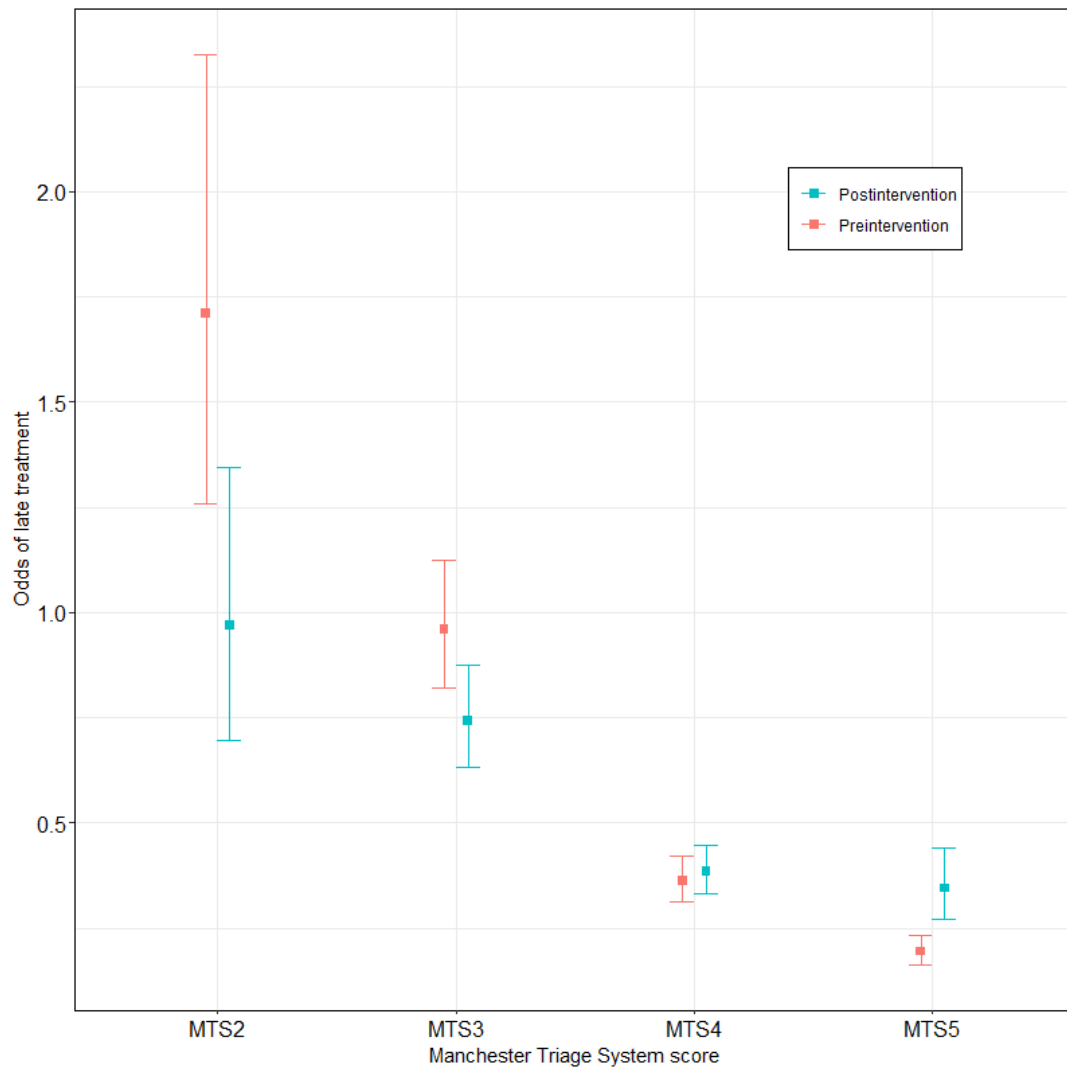
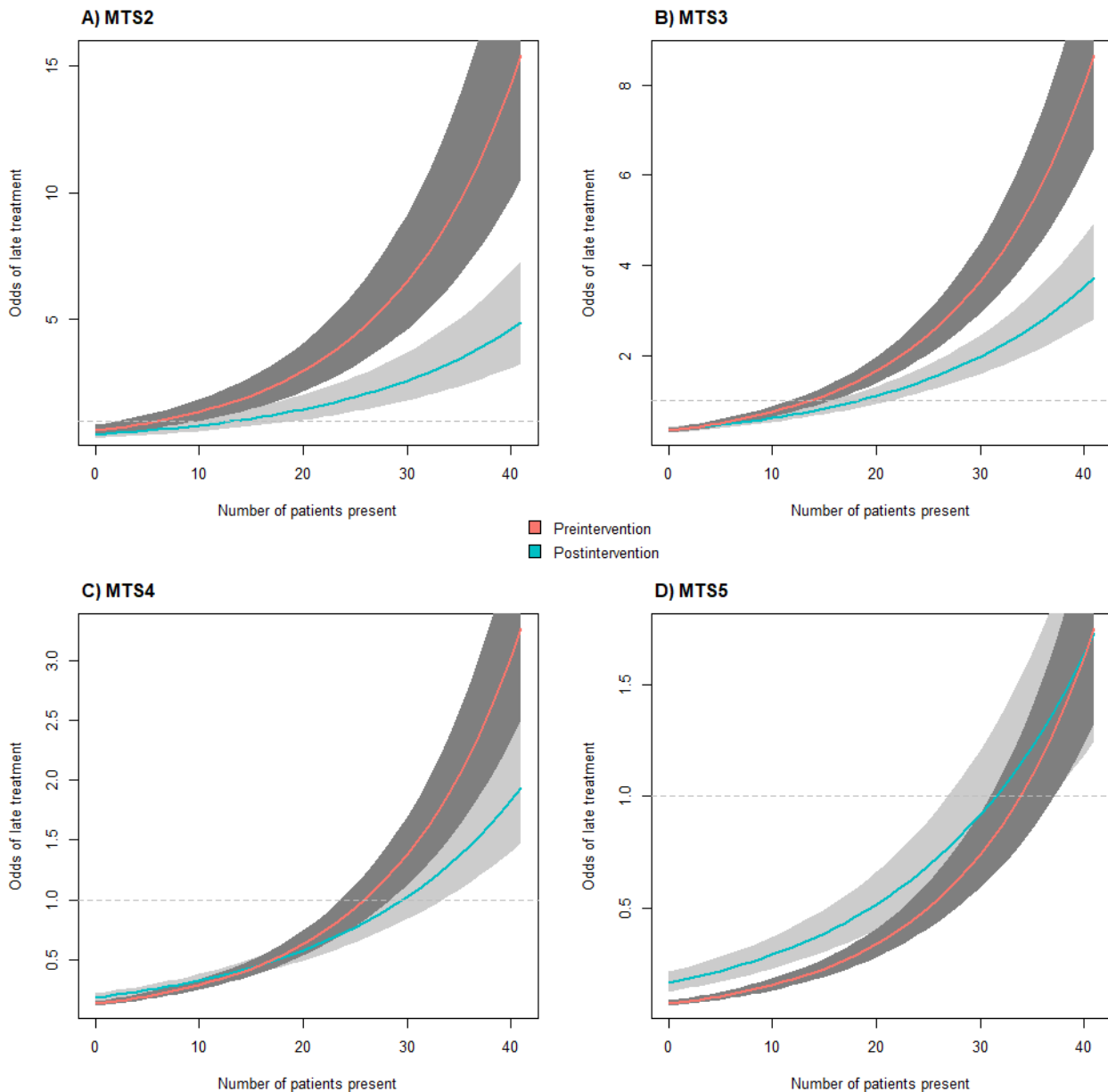


Figure 5. Odds of late treatment by the number of patients present within the emergency department (ED) and study phase for different triage scores A) MTS2, B) MTS3, C) MTS4, D) MTS5 at a fixed time (winter at 6 AM on a weekday) with a standard normal deviation ($\alpha=5\%$). The Manchester Triage System (MTS) score determines the time target for timely treatment. Preintervention, the time target was displayed to physicians at all times in the ED information system (EDIS), while it was not postintervention. The odds were calculated using a generalized additive regression model, assuming a logistic regression for delayed treatment. While the odds for late treatment in general increased by 2.32 (CI) when using the new EDIS version (postintervention) that did not show the time target to physicians, late treatment was considerably less likely when crowding (as indicated by the number of patients waiting) occurred. Severe cases (MTS2, MTS3, and MTS4) were less likely to receive late treatment postintervention. Patients with MTS5 were less likely to be treated on time postintervention.



Limitations

This study had several limitations, making further research necessary. In the postintervention phase, data were collected over a shorter time period. However, the number of patients per hour of the day and the total number of patients were comparable. The selection bias should be low; outcomes were measured over time across the whole population of ED attendees. Further, our intervention targeted the delivery and organization of services within the ED and was hence on the service level [38]. A controlled evaluation was not possible. A previously proposed prospective study with an on-off study design [39] was not feasible. Because of this, we cannot assess

the effects of minor changes accompanying the introduction of the new EDIS module. However, we assume that these can be neglected, as the changes were either cosmetic or impacted the triage process itself, which does not influence the process times after triage. The latter was the case with the changed triage process in the postintervention phase—the only significant noncosmetic change in this study. The workflow and the processing of patients did not change.

There is evidence that more formally structured triage leads to overtriage, especially when using the MTS [13,40-42]. The use of electronic presentation diagrams could thus explain the upcoding in treatment priority that we observed. This fails to

explain, especially for nonurgent cases, the fact that the time target for timely treatment was missed in greater numbers, yet patient flow improved. We were unable to assess the influence of raised awareness among ED personnel in general, given the setting of the study. Further work is necessary to systematically address the effects on ED personnel and the quality of treatment from a provider perspective. Further, future work will have to address patient satisfaction, as the majority of patients had a prolonged ED LOS. We intend to base further work on data from multiple hospitals, which is possible using the infrastructure of the AKTIN Emergency Department Data Registry [31].

Conclusions

The results suggest that it is beneficial not to display time targets when using triage systems, thus confirming the validity of

Goodhart's law. Similar to what others have reported [15,17,19], we also showed that the update to the triage system had an unforeseen impact on ED waiting times. Rather than improving the quality of treatment through accelerating processes within the ED, we saw an improvement in patient flow for patients with more severe injuries. Although it was only anecdotal evidence, the improvement was much appreciated by the attending physicians and the head of the ED. Our work highlights that working better is not the same as working faster; working more quickly does not automatically imply better care or results. It is essential to discuss how time is spent instead of focusing on how to save it. Furthermore, our results suggest that using the number of patients present in the ED as an isolated metric for crowding can be misleading.

Acknowledgments

The authors acknowledge the following members of the AKTIN-Research-Group: Susanne Drynda, Department of Trauma Surgery, Otto von Guericke University; Wiebke Schirrmeister, Department of Trauma Surgery, Otto von Guericke University; Saskia Ehrentreich, Department of Trauma Surgery, Otto von Guericke University; Volker Thiemann, Faculty of Medicine and Health Sciences, Carl von Ossietzky University Oldenburg; Felix Walcher, Department of Trauma Surgery, Otto von Guericke University; Lucas Triefenbach, Institute of Medical Informatics, Medical Faculty, RWTH Aachen University; Insa Seeger Research Network Emergency and Intensive Care Medicine Oldenburg, Faculty of Medicine and Health Sciences, Carl von Ossietzky University Oldenburg; Tolga Philipp Naziyok, Faculty of Medicine and Health Sciences, Carl von Ossietzky University Oldenburg; Marc Wilken, Faculty of Medicine and Health Sciences, Carl von Ossietzky University Oldenburg; Myriam Lipprandt, Institute of Medical Informatics, Medical Faculty, RWTH Aachen University.

This publication was funded by the German Federal Ministry of Education and Research and Network of University Medicine 2.0: "NUM 2.0" (01KX2121), Project "AKTIN@NUM" (01KX1319A), and Project "AKTIN."

Data Availability

The data sets analyzed in this study are not publicly accessible and cannot be transmitted to a third party, in compliance with data protection regulations and the AKTIN Emergency Department Data Registry's policies on data use and access. However, they can be made available by the corresponding author upon reasonable request.

Authors' Contributions

The original draft was written by JB and critically revised by GB, BE, AK, RO, FG, RR, and FOS for important intellectual content. JB contributed to conceptualization, data curation, methodology, formal analysis, validation, and visualization of results together. RR, GB, and BE provided access to data and expertise in clinical processes in emergency departments and data management within clinical information systems. They contributed to conceptualization, investigation, data curation, and formal analysis. RO, FG, RR, and FOS provided methodological expertise and contributed to methodology and formal analysis. AK and JB developed software components of the AKTIN Emergency Department Data Registry. RR and BE secured funding and provided supervision. FOS directed the methodological design, visualization of results, ensured research validation, and supervised the work.

Conflicts of Interest

Guido Becker is employed by Dedalus HealthCare GmbH, which manufactures a product related to the subject matter. All other authors declare no conflicts of interest.

Multimedia Appendix 1

Supplementary materials.

[\[DOCX File, 3981 KB-Multimedia Appendix 1\]](#)

References

1. Gräff I, Goldschmidt B, Glien P, Bogdanow M, Fimmers R, Hoeft A, et al. The German version of the Manchester Triage System and its quality criteria—first assessment of validity and reliability. *PLoS One*. 2014;9(2):e88995. [FREE Full text] [doi: [10.1371/journal.pone.0088995](https://doi.org/10.1371/journal.pone.0088995)] [Medline: [24586477](https://pubmed.ncbi.nlm.nih.gov/24586477/)]
2. Fernandes CMB, Tanabe P, Gilboy N, Johnson LA, McNair RS, Rosenau AM, et al. Five-level triage: a report from the ACEP/ENA Five-Level Triage Task Force. *J Emerg Nurs*. 2005;31(1):39-50; quiz 118. [doi: [10.1016/j.jen.2004.11.002](https://doi.org/10.1016/j.jen.2004.11.002)] [Medline: [15682128](https://pubmed.ncbi.nlm.nih.gov/15682128/)]
3. Iseron KV, Moskop JC. Triage in medicine, part I: concept, history, and types. *Ann Emerg Med*. 2007;49(3):275-281. [doi: [10.1016/j.annemergmed.2006.05.019](https://doi.org/10.1016/j.annemergmed.2006.05.019)] [Medline: [17141139](https://pubmed.ncbi.nlm.nih.gov/17141139/)]
4. Moskop JC, Iseron KV. Triage in medicine, part II: underlying values and principles. *Ann Emerg Med*. 2007;49(3):282-287. [doi: [10.1016/j.annemergmed.2006.07.012](https://doi.org/10.1016/j.annemergmed.2006.07.012)] [Medline: [17141137](https://pubmed.ncbi.nlm.nih.gov/17141137/)]
5. Friedman CP, Wong AK, Blumenthal D. Achieving a nationwide learning health system. *Sci Transl Med*. 2010;2(57):57cm29. [FREE Full text] [doi: [10.1126/scitranslmed.3001456](https://doi.org/10.1126/scitranslmed.3001456)] [Medline: [21068440](https://pubmed.ncbi.nlm.nih.gov/21068440/)]
6. Jones P, Wells S, Ameratunga S. Towards a best measure of emergency department crowding: lessons from current Australasian practice. *Emerg Med Australas*. 2018;30(2):214-221. [doi: [10.1111/1742-6723.12868](https://doi.org/10.1111/1742-6723.12868)] [Medline: [28941074](https://pubmed.ncbi.nlm.nih.gov/28941074/)]
7. Badr S, Nyce A, Awan T, Cortes D, Mowdawalla C, Rachoin JS. Measures of emergency department crowding, a systematic review. How to make sense of a long list. *Open Access Emerg Med*. 2022;14:5-14. [FREE Full text] [doi: [10.2147/OAEM.S338079](https://doi.org/10.2147/OAEM.S338079)] [Medline: [35018125](https://pubmed.ncbi.nlm.nih.gov/35018125/)]
8. FitzGerald G, Jelinek GA, Scott D, Gerdtz MF. Emergency department triage revisited. *Emerg Med J*. 2010;27(2):86-92. [FREE Full text] [doi: [10.1136/emj.2009.077081](https://doi.org/10.1136/emj.2009.077081)] [Medline: [20156855](https://pubmed.ncbi.nlm.nih.gov/20156855/)]
9. Slagman A, Greiner F, Searle J, Harriss L, Thompson F, Frick J, et al. Suitability of the German version of the Manchester Triage System to redirect emergency department patients to general practitioner care: a prospective cohort study. *BMJ Open*. 2019;9(5):e024896. [FREE Full text] [doi: [10.1136/bmjopen-2018-024896](https://doi.org/10.1136/bmjopen-2018-024896)] [Medline: [31064804](https://pubmed.ncbi.nlm.nih.gov/31064804/)]
10. Di Laura D, D'Angiolella L, Mantovani L, Squassabia G, Clemente F, Santalucia I, et al. Efficiency measures of emergency departments: an Italian systematic literature review. *BMJ Open Qual*. 2021;10(3):e001058. [FREE Full text] [doi: [10.1136/bmjopen-2020-001058](https://doi.org/10.1136/bmjopen-2020-001058)] [Medline: [34493488](https://pubmed.ncbi.nlm.nih.gov/34493488/)]
11. Baumlin KM, Shapiro JS, Weiner C, Gottlieb B, Chawla N, Richardson LD. Clinical information system and process redesign improves emergency department efficiency. *Jt Comm J Qual Patient Saf*. 2010;36(4):179-185. [doi: [10.1016/s1553-7250\(10\)36030-2](https://doi.org/10.1016/s1553-7250(10)36030-2)] [Medline: [20402375](https://pubmed.ncbi.nlm.nih.gov/20402375/)]
12. Mahmoodian F, Eqtesadi R, Ghareghani A. Waiting times in emergency department after using the emergency severity index triage tool. *Arch Trauma Res*. 2014;3(4):e19507. [FREE Full text] [doi: [10.5812/atr.19507](https://doi.org/10.5812/atr.19507)] [Medline: [25738132](https://pubmed.ncbi.nlm.nih.gov/25738132/)]
13. Storm-Versloot MN, Ubbink DT, Kappelhof J, Luitse JSK. Comparison of an informally structured triage system, the Emergency Severity Index, and the Manchester Triage System to distinguish patient priority in the emergency department. *Acad Emerg Med*. 2011;18(8):822-829. [FREE Full text] [doi: [10.1111/j.1553-2712.2011.01122.x](https://doi.org/10.1111/j.1553-2712.2011.01122.x)] [Medline: [21843217](https://pubmed.ncbi.nlm.nih.gov/21843217/)]
14. Zachariasse JM, van der Hagen V, Seiger N, Mackway-Jones K, van Veen M, Moll HA. Performance of triage systems in emergency care: a systematic review and meta-analysis. *BMJ Open*. 2019;9(5):e026471. [FREE Full text] [doi: [10.1136/bmjopen-2018-026471](https://doi.org/10.1136/bmjopen-2018-026471)] [Medline: [31142524](https://pubmed.ncbi.nlm.nih.gov/31142524/)]
15. Storm-Versloot MN, Vermeulen H, van Lammeren N, Luitse JS, Goslings JC. Influence of the Manchester Triage System on waiting time, treatment time, length of stay and patient satisfaction; a before and after study. *Emerg Med J*. 2014;31(1):13-18. [FREE Full text] [doi: [10.1136/emered-2012-201099](https://doi.org/10.1136/emered-2012-201099)] [Medline: [23302504](https://pubmed.ncbi.nlm.nih.gov/23302504/)]
16. van Bockstal E, Maenhout B. A study on the impact of prioritising emergency department arrivals on the patient waiting time. *Health Care Manag Sci*. 2019;22(4):589-614. [doi: [10.1007/s10729-018-9447-5](https://doi.org/10.1007/s10729-018-9447-5)] [Medline: [29725894](https://pubmed.ncbi.nlm.nih.gov/29725894/)]
17. Vegting IL, Alam N, Ghanes K, Jouini O, Mulder F, Vreeburg M, et al. What are we waiting for? factors influencing completion times in an academic and peripheral emergency department. *Neth J Med*. 2015;73(7):331-340. [FREE Full text] [Medline: [26314716](https://pubmed.ncbi.nlm.nih.gov/26314716/)]
18. Taylor C, Bengner JR. Patient satisfaction in emergency medicine. *Emerg Med J*. 2004;21(5):528-532. [FREE Full text] [doi: [10.1136/emj.2002.003723](https://doi.org/10.1136/emj.2002.003723)] [Medline: [15333521](https://pubmed.ncbi.nlm.nih.gov/15333521/)]
19. Marohl R, Medghaltschi H, Herchenbach C. Patientenzufriedenheit in der notfallambulanz—einfluss der triage auf die patientenzufriedenheit. In: Abstracts zu vorträgen und postern der 10. Jahrestagung der deutschen gesellschaft interdisziplinäre Notfall- und Akutmedizin. 2015.:15-16. [doi: [10.1007/s10049-015-0058-0](https://doi.org/10.1007/s10049-015-0058-0)]
20. Pak A, Gannon B, Staib A. Predicting waiting time to treatment for emergency department patients. *Int J Med Inform*. 2021;145:104303. [doi: [10.1016/j.ijmedinf.2020.104303](https://doi.org/10.1016/j.ijmedinf.2020.104303)] [Medline: [33126060](https://pubmed.ncbi.nlm.nih.gov/33126060/)]
21. Ataman MG, Saryyer G. Predicting waiting and treatment times in emergency departments using ordinal logistic regression models. *Am J Emerg Med*. 2021;46:45-50. [doi: [10.1016/j.ajem.2021.02.061](https://doi.org/10.1016/j.ajem.2021.02.061)] [Medline: [33721589](https://pubmed.ncbi.nlm.nih.gov/33721589/)]
22. Sun Y, Teow KL, Heng BH, Ooi CK, Tay SY. Real-time prediction of waiting time in the emergency department, using quantile regression. *Ann Emerg Med*. 2012;60(3):299-308. [doi: [10.1016/j.annemergmed.2012.03.011](https://doi.org/10.1016/j.annemergmed.2012.03.011)] [Medline: [22579492](https://pubmed.ncbi.nlm.nih.gov/22579492/)]
23. Trivedy M. If I were minister for health, I would ... review the four-hour waiting time in the emergency department. *J R Soc Med*. 2021;114(4):218-221. [FREE Full text] [doi: [10.1177/0141076820975363](https://doi.org/10.1177/0141076820975363)] [Medline: [33325759](https://pubmed.ncbi.nlm.nih.gov/33325759/)]
24. Crawford SM. Goodhart's law: when waiting times became a target, they stopped being a good measure. *BMJ*. 2017;359:j5425. [doi: [10.1136/bmj.j5425](https://doi.org/10.1136/bmj.j5425)] [Medline: [29180439](https://pubmed.ncbi.nlm.nih.gov/29180439/)]

25. Goodhart C, editor. *Monetary Theory and Practice*. London. Macmillan Education UK; 1984.
26. Campbell P, Boyle A, Higginson I. Should we scrap the target of a maximum four hour wait in emergency departments? *BMJ*. 2017;359:j4857. [doi: [10.1136/bmj.j4857](https://doi.org/10.1136/bmj.j4857)] [Medline: [29070598](https://pubmed.ncbi.nlm.nih.gov/29070598/)]
27. Wilken M, Hüske-Kraus D, Klausen A, Koch C, Schlauch W, Röhrig R. Alarm fatigue: causes and effects. *Stud Health Technol Inform*. 2017;243:107-111. [Medline: [28883181](https://pubmed.ncbi.nlm.nih.gov/28883181/)]
28. Heng KW. Teaching and evaluating multitasking ability in emergency medicine residents—what is the best practice? *Int J Emerg Med*. 2014;7:41. [FREE Full text] [doi: [10.1186/s12245-014-0041-4](https://doi.org/10.1186/s12245-014-0041-4)] [Medline: [25635201](https://pubmed.ncbi.nlm.nih.gov/25635201/)]
29. ALQahtani DA, Rotgans JI, Mamede S, ALAlwan I, Magzoub MEM, Altayeb FM, et al. Does time pressure have a negative effect on diagnostic accuracy? *Acad Med*. 2016;91(5):710-716. [FREE Full text] [doi: [10.1097/ACM.0000000000001098](https://doi.org/10.1097/ACM.0000000000001098)] [Medline: [26826069](https://pubmed.ncbi.nlm.nih.gov/26826069/)]
30. Norman GR, Monteiro SD, Sherbino J, Ilgen JS, Schmidt HG, Mamede S. The causes of errors in clinical reasoning: cognitive biases, knowledge deficits, and dual process thinking. *Acad Med*. 2017;92(1):23-30. [FREE Full text] [doi: [10.1097/ACM.0000000000001421](https://doi.org/10.1097/ACM.0000000000001421)] [Medline: [27782919](https://pubmed.ncbi.nlm.nih.gov/27782919/)]
31. Ahlbrandt J, Brammen D, Majeed RW, Lefering R, Semler SC, Thun S, et al. Balancing the need for big data and patient data privacy—an IT infrastructure for a decentralized emergency care research database. *Stud Health Technol Inform*. 2014;205:750-754. [Medline: [25160287](https://pubmed.ncbi.nlm.nih.gov/25160287/)]
32. Brammen D, Greiner F, Kulla M, Otto R, Schirrmeyer W, Thun S, et al. Das AKTIN-notaufnahmeregister—kontinuierlich aktuelle daten aus der akutmedizin: ergebnisse des registeraufbaus und erste datenauswertungen aus 15 notaufnahmen unter besonderer berücksichtigung der vorgaben des Gemeinsamen bundesausschusses zur ersteinschätzung [AKTIN—the German emergency department data registry—real-time data from emergency medicine : implementation and first results from 15 emergency departments with focus on federal joint committee's guidelines on acuity assessment]. *Med Klin Intensivmed Notfmed*. 2022;117(1):24-33. [FREE Full text] [doi: [10.1007/s00063-020-00764-2](https://doi.org/10.1007/s00063-020-00764-2)] [Medline: [33346852](https://pubmed.ncbi.nlm.nih.gov/33346852/)]
33. Cuschieri S. The STROBE guidelines. *Saudi J Anaesth*. 2019;13(Suppl 1):S31-S34. [FREE Full text] [doi: [10.4103/sja.SJA_543_18](https://doi.org/10.4103/sja.SJA_543_18)] [Medline: [30930717](https://pubmed.ncbi.nlm.nih.gov/30930717/)]
34. Cicolo EA, Nishi FA, Peres HHC, Monteiro da Cruz DDAL. Effectiveness of the Manchester triage system on time to treatment in the emergency department: a systematic review. *JBI Evid Synth*. 2020;18(1):56-73. [doi: [10.11124/JBISIRIR-2017-003825](https://doi.org/10.11124/JBISIRIR-2017-003825)] [Medline: [31453842](https://pubmed.ncbi.nlm.nih.gov/31453842/)]
35. Tai-Seale M, McGuire T. Time is up: increasing shadow price of time in primary-care office visits. *Health Econ*. 2012;21(4):457-476. [FREE Full text] [doi: [10.1002/hec.1726](https://doi.org/10.1002/hec.1726)] [Medline: [21442688](https://pubmed.ncbi.nlm.nih.gov/21442688/)]
36. Wood W, Tam L, Witt MG. Changing circumstances, disrupting habits. *J Pers Soc Psychol*. 2005;88(6):918-933. [doi: [10.1037/0022-3514.88.6.918](https://doi.org/10.1037/0022-3514.88.6.918)] [Medline: [15982113](https://pubmed.ncbi.nlm.nih.gov/15982113/)]
37. Otto R, Blaschke S, Schirrmeyer W, Drynda S, Walcher F, Greiner F. Length of stay as quality indicator in emergency departments: analysis of determinants in the German Emergency Department Data Registry (AKTIN registry). *Intern Emerg Med*. 2022;17(4):1199-1209. [FREE Full text] [doi: [10.1007/s11739-021-02919-1](https://doi.org/10.1007/s11739-021-02919-1)] [Medline: [34989969](https://pubmed.ncbi.nlm.nih.gov/34989969/)]
38. Goodacre S. Uncontrolled before-after studies: discouraged by cochrane and the EMJ. *Emerg Med J*. 2015;32(7):507-508. [FREE Full text] [doi: [10.1136/emered-2015-204761](https://doi.org/10.1136/emered-2015-204761)] [Medline: [25820301](https://pubmed.ncbi.nlm.nih.gov/25820301/)]
39. Mathe N, Johnson ST, Wozniak LA, Majumdar SR, Johnson JA. Alternation as a form of allocation for quality improvement studies in primary healthcare settings: the on-off study design. *Trials*. 2015;16:375. [FREE Full text] [doi: [10.1186/s13063-015-0904-x](https://doi.org/10.1186/s13063-015-0904-x)] [Medline: [26303892](https://pubmed.ncbi.nlm.nih.gov/26303892/)]
40. Hinson JS, Martinez DA, Cabral S, George K, Whalen M, Hansoti B, et al. Triage performance in emergency medicine: a systematic review. *Ann Emerg Med*. 2019;74(1):140-152. [doi: [10.1016/j.annemergmed.2018.09.022](https://doi.org/10.1016/j.annemergmed.2018.09.022)] [Medline: [30470513](https://pubmed.ncbi.nlm.nih.gov/30470513/)]
41. Zachariasse JM, Seiger N, Rood PPM, Alves CF, Freitas P, Smit FJ, et al. Validity of the Manchester Triage System in emergency care: a prospective observational study. *PLoS One*. 2017;12(2):e0170811. [FREE Full text] [doi: [10.1371/journal.pone.0170811](https://doi.org/10.1371/journal.pone.0170811)] [Medline: [28151987](https://pubmed.ncbi.nlm.nih.gov/28151987/)]
42. Parenti N, Reggiani MLB, Iannone P, Percudani D, Dowding D. A systematic review on the validity and reliability of an emergency department triage scale, the Manchester Triage System. *Int J Nurs Stud*. 2014;51(7):1062-1069. [doi: [10.1016/j.ijnurstu.2014.01.013](https://doi.org/10.1016/j.ijnurstu.2014.01.013)] [Medline: [24613653](https://pubmed.ncbi.nlm.nih.gov/24613653/)]

Abbreviations

- AKTIN:** alliance for information and communication technology in intensive care and emergency medicine (abbreviated in German as AKTIN)
- ED:** emergency department
- EDIS:** emergency department information system
- ESI:** Emergency Severity Index
- LOS:** length of stay
- MTS:** Manchester Triage System
- OR:** odds ratio
- STROBE:** Strengthening the Reporting of Observational Studies in Epidemiology

UI: user interface

Edited by T Leung; submitted 09.01.23; peer-reviewed by A Tomar, J Walsh, T Aslanidis, R Matin, A Venkataraman; comments to author 23.12.23; revised version received 02.02.24; accepted 31.03.24; published 14.05.24

Please cite as:

Bienzeisler J, Becker G, Erdmann B, Kombeiz A, Majeed RW, Röhrig R, Greiner F, Otto R, Otto-Sobotka F, AKTIN Research Group. The Effects of Displaying the Time Targets of the Manchester Triage System to Emergency Department Personnel: Prospective Crossover Study

J Med Internet Res 2024;26:e45593

URL: <https://www.jmir.org/2024/1/e45593>

doi: [10.2196/45593](https://doi.org/10.2196/45593)

PMID:

©Jonas Bienzeisler, Guido Becker, Bernadett Erdmann, Alexander Kombeiz, Raphael W Majeed, Rainer Röhrig, Felix Greiner, Ronny Otto, Fabian Otto-Sobotka, AKTIN Research Group. Originally published in the Journal of Medical Internet Research (<https://www.jmir.org>), 14.05.2024. This is an open-access article distributed under the terms of the Creative Commons Attribution License (<https://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work, first published in the Journal of Medical Internet Research, is properly cited. The complete bibliographic information, a link to the original publication on <https://www.jmir.org/>, as well as this copyright and license information must be included.

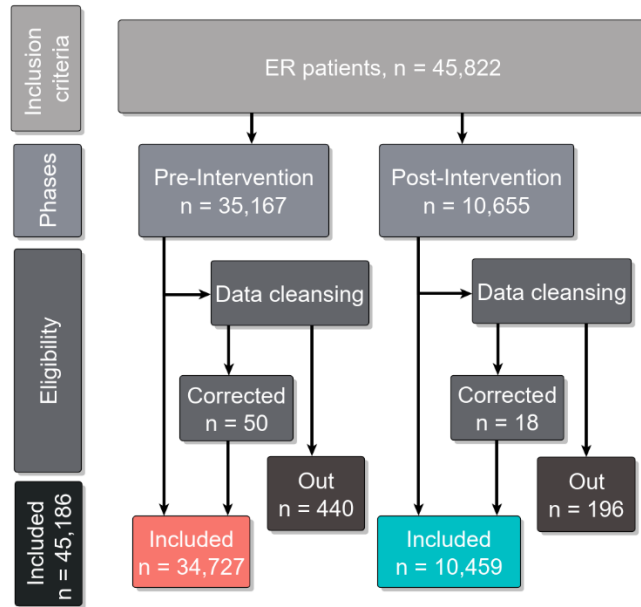


Figure S1: Data cleansing and sample sizes. Preintervention, treatment time targets provided by the Manchester Triage System score were displayed to emergency department personnel. Post-intervention, time targets were not shown. From 48,822 data sets, a total of 45,186 data sets were analyzed.

Table S1. Comparative analysis of pre-intervention and post-intervention study sample characteristics for patients with Manchester Triage System (MTS) Level MTS1. Categorical variables are presented as frequencies (percentages) and were analyzed using chi-square test. Continuous variables are presented as means with SDs and reported along with their median, ranges and quartiles.

	Pre Intervention (N=0)	Post Intervention (N=15)	Total (N=15)
LOS			
N-Miss	-	1	1
Mean (SD)	-	115.786 (96.907)	115.786 (96.907)
Median (Range)	-	94.500 (20.000, 377.000)	94.500 (20.000, 377.000)
Q1, Q3	-	65.750, 117.500	65.750, 117.500
IQR	-	51.750	51.750
Time to Triage			
Mean (SD)	-	18.600 (18.302)	18.600 (18.302)
Median (Range)	-	12.000 (2.000, 67.000)	12.000 (2.000, 67.000)
Q1, Q3	-	7.500, 21.500	7.500, 21.500
IQR	-	14.000	14.000
Waiting time in minutes			
N-Miss	-	5	5
Mean (SD)	-	9.200 (9.875)	9.200 (9.875)
Median (Range)	-	3.500 (2.000, 32.000)	3.500 (2.000, 32.000)
Q1, Q3	-	2.250, 13.750	2.250, 13.750
IQR	-	11.500	11.500
Patients present at Physician Contact			
N-Miss	-	1	1
Mean (SD)	-	11.429 (6.745)	11.429 (6.745)
Median (Range)	-	9.500 (2.000, 21.000)	9.500 (2.000, 21.000)
Q1, Q3	-	7.250, 17.750	7.250, 17.750
IQR	-	10.500	10.500
Adherence to MTS time target			
N-Miss	-	5	5

On-time	-	0 (0.0%)	0 (0.0%)
Late	-	10 (100.0%)	10 (100.0%)

Table S2. Comparative analysis of pre-intervention and post-intervention study sample characteristics for patients with Manchester Triage System (MTS) Level MTS2. Categorical variables are presented as frequencies (percentages) and were analyzed using chi-square test. Continuous variables are presented as means with SDs and reported along with their median, ranges and quartiles. Patients present at physician contact are assumed to be normally distributed and were compared using independent sample *t* tests. Nonnormal distributed processing times were compared using Mann-Whitney *U* tests.

	Pre Intervention (N=220)	Post Intervention (N=186)	Total (N=406)	<i>P</i> value
LOS				.461
N-Miss	16	0	16	
Mean (SD)	165.676 (104.238)	173.532 (105.611)	169.423 (104.834)	
Median (Range)	138.500 (19.000, 591.000)	139.000 (24.000, 484.000)	139.000 (19.000, 591.000)	
Q1, Q3	93.500, 212.000	101.000, 222.000	97.000, 215.000	
IQR	118.500	121.000	118.000	
Time to Triage				.007
Mean (SD)	11.227 (9.562)	8.978 (6.683)	10.197 (8.432)	
Median (Range)	8.000 (1.000, 66.000)	8.000 (1.000, 49.000)	8.000 (1.000, 66.000)	
Q1, Q3	6.000, 12.000	6.000, 11.000	6.000, 11.000	
IQR	6.000	5.000	5.000	
Waiting time in minutes				< .001
N-Miss	0	2	2	
Mean (SD)	20.109 (22.175)	13.071 (14.139)	16.903 (19.244)	
Median (Range)	12.000 (0.000, 122.000)	10.000 (1.000, 139.000)	11.000 (0.000, 139.000)	
Q1, Q3	5.000, 25.500	5.000, 16.250	5.000, 20.000	
IQR	20.500	11.250	15.000	
Patients present at Physician Contact				.007
N-Miss	0	6	6	
Mean (SD)	12.536 (6.085)	14.511 (8.418)	13.425 (7.286)	
Median (Range)	12.500 (2.000, 29.000)	14.000 (1.000, 38.000)	13.000 (1.000, 38.000)	
Q1, Q3	7.000, 17.000	7.000, 20.000	7.000, 18.000	
IQR	10.000	13.000	11.000	

Adherence to MTS time target				.047
N-Miss	0	2	2	
On-time	93 (42.3%)	96 (52.2%)	189 (46.8%)	
Late	127 (57.7%)	88 (47.8%)	215 (53.2%)	

Table S3. Comparative analysis of pre-intervention and post-intervention study sample characteristics for patients with Manchester Triage System (MTS) Level MTS3. Categorical variables are presented as frequencies (percentages) and were analyzed using chi-square test. Continuous variables are presented as means with SDs and reported along with their median, ranges and quartiles. Patients present at physician contact are assumed to be normally distributed and were compared using independent sample *t* tests. Non-normal distributed processing times were compared using Mann-Whitney *U* tests.

	Pre Intervention (N=4369)	Post Intervention (N=2004)	Total (N=6373)	<i>P</i> value
LOS				< .001
N-Miss	294	10	304	
Mean (SD)	160.064 (94.976)	188.884 (105.028)	169.533 (99.310)	
Median (Range)	138.000 (10.000, 588.000)	171.000 (11.000, 599.000)	148.000 (10.000, 599.000)	
Q1, Q3	92.000, 208.000	112.000, 246.000	98.000, 221.000	
IQR	116.000	134.000	123.000	
Time to Triage				< .001
N-Miss	0	1	1	
Mean (SD)	12.682 (12.466)	11.468 (11.104)	12.301 (12.067)	
Median (Range)	9.000 (0.000, 191.000)	8.000 (0.000, 158.000)	9.000 (0.000, 191.000)	
Q1, Q3	5.000, 15.000	5.000, 14.000	5.000, 15.000	
IQR	10.000	9.000	10.000	
Waiting time in minutes				.021
N-Miss	0	28	28	
Mean (SD)	41.037 (43.660)	38.350 (40.773)	40.200 (42.797)	
Median (Range)	26.000 (0.000, 294.000)	24.000 (1.000, 269.000)	25.000 (0.000, 294.000)	
Q1, Q3	12.000, 53.000	11.750, 49.000	12.000, 52.000	
IQR	41.000	37.250	40.000	
Patients present at Physician Contact				< .001
N-Miss	0	56	56	

Mean (SD)	12.685 (5.914)	15.209 (6.922)	13.463 (6.350)	
Median (Range)	12.000 (1.000, 33.000)	15.000 (1.000, 41.000)	13.000 (1.000, 41.000)	
Q1, Q3	8.000, 17.000	10.000, 20.000	9.000, 18.000	
IQR	9.000	10.000	9.000	
Adherence to MTS time target				.046
N-Miss	0	28	28	
On-time	2441 (55.9%)	1157 (58.6%)	3598 (56.7%)	
Late	1928 (44.1%)	819 (41.4%)	2747 (43.3%)	

Table S4. Comparative analysis of pre-intervention and post-intervention study sample characteristics for patients with Manchester Triage System MTS Level MTS4. Categorical variables are presented as frequencies (percentages) and were analyzed using chi-square test. Continuous variables are presented as means with SDs and reported along with their median, ranges and quartiles. Patients present at physician contact are assumed to be normally distributed and were compared using independent sample *t* tests. Non-normal distributed processing times were compared using Mann-Whitney *U* tests.

	Pre Intervention (N=10828)	Post Intervention (N=5049)	Total (N=15877)	p value
LOS				< .001
N-Miss	572	27	599	
Mean (SD)	158.945 (94.934)	180.856 (107.069)	166.147 (99.616)	
Median (Range)	141.000 (6.000, 599.000)	162.000 (4.000, 598.000)	147.000 (4.000, 599.000)	
Q1, Q3	89.000, 211.000	100.000, 238.000	92.000, 219.000	
IQR	122.000	138.000	127.000	
Time to Triage				< .001
N-Miss	1	1	2	
Mean (SD)	15.642 (16.933)	12.882 (13.875)	14.764 (16.075)	
Median (Range)	10.000 (0.000, 239.000)	8.000 (0.000, 185.000)	9.000 (0.000, 239.000)	
Q1, Q3	6.000, 19.000	5.000, 16.000	5.000, 18.000	
IQR	13.000	11.000	13.000	
Waiting time in minutes				< .001
N-Miss	1	183	184	
Mean (SD)	61.339 (53.209)	66.366 (56.342)	62.898 (54.248)	
Median (Range)	46.000 (0.000, 292.000)	50.000 (0.000, 291.000)	47.000 (0.000, 292.000)	
Q1, Q3	20.000, 88.000	23.000, 95.000	21.000, 90.000	
IQR	68.000	72.000	69.000	
Patients present at Physician Contact				< .001
N-Miss	0	156	156	
Mean (SD)	12.978 (5.802)	15.301 (6.793)	13.701 (6.221)	
Median (Range)	13.000 (1.000, 33.000)	15.000 (1.000, 40.000)	13.000 (1.000, 40.000)	

Q1, Q3	9.000, 17.000	10.000, 20.000	9.000, 18.000	
IQR	8.000	10.000	9.000	
Adherence to MTS time target				< .001
N-Miss	1	183	184	
On-time	8230 (76.0%)	3540 (72.7%)	11770 (75.0%)	
Late	2597 (24.0%)	1326 (27.3%)	3923 (25.0%)	

Table S5. Comparative analysis of pre-intervention and post-intervention study sample characteristics for patients with Manchester Triage System (MTS) Level MTS5. Categorical variables are presented as frequencies (percentages) and were analyzed using chi-square test. Continuous variables are presented as means with SDs and reported along with their median, ranges and quartiles. are assumed to be normally distributed and were compared using independent sample *t* tests. Nonnormal distributed processing times were compared using Mann-Whitney *U* tests.

	Pre Intervention (N=3059)	Post Intervention (N=589)	Total (N=3648)	p value
LOS				.018
N-Miss	112	3	115	
Mean (SD)	176.396 (104.048)	187.867 (122.918)	178.299 (107.473)	
Median (Range)	157.000 (6.000, 598.000)	170.000 (3.000, 578.000)	159.000 (3.000, 598.000)	
Q1, Q3	100.000, 233.000	87.250, 254.000	98.000, 237.000	
IQR	133.000	166.750	139.000	
Time to Triage				< .001
Mean (SD)	13.947 (15.405)	18.080 (23.848)	14.615 (17.117)	
Median (Range)	9.000 (0.000, 274.000)	11.000 (0.000, 202.000)	9.000 (0.000, 274.000)	
Q1, Q3	6.000, 17.000	6.000, 21.000	6.000, 17.000	
IQR	11.000	15.000	11.000	
Waiting time in minutes				< .001
N-Miss	0	59	59	
Mean (SD)	60.039 (55.501)	83.783 (64.902)	63.545 (57.597)	
Median (Range)	41.000 (0.000, 286.000)	67.000 (1.000, 274.000)	44.000 (0.000, 286.000)	
Q1, Q3	17.000, 87.000	31.000, 120.750	19.000, 92.000	
IQR	70.000	89.750	73.000	
Patients present at Physician Contact				< .001
N-Miss	0	14	14	
Mean (SD)	12.720 (5.853)	15.610 (6.858)	13.177 (6.114)	
Median (Range)	12.000 (1.000, 33.000)	16.000 (1.000, 35.000)	13.000 (1.000, 35.000)	
Q1, Q3	8.000, 17.000	11.000, 20.000	9.000, 17.000	

IQR	9.000	9.000	8.000	
Adherence to MTS time target				< .001
N-Miss	0	59	59	
On-time	2617 (85.6%)	397 (74.9%)	3014 (84.0%)	
	442 (14.4%)	133 (25.1%)	575 (16.0%)	

Table S6. Results of the generalized additive regression models for positive waiting times between triage and treatment. Waiting times increased by a factor of 1.27 (CI) when no time target was displayed to physicians (postintervention). However, the estimated interaction effects showed that waiting times postintervention were only 0.15 as high as preintervention for MTS1, 0.49 as high for MTS2, and 0.68 as high for MTS3. These results can be multiplied on top of the main effects that waiting times for MTS1 were, on average, only a third of the waiting times for MTS5, and waiting times for MTS2 were 0.68 of MTS5 waiting times. The effects of weekends and annual seasons in the model were negligible.

Factor	multiplicative	Estimate	Std. Error
(Intercept)	61.92	4.13	0.02
Phase Post-intervention	1.27	0.24	0.04
Weekday Non-working day	1.01	0.01	0.01
Season Summer	0.97	-0.04	0.02
Season Fall	0.96	-0.05	0.02
Season Winter	0.99	-0.01	0.02
Triage Score MTS4	1.00	0.00	0.02
Triage Score MTS3	0.68	-0.39	0.02
Triage Score MTS2	0.33	-1.11	0.06
Triage Score MTS1	1.00	0.00	0.00
Post-intervention:Triage Score MTS4	0.80	-0.23	0.05
Post-intervention:Triage Score MTS3	0.68	-0.38	0.05
Post-intervention:Triage Score MTS2	0.49	-0.71	0.10
Post-intervention:Triage Score MTS1	0.15	-1.90	0.29

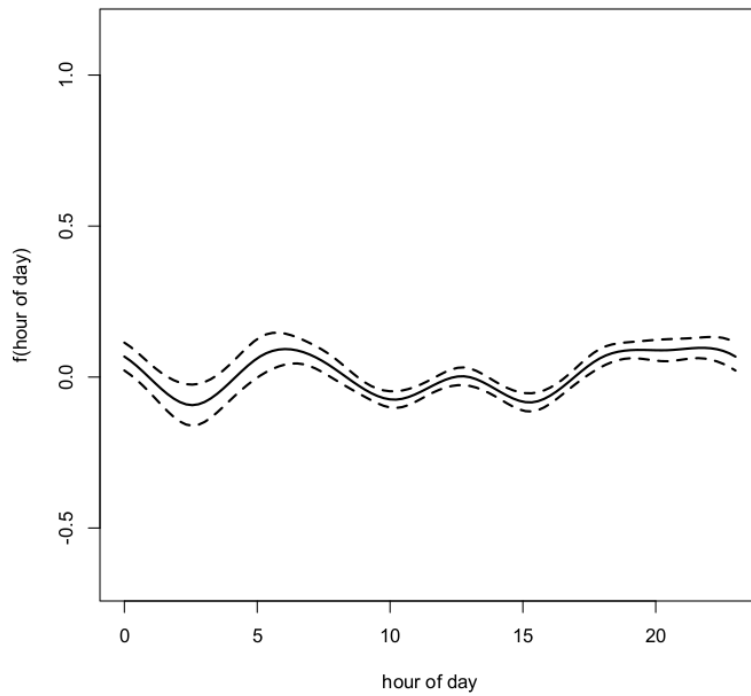


Figure S2. Effect of hour of day on the generalized additive regression models for positive waiting times between (re)triage and treatment. The covariate hour of day was included with a cyclic P-spline basis. The effects of weekends and annual seasons in the model were negligible. Waiting times increased at around 6 AM and from 6 PM to midnight.

Table S7. Results of the generalized additive regression models for delayed treatment assuming a logistic regression reported as odds ratio. The covariate hour of day was included with a cyclic P-spline basis. The number of patients present in the emergency department (ED) was modeled with a regular P-spline basis and 2-way interactions of Manchester Triage System (MTS) score and study phase, as well as patients present and study phase. Although late treatment of patients was more likely when no time target was displayed to physicians (post-intervention), late treatment was considerably less likely when crowding (as indicated by the number of patients waiting) occurred and for urgent cases (as indicated by the triage score).

Factor	OR	Estimate	Std. Error
(Intercept)	0.06	-2.78	0.08
Studyphase Post-intervention	2.32	0.84	0.14
Weekday Non-working day	0.99	-0.01	0.03
Season Summer	0.92	-0.08	0.05
Season Fall	0.89	-0.12	0.05
Season Winter	0.97	-0.03	0.05
Triage Score MTS4	1.86	0.62	0.06
Triage Score MTS3	4.93	1.60	0.06
Triage Score MTS2	8.79	2.17	0.15
Patients present at encounter	1.08	0.08	0.00
Post-intervention:Patients present at encounter	0.98	-0.02	0.00
Post-intervention:Triage Score MTS5	1.00	0.00	0.00
Post-intervention:Triage Score MTS4	0.60	-0.51	0.12
Post-intervention:Triage Score MTS3	0.44	-0.83	0.13
Post-intervention:Triage Score MTS2	0.32	-1.14	0.24

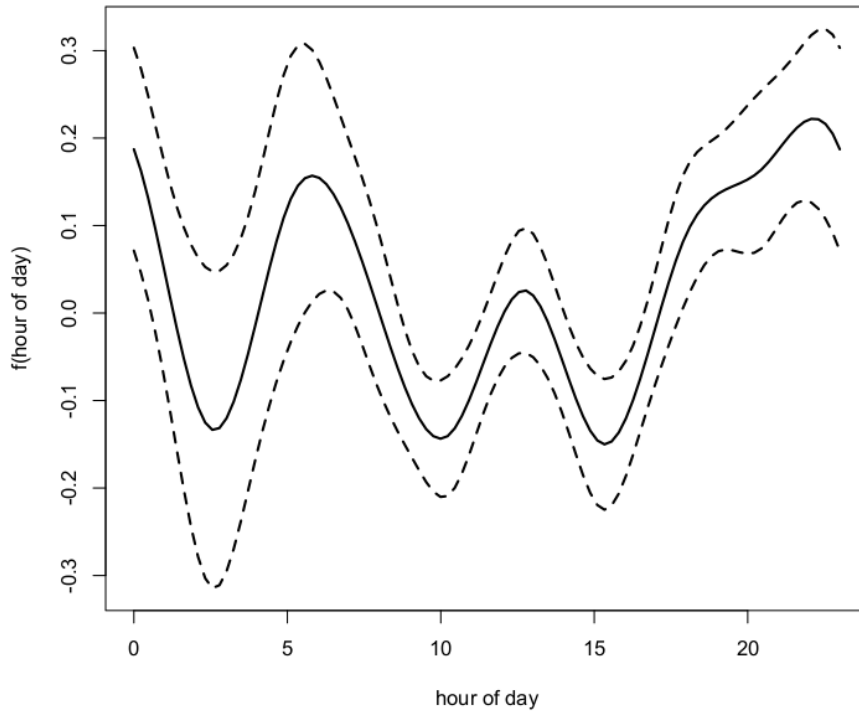


Figure S3. Effect of hour of day on the generalized additive regression models for delayed treatment. While the effects of weekends and annual seasons in the model were negligible, odds for delayed treatment increased at around 6 AM and from 6 PM to midnight.

Appendix

Synopsis: Federated research infrastructures for a learning healthcare system in acute, intensive, and emergency care

Treating critically ill patients demands quick action, minimal errors, and reliance on the best available medical knowledge, so-called evidence [1–3]. The deliberate application of evidence for clinical decision-making is known as evidence-based medicine [4]. However, evidence does not arise spontaneously. Evidence is produced from information, which is itself derived from contextualized data, the basic unit of meaning¹. In acute stroke management, for instance, time is brain. This piece of information arises from data measured in studies demonstrating that the earlier a patient receives thrombolytic therapy or endovascular intervention, the better their neurological outcomes [6]. Research bridges the gap between data and actionable evidence through systematically and critically exploring hypotheses [7]. By hurrying a patient with a suspected stroke to the computer tomography, physicians are, in fact, following evidence. Building on these principles, this thesis investigates how federated research infrastructures can systematically facilitate the collection and utilization of data to support evidence-based medicine in acute, intensive and emergency care.

Introduction

Medical progress relies on collecting empirical data to assess and improve human health [4]. In epidemiological research, the distribution and determinants of health and disease in populations are studied; medical registries play a pivotal role by systematically collecting data on defined groups of individuals to answer research questions. [8, 9]. Clinical research, such as randomized controlled trials, provides a structured approach to experimentally testing the effects of medical treatments. In these trials, participants are randomly assigned to treatment groups to ensure that outcome differences result from the intervention rather than other influences. [10]. While randomized controlled trials are the highest methodological standard for demonstrating that an intervention causes an observed effect, real-world data have become an important complement [11–13]. Medical real-world data are routinely collected in the course of health care delivery². If such data are used for research, they are re-purposed beyond their primary intent for a secondary purpose [15].

In primary research, such as clinical trials, participants are typically selected based on stringent inclusion and exclusion criteria, often resulting in a small, homogeneous population that may not reflect the diversity of patients encountered in everyday clinical practice [16]. This selection process can introduce bias, a systematic deviation from true effects that affects the validity and generalizability of trial results³. The lower real-world effectiveness of COVID-19 vaccines in reducing disease risk is a prominent example of the discrepancy between efficacy, answering “*Can it work?*” as measured in controlled trials, and effectiveness, answering “*Does it work?*” in real-world settings [14, 19, 20]. Thus, real-world data are indispensable for capturing healthcare as it truly happens, bridging the gap between causal evidence and reality [12, 21].

¹ Following Aamodt and Nygård [5], data, information, and knowledge form a hierarchical framework in which raw inputs are progressively structured and contextualized to generate meaning. At its base, symbols serve as fundamental building blocks, which, when organized, become data. When contextualized, data turn into information, which is further processed into knowledge informing action.

² Here used is the definition provided by the United States Food and Drug Administration (FDA), which defines real-world data as those data related to patient health status and healthcare delivery, routinely collected from sources such as electronic health records, medical claims, and product or disease registries. The FDA utilizes such data to generate real-world evidence for the development of therapeutic products and regulatory oversight of medical products throughout their lifecycle. [14].

³ For a detailed account of potential biases in trials, including flaws in study design, execution, analysis, and reporting, refer to the Cochrane Collaboration’s tool for assessing risk of bias [17] and Cochrane Handbook for Systematic Reviews of Interventions [18].

The patient-centered digital records of medical treatment, electronic health records (EHRs), are typical real world data, varying in formats, heterogeneous, and noisy [15]. These records contain information on procedures, diagnoses, and patient outcomes. They are stored within health information systems, which manage all data, information, and knowledge in healthcare environments¹.

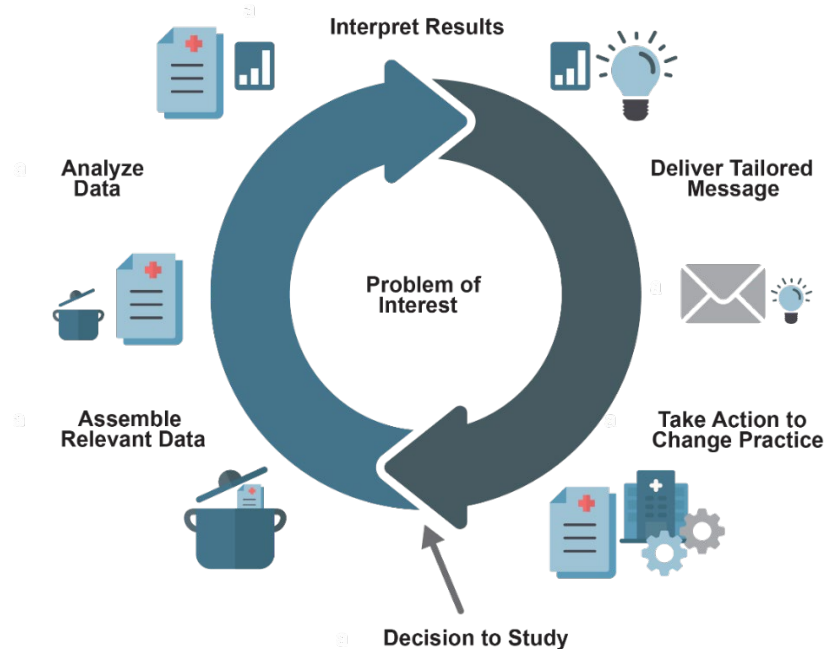


Figure 1 A learning healthcare system, transforming electronic health record data into actionable insights, follows a continuous cycle. This framework illustrates how research infrastructures act as the cooking pots in which data are gathered, processed, and refined into meaningful results. Results must be systematically transformed into actionable improvements in clinical practice through tailored messages — closing the feedback loop in a learning healthcare system (Adapted from [24]).

EHRs are more than just practical necessities for implementing medical care; their use can be the foundation for a healthcare system that does not simply store data but takes lessons from it (Figure 1). Charles Friedman [25] coined the term *learning healthcare system* to describe a model in which healthcare continuously improves by systematically analyzing the EHR data it produces. Instead of merely archiving records for administrative purposes, these healthcare systems generate actionable insights that refine medical knowledge and optimize patient care—provided the necessary infrastructures are in place to support their use². As the backbone of a learning healthcare system, research infrastructures such as clinical registries or biobanks are the resources and services needed to enable systematic access, storage, analysis of data, and feedback to patient care³.

¹ The socio-technical nature of health information systems in clinical practice is beyond the scope of this thesis. For a comprehensive overview of information management in hospitals and the socio-technical aspects of health information systems, see Haux et al. [22, 23].

² Friedman [26] explicitly emphasized that a learning healthcare system requires more than just data access. Integrated platforms are demanded to facilitate continuous improvement in learning cycles. Without a re-usable platform, each research initiative risks developing isolated, potentially suboptimal methods, leading to inefficiencies and scalability challenges. For a learning healthcare system to be sustainable, infrastructures must not only aggregate and analyze data but also close the feedback loop by transforming insights into actionable knowledge (c.f. Figure 1). For a detailed discussion on the role of infrastructures in enabling a learning health system and their socio-technical nature, see [27].

³ Research Infrastructures in medicine or elsewhere are not limited to data. Following the European commission's definition [28], research infrastructures provide resources and services for research communities to conduct research and foster innovation. While they do not have to be technical systems, modern infrastructures typically rely on technical components and governance structures, depending on the use case. They can extend beyond research, serving purposes such as education or public services, and may be single-sited, distributed, or virtual. Examples include major scientific equipment, collections and archives, computing systems, communication networks, and other unique infrastructures open to external users for research.

The COVID-19 pandemic exposed a broader gap in data for guiding the pandemic response; while vast amounts of EHR data existed, much remained siloed [29, 30]. A relevant example for this thesis is the DIVI Intensive Care Registry in Germany [31], which was critical in monitoring intensive care capacities during the pandemic and directly impacted political decision-making [32]. While the necessity of tracking intensive care resources was acknowledged [33] and relevant datasets were collected in German hospitals, the system still relied on manual, error-prone, and time-consuming data entry by physicians. The registry was limited to reporting the aggregated number of available intensive care unit beds and ventilator beds per hospital because legal and overarching EHR data processing frameworks were absent [32, 29, 34]. The infrastructure thus provided only a partial picture of medical reality. Medical reality is often fragmented in data. Data sharing and use introduces complexities surrounding ownership, privacy, and technical implementation [35, 36]. Coordinated efforts in data standardization, regulatory frameworks, and information security are required to overcome the fragmentation of EHR data [36]. Recognizing this, the WHO has identified enabling EHR use as a global health priority [37–39].

The objective of this thesis is to investigate how federated research infrastructures can systematically facilitate the secondary use of EHRs to improve evidence-based decision-making in acute, intensive and emergency settings. Using the *German National Emergency Department Data Registry* as a foundation, it explores how EHRs can be leveraged for research while maintaining the data sovereignty of data holders. By developing methods to integrate routine clinical data into research and healthcare improvement, this thesis contributes to the foundation of a learning healthcare system so that critically ill patients receive prompt care, with as few mistakes as possible and following the best medical knowledge available.

Background

Research infrastructures in medicine typically provide resources, tools, and frameworks for generating evidence. At their core, they encompass data platforms, computational resources, and governance structures that facilitate the process from data collection to storage and controlled access [40]. Many of these infrastructures are established through research networks—collaborative efforts of multiple institutions working toward a shared research objective, such as multi-center clinical trials or clinical registries. Because this thesis focuses on research infrastructures that provide access to EHRs, the following sections outline their role in integrating real-world data into research and the challenges associated with interoperability and data governance. Finally, the potential of federated approaches to balance data accessibility with data privacy is exemplified by the German National Emergency Department Data Registry.

Electronic Health Records

EHRs are patient-centered digital records of medical treatment generated as a byproduct of medical treatment. Their primary function is to document medical services, ensuring continuity of care and supporting administrative processes such as reimbursement. EHR data are highly heterogeneous, encompassing vital signs, diagnoses, procedures, process metrics, imaging data, and demographics [41]. These records are entered by clinical personnel via workstation interfaces or automatically generated through medical devices before being stored in hospital information systems or specialized subsystems.

As the volume of EHR data continues to grow, they play a pivotal role in the digital transformation of healthcare [15, 42, 43]. Beyond their immediate clinical purpose, EHRs serve as real-world data resources for healthcare research, artificial intelligence applications, medical device development, public health surveillance, and quality management—all contributing to the evolution of a learning healthcare system [44]. The adoption of the FAIR

(Findable, Accessible, Interoperable, and Reusable) principles [45] is expected to drive the use of EHRs for research [46].

Re-purposing EHRs for research presents great challenges due to their primary function as clinical documentation rather than structured research data [47]. EHRs often contain inconsistencies, incomplete records, and variations in documentation practices across institutions [48, 49]. These limitations impact data quality, introduce biases, and complicate secondary use¹.

EHRs are fragmented across numerous clinical information systems and healthcare providers [23]. When integrating data from different subsystems and hospitals or re-purposing EHRs for research, it is essential that third parties can accurately interpret the data [50]. Interoperability refers to the capability of these systems to exchange data with other systems universally. Through syntactic interoperability, data can be exchanged in a standard format. Semantic interoperability guarantees that the meaning of the data remains consistent across systems through standardized coding and ontologies. An ontology is a structured framework that defines relationships between medical concepts, ensuring that terms used across different systems refer to the same clinical entities.

Interoperability standards are crucial for making EHRs usable beyond their intended purpose. FHIR (Fast Healthcare Interoperability Resources) and CDA (Clinical Document Architecture) are widely used standards initiated by the Health Level 7 (HL7) organization that facilitate structured data exchange. FHIR provides a modern, web-technology approach to interoperability, while CDA focuses on document-based data exchange². Both frameworks support integrating healthcare information across systems, improving accessibility for clinical and research applications.

While standardized terminologies and interoperability standards can enhance data integration, they cannot fully mitigate the challenges associated with heterogeneous documentation. Research infrastructures utilizing EHR data operate within complex socio-technical environments, requiring coordination between diverse stakeholders, including clinicians, IT professionals, data stewards, and researchers. Ensuring the validity and reliability of EHR data remains a resource-intensive task that demands continuous quality control efforts, particularly as EHR data move further from clinical routine.

Centralized and Federated Research Infrastructures

EHRs contain valuable information but require systematic utilization to generate meaningful insights. For example, assessing the impact of COVID-19 countermeasures required continuous monitoring of intensive care unit occupancy across multiple hospitals [33]. To facilitate large-scale analyses of multiple EHRs, research infrastructures in medicine are typically multi-centered, enabling research networks to integrate data across institutions. Depending on the research objectives, these networks require sophisticated data management architectures to address challenges in data storage, provenance, and access control [40].

Traditional data repositories (Figure 2a), such as clinical registries like the DIVI Intensive Care Registry, rely on centralized storage, where data is collected, transferred, and maintained in a single location for access [51]. In contrast, federated research infrastructures (Figure 2b)

¹ For a detailed overview of the opportunities and challenges associated with the secondary use of electronic health records see [47].

² HL7 FHIR follows a RESTful (Representational State Transfer) architecture, a design commonly used in web technologies, where *Application Programming Interfaces* (APIs, structured rules for data exchange between systems) are used to fetch and exchange data over the internet. In contrast, HL7 CDA, the predecessor to FHIR, is designed for document-based data exchange, inspired by structured clinical summaries such as discharge letters. CDAs ensure interoperability through standardized templates and coded medical terminology.

keep data stored locally at the collection point while enabling controlled access, creating a distributed network of data-holding nodes [52].

Due to varying data protection laws and institutional policies, the technical and organizational processes to access data become increasingly complex in distributed research networks [53, 54]. Federated infrastructures operate under imperfect conditions due to challenges in interoperability, data quality, and heterogeneous documentation practices. Hence, robust systems are required that can adapt to varying technical and organizational environments reliably [55, 52].

Several European initiatives have adopted federated approaches to research data management to address these challenges. Examples include the Medical Informatics Initiative [56], the German Consortium for Translational Cancer Research [57], the Norwegian Primary Care Research Network [58], the French Health Data Hub [59], and the German National Emergency Department Data Registry [60]. Federated infrastructures aim to facilitate large-scale research while preserving institutional control over sensitive health data, ensuring compliance with ethical, legal, and technical requirements. Such approaches thus leverage data privacy and structured oversight mechanisms to ensure compliance with data protection regulations while maintaining ethical standards.

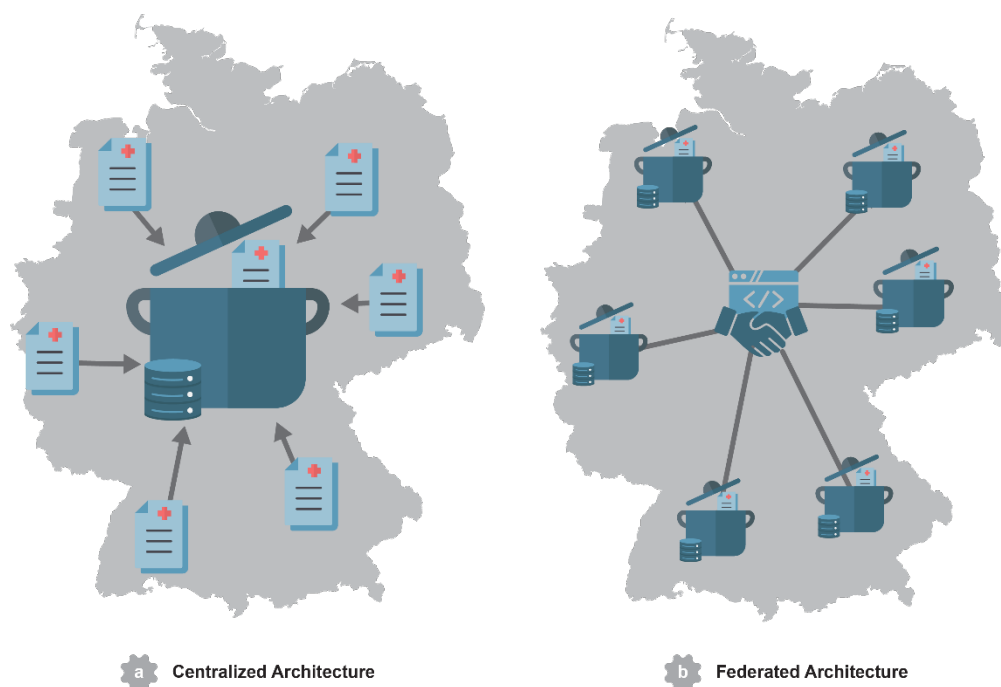


Figure 2 Comparison Comparison of infrastructure architectures. (a) A centralized model collects all data in a single repository, whereas (b) a federated model connects locally maintained repositories through centralized services. Federated infrastructures are decentralized systems in which data remain stored at their original locations. Data access and analysis are conducted through a coordinated network.

As a rule of thumb, centralized data collections are more straightforward to set up and maintain but must be limited to specific purposes to comply with data minimization principles and adhere to data privacy obligations [55]. In contrast, federated architectures enforce data minimization at the extraction point, tailoring access to broad purposes. They provide greater security and flexibility but are complex to operate [61].

The AKTIN Infrastructure

The German National Emergency Department Data Registry exemplifies how federated research infrastructures enable the secondary use of EHRs, giving access to data from German emergency departments (EDs). Initiated by the *Alliance for Information and Communication Technology in Intensive Care and Emergency Medicine (AKTIN)*, by its

German abbreviation), the registry is called the AKTIN ED Registry and operates on the federated AKTIN infrastructure [1, 62]. The AKTIN infrastructure forms a network of ED nodes providing the technical and organizational framework for secure and standardized data exchange (Figure 3).

The AKTIN infrastructure facilitates the interoperable collection of EHRs entered by emergency department staff during patient care. Data follow the HL7 CDA standard established by the *German Interdisciplinary Association for Intensive Care and Emergency Medicine* (DIVI e.V.) in cooperation with HL7 Germany [63]. The AKTIN ED Registry enables data access for health care research, public health surveillance [64–66], and quality management [67–69].

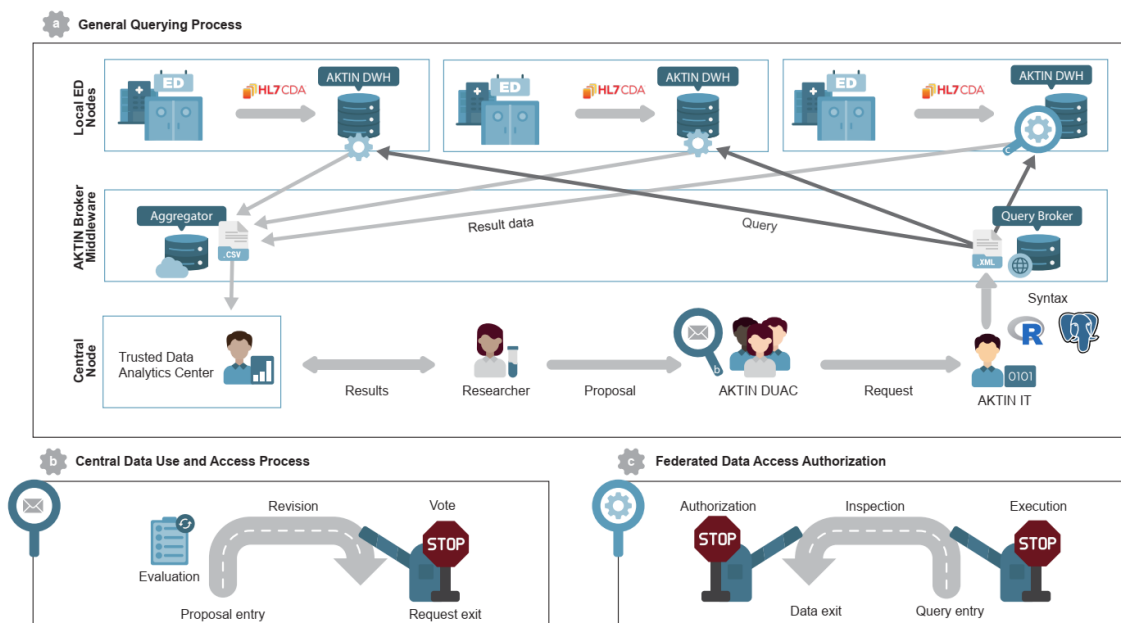


Figure 3: AKTIN Infrastructure processes [70, 71]. (a) Electronic Health Record data are captured in the participating emergency department (ED) nodes within an AKTIN Data Warehouse. After approval from the Data Use and Access Committee (DUAC), the AKTIN IT group translates proposals into R or SQL syntax. A data query is created from the syntax, which is communicated to the nodes using the AKTIN Broker via xml data structure, including additional descriptive- and provenance metadata. The local ED node must authorize data access for each query. **(b)** The DUAC evaluates proposals and formulates a vote translated into a technical request. **(c)** A federated data access authorization process is implemented within the AKTIN DWH software. The AKTIN IT group receives technical requests and then uses the AKTIN Broker middleware to send queries to AKTIN DWHs in the ED nodes. The ED nodes may execute the query, inspect the results in csv format, and authorize data access.

Each participating ED operates its own AKTIN data warehouse, a database optimized for analytical purposes that integrates EHR data. EDs can use the data internally for quality management and research, while external researchers can request de-identified data to be queried from the ED nodes through a predefined data use and access process. Requests are reviewed centrally by the AKTIN Data Use and Access Committee before being sent out to individual ED using the AKTIN Broker Software. Within each ED node, ED personnel perform an additional local review. To strengthen data privacy, datasets remain within the AKTIN Trusted Data Analytics Center, where they are analyzed under strict information security protocols. As of February 2025, 90 emergency departments are connected to the registry, with more than 1.7 million cases available in 2023 [67]. The AKTIN infrastructure is currently operated within the Network University Medicine in Germany.

A federated approach was required to balance the need for research with data privacy concerns and local stakeholder interests. Obtaining informed consent for data use is

infeasible in emergency care settings.[72]. As a result, only anonymous data may be shared with external parties. However, the definition of data anonymity in practice is widely debated and interpreted differently across legal, technical, and ethical contexts [40]. Data privacy requirements and legislation further vary across the federal states of Germany. Consequently, each node must determine whether data sharing fulfills data privacy requirements and aligns with its organizational interests.

Publications

When coupled with robust research infrastructures, EHR data supports evidence-based decision-making within a learning healthcare system. The objective of this thesis is thus to investigate how federated EHR collections can improve evidence-based decision-making in acute, intensive and emergency care settings. To tackle this objective, we conducted three studies. The three works build on the core processes of building, maintaining, and expanding federated research infrastructures to enable the structured use of EHR data within a learning healthcare system. The first publication [73] focuses on building a federated data infrastructure for intensive care units (ICUs), addressing a critical clinical and public health need for real-time surveillance. The second publication [71] examines the maintenance and expansion of the AKTIN infrastructure, optimizing federated data access in emergency medicine while balancing institutional autonomy and scalability. The third publication [74] demonstrates how the collected EHR data can generate evidence to improve clinical practice, evaluating the impact of triage time targets on patient care.

A Federated and Distributed Data Management Infrastructure to Enable Public Health Surveillance from Intensive Care Unit Data

During the COVID-19 pandemic, German public health authorities faced challenges accessing data on individual patients from ICUs for public health surveillance. Without timely and comprehensive data, the ability to adapt policies and measures in response to shifting pandemic conditions is constrained. The Robert Koch Institute (RKI), responsible for national health surveillance, relied on aggregated ICU capacity reports submitted by hospitals through the DIVI Intensive Care Registry. However, this data lacked individual clinical parameters necessary for accurate modeling and prediction of ICU occupancy.

Although routine ICU documentation captured vital parameters and clinical scores relevant to patient severity and resource allocation, there was no infrastructure to use this data for public health purposes. Given the urgency of the pandemic, establishing a centralized national database was neither feasible nor legally permissible under data privacy regulations.

To address this gap, we implemented a federated research infrastructure that enabled secure access to patient-level ICU data for public health surveillance. For swift setup, the prototype was built on the software components of the AKTIN Infrastructure, which had already demonstrated feasibility for federated data access in emergency medicine [60]. The adapted infrastructure allowed the RKI to submit structured data queries processed locally within the participating ICU. Rather than pooling data in a central repository, hospitals retained complete control over their data, responding to queries with de-identified or aggregated results.

The system architecture consisted of locally operated data warehouses that stored structured ICU data extracted from patient data management systems. The data were mapped to standardized terminologies (i.e., ICD-10 codes for diagnoses), ensuring semantic and syntactic interoperability across hospitals. A secure query interface, adapted from the existing AKTIN Broker, enabled authorized public health institutions to access the data in a controlled and auditable manner.

The prototype was deployed in a pilot ICU, where structured clinical data from over 13,000 cases were imported into the local data warehouse and sent to the RKI. The first data query

confirmed that ICU documentation could be re-purposed for real-time public health surveillance. While the prototype did not implement interoperable standards, it leveraged a pragmatic approach based on available infrastructure components.

The implications of this research extend beyond the feasibility of pandemic surveillance from ICU data. The re-use of software components from the AKTIN infrastructure demonstrates how federated research infrastructures can be extended from emergency to intensive care settings. As a result, the infrastructure serves as the blueprint for the currently proposed NUM-Rapid platform, a nationwide federated research infrastructure for ICU data within the Network University Medicine.

Implementation Report on Pioneering Federated Data Access for the German National Emergency Department Data Registry

Moving beyond an infrastructure prototype, the second study focuses on how continuous, scalable, and sustainable access to EHR data can be realized in federated research infrastructures. We report on the digital health intervention of the federated data access authorization system, a key component used in the AKTIN infrastructure. We examined if the system efficiently facilitates the secondary use of EHR data.

A federated data access authorization system enables controlled data sharing by allowing data holders to review requests individually. Such an approach is necessary because hospitals operate in a competitive healthcare landscape, where concerns about data sharing can hinder collaboration. For example, a hospital may hesitate to share data that exposes prolonged ED waiting times or resource limitations, fearing reputational or competitive disadvantages. Addressing these concerns is essential for scaling research infrastructures to a national level.

We developed and used a federated data access authorization system within the AKTIN infrastructure to overcome the challenges associated with data sharing. The system enables ED nodes to review and approve requests independently. Unlike centralized approaches, a federated approach ensures that hospitals retain complete control over their data and can opt out of sharing requests that conflict with their local interests.

We evaluated the implemented system using key performance indicators (KPIs) obtained during operation. Over 7.9 million EHR cases were made available through the AKTIN infrastructure, reflecting the increasing system adoption. The number of queries grew exponentially, from only 15 in 2017 to more than 23,000 in 2024, of which 75% of queries were approved in a reasonable time within 15 days.

Our findings have direct implications for the development of learning healthcare systems. Resource-intensive infrastructure maintenance and overburdening clinical staff are common barriers in health information systems [75, 36]. The study results demonstrate that federated architectures, in combination with voluntary data sharing, can provide nationwide, continuous, and secure access to EHR. This methodology could serve as a scalable blueprint for the secondary use of healthcare data.

The findings are particularly relevant for the European Health Data Space (EHDS), which aims to facilitate the secure exchange and secondary use of health data across EU member states. The EHDS proposes centralized data access bodies where data holders proactively submit data without being consulted for data requests [76]. While the medical community advocates for open data, actual implementation is often constrained by practical, ethical, and regulatory considerations [77]. In contrast, our approach demonstrates how federated architectures enable purpose-driven data sharing without requiring blanket data transfers. It also allows data holders to assess whether queries align with the content and limitations of their data, ensuring that research is conducted on suitable datasets.

The Effects of Displaying the Time Targets of the Manchester Triage System to Emergency Department Personnel: Prospective Crossover Study

The true value of EHR data lies in their meaningful application. While building and maintaining federated infrastructures is essential, their impact is measured by how they can improve clinical care. The third study demonstrates how EHR data collected within the AKTIN infrastructure can be used to enhance emergency department workflows.

Before receiving treatment, patients often face waiting times [78]. To prevent critically ill patients from waiting too long, emergency departments use triage systems to prioritize care [79]. In the Manchester Triage System, a maximum acceptable waiting time¹ is assigned to each patient based on the urgency of their condition. The study investigates whether or not these time targets should be displayed to emergency department personnel.

At its core, the study engages with the widely observed phenomenon that work expands to fill the time allocated to it. In the context of acute care in EDs, this suggests that rigid time targets for triage and treatment may inadvertently shape clinical workflows without necessarily improving patient outcomes. It aligns with Goodhart's Law from economics, which states that once a measure becomes a target, it loses effectiveness [80, 81].

Using a crossover study design, where routine operations are first observed before implementing the intervention, the study analyzed over 45,000 emergency department cases from one ED node participating in the AKTIN infrastructure. The emergency department information system first displayed triage-based time targets to emergency staff, which was then replaced with a priority-based list. EHR data were analyzed for evaluation, focusing on waiting times, adherence to triage targets, and overall emergency department efficiency.

The study found that removing fixed time targets from the emergency department information system significantly impacted treatment times. While the odds of late treatment increased overall, severely ill patients benefited from improved prioritization. Most notably, patients in high-acuity categories experienced faster treatment, even under crowding conditions, a major challenge for EDs worldwide [82]. Moreover, the emergency department leadership opted not to return to the previous system. While not a formal part of the study's quantitative results, this decision indicates that the changes were perceived as beneficial in daily clinical practice. The intervention improved emergency department efficiency meaningfully to the clinicians responsible for patient care. These findings may also have implications for policy-making, as waiting time limits introduced by policymakers might create similar false incentives.

Even though the study was single-sited and the crossover study designs have limitations in addressing many biases [83], it confirms that EHR from ED treatment can generate evidence to be fed back for local process optimization. The models for timely care used in the study further demonstrated moderate generalizability across different ED settings and could serve as the foundation for a new risk-adjusted crowding score [84].

Synthesis

Federated research infrastructures enable evidence-based decision-making by serving as the platforms for a learning healthcare system envisioned by Friedman [26]. The presented studies make evident that federated data infrastructures support the secure and scalable reuse of EHRs to enhance clinical workflows, optimize acute, intensive and emergency care processes, and inform evidence-based decision-making. More specifically, we demonstrated that EHR data from the AKTIN infrastructure can generate evidence to optimize patient flow

¹ The German Version of the Manchester Triage System categorizes emergency department patients into five priority levels based on urgency: MTS1 Immediate requiring immediate intervention for life-threatening conditions, MTS2 Very Urgent requiring treatment within 10 minutes for serious conditions, MTS3 Urgent requiring medical attention within 30 minutes for moderate conditions, MTS4 Standard requiring evaluation within 60 minutes for less severe cases, and MTS5 Non-Urgent for minor conditions that can safely wait up to 120 minutes.

in overcrowded emergency departments. Thus, in alignment with Friedman's vision of a learning healthcare system, we show that the federated infrastructures we implemented can perform a full learning cycle by systematically transforming EHR data into actionable insights and integrating these insights into clinical workflows (Figure 1). However, robust feedback mechanisms are required to systematically deliver tailored and trusted messages to clinicians to ensure lasting improvements beyond a single site and study.

Federated approaches foster trust among participating sites through local sovereignty and access control [85–87]. The AKTIN infrastructure has encouraged broad participation from emergency departments across Germany. Moreover, we proved that this concept can be extended to ICU data, reinforcing its adaptability to other clinical domains. Beyond the scope of this thesis, decentralizing information is not merely a matter of data privacy and security—it has broader political and societal implications [88]. By redistributing authority and resources to local entities, federated frameworks enhance data sovereignty and promote greater transparency, accountability, and responsiveness by empowering local actors¹. The design is thus based on the assumption that data are best stored in secure local environments, ensuring that healthcare providers retain control over their own EHR data. However, if these safeguards fail, stringent protocols must be in place to mitigate the risk of data breaches [93].

From a regulatory perspective, decentralized models offer distinct advantages in navigating complex legal landscapes, particularly regarding patient consent. This is particularly relevant in acute and intensive care settings, where obtaining informed consent is often impractical [72, 94]. By leveraging data privacy and structured oversight mechanisms, federated approaches ensure compliance with diverse data protection regulations while maintaining ethical standards. The AKTIN data access model exemplifies how federated infrastructures can balance regulatory requirements with the need for flexible and responsible data use. However, variations in national legal frameworks and data governance policies necessitate adaptive solutions to ensure compatibility across settings. Long-term sustainability depends on the adaptation to evolving regulatory environments. In Germany, new opportunities for acute and intensive care have recently emerged with the Health Data Utilization Act, which yet needs to be incorporated within the AKTIN infrastructure [95].

The generalizability of our approach to universal healthcare systems remains to be formally evaluated. However, since the AKTIN infrastructure's first draft in 2014 [70], multiple federated initiatives have emerged, including the Medical Informatics Initiative, which follows a similar architectural concept but focuses on making EHR data from all university hospital departments available [96]. A comparable approach is seen in the Norwegian Praksisnet infrastructure, which relies on federated access authorization from general practitioners but integrates more distributed computing methodologies [58]. Privacy-preserving methods and distributed computing could enhance federated approaches by enabling secure data analysis without centralizing sensitive information [97]. However, their large-scale implementation in federated research networks remains challenging due to technical complexity, complex quality assurance, and the need for standardized protocols across diverse institutions.

Federated infrastructures require robust validation mechanisms to maintain comparability and interoperability across institutions [98]. Poor data quality inevitably leads to flawed evidence, often summarized by the phrase “garbage in, garbage out” [99, 100, 48]. While interoperable formats help reduce discrepancies, variations in hospital documentation practices persist. Moreover, as data become further removed from their clinical context, the risk of biases grows

¹For a detailed account, refer to Foucault's discussion of governmentality in *Security, Territory, Population* [89] and *The Birth of Biopolitics* [90], where he examines how modern states govern populations through decentralized mechanisms of control rather than direct sovereign power. Building on and extending such analyses, the Actor–Network Theory offers a more contemporary approach to understanding power and organization in sociotechnical systems [91]. Very recently, Harari explores these themes from a more technical perspective in *Nexus: A Brief History of Information Networks from the Stone Age to AI* [92].

[15]. Federated research infrastructures function as prospective cohort studies capturing EHR data over time. In such studies, generalizability is affected by the characteristics of the observed sub-population, potential selection bias—where certain groups may be over- or underrepresented—and the data collection process itself [101]. Issues such as unclear data collection guidelines, interface design, the role of data capturers, and insufficient data checks can affect the reliability and applicability of study findings across different settings [99, 102]. EHR-based Machine learning models were shown to generalize with varying success across different EDs, indicating that site-specific factors influence method performance [103]. EHR-based artificial intelligence systems could amplify biases, leading to disparities in patient care and ultimately impacting treatment quality and healthcare equity [104].

Federated infrastructures and EHR are not a silver bullet for medical research; when feasible, centralized approaches often yield more consistent results, are easier to implement, and require less maintenance [55]. Well-conducted randomized controlled trials remain the gold standard for establishing causal relationships in clinical research [18]. Despite these limitations, the presented infrastructures, combined with interoperable datasets, could form the foundation of a learning healthcare system for critically ill patients in Germany. Hence, seamless data integration across pre-hospital emergency services, emergency departments, and ICUs is required, creating a digital rescue chain [105]. Nevertheless, the digital transformation of acute, intensive and emergency care is not an end in itself but a means to enable methodologies such as artificial intelligence [106], process mining [107], and rigorously conducted trials. Federated infrastructures prove their worth only when they facilitate high-impact evidence generation and provide a framework for integrating these innovations into routine care, ensuring that critically ill patients receive the best possible treatment based on evolving knowledge.

Declarations

The author declares no conflict of interest. During the preparation of this work, the author used Grammarly and OpenAI's ChatGPT-4o language model to assist with language refinement in the manuscript. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the final content of the work.

References

1. Drynda S, Schindler W, Slagman A, Pollmanns J, Horenkamp-Sonntag D, Schirrmeyer W et al. Evaluation of outcome relevance of quality indicators in the emergency department (ENQUIRE): study protocol for a prospective multicentre cohort study. *BMJ Open* 2020; 10(9):e038776.
2. Christ M, Grossmann F, Winter D, Bingisser R, Platz E. Modern triage in the emergency department. *Dtsch Arztebl Int* 2010; 107(50):892–8.
3. Eitel DR, Rudkin SE, Malvey MA, Killeen JP, Pines JM. Improving service quality by understanding emergency department flow: a White Paper and position statement prepared for the American Academy of Emergency Medicine. *J Emerg Med* 2010; 38(1):70–9.
4. Sackett DL. Evidence-based medicine. *Semin Perinatol* 1997; 21(1):3–5.
5. Aamodt A, Nygård M. Different roles and mutual dependencies of data, information, and knowledge — An AI perspective on their integration. *Data & Knowledge Engineering* 1995; 16(3):191–222.
6. Saver JL. Time is brain—quantified. *Stroke* 2006; 37(1):263–6.
7. Popper KR. *Logik der Forschung*. 6., verb. Aufl. Tübingen: Mohr; 1976. (Die Einheit der Gesellschaftswissenschaften; vol 4).
8. Bhatt A. Evolution of Clinical Research: A History Before and Beyond James Lind. *Perspect Clin Res* 2010; 1(1):6–10.
9. Collier R. Legumes, lemons and streptomycin: a short history of the clinical trial. *CMAJ* 2009; 180(1):23–4.

10. Zabor EC, Kaizer AM, Hobbs BP. Randomized Controlled Trials. *Chest* 2020; 158(1S):S79-S87.
11. Bian J, Lyu T, Loiacono A, Viramontes TM, Lipori G, Guo Y et al. Assessing the practice of data quality evaluation in a national clinical data research network through a systematic scoping review in the era of real-world data. *J Am Med Inform Assoc* 2020; 27(12):1999–2010.
12. Corrigan-Curay J, Sacks L, Woodcock J. Real-World Evidence and Real-World Data for Evaluating Drug Safety and Effectiveness. *JAMA* 2018; 320(9):867–8.
13. Ricotta EE, Bustos Carrillo FA, Angelli-Nichols S, Barugahare J, Benton A, Carlson CJ et al. Observational research in epidemic settings: a roadmap to reform. *BMJ Glob Health* 2025; 10(2).
14. Jarow JP, LaVange L, Woodcock J. Multidimensional Evidence Generation and FDA Regulatory Decision Making: Defining and Using "Real-World" Data. *JAMA* 2017; 318(8):703–4.
15. Botsis T, Hartvigsen G, Chen F, Weng C. Secondary Use of EHR: Data Quality Issues and Informatics Opportunities. *Summit on Translat Bioinforma* 2010; 2010:1–5.
16. Petersen JM, Ranker LR, Barnard-Mayers R, MacLehose RF, Fox MP. A systematic review of quantitative bias analysis applied to epidemiological research. *Int J Epidemiol* 2021; 50(5):1708–30.
17. Higgins JPT, Altman DG, Gøtzsche PC, Jüni P, Moher D, Oxman AD et al. The Cochrane Collaboration's tool for assessing risk of bias in randomised trials. *BMJ* 2011; 343:d5928.
18. Higgins JP, Thomas J, Chandler J, Cumpston M, Li T, Page MJ et al., editors. *Cochrane Handbook for Systematic Reviews of Interventions*. Wiley; 2019.
19. Tregoning JS, Flight KE, Higham SL, Wang Z, Pierce BF. Progress of the COVID-19 vaccine effort: viruses, vaccines and variants versus efficacy, effectiveness and escape. *Nat Rev Immunol* 2021; 21(10):626–36.
20. Wilson BE, Booth CM. Real-world data: bridging the gap between clinical trials and practice. *EClinicalMedicine* 2024; 78:102915.
21. Liu F, Panagiotakos D. Real-world data: a brief review of the methods, applications, challenges and opportunities. *BMC Med Res Methodol* 2022; 22(1):287.
22. Hannah KJ, Ball MJ, Haux R, Winter A, Ammenwerth E, Brigl B. *Strategic Information Management in Hospitals*. New York, NY: Springer New York; 2004.
23. Haux R. Health information systems - past, present, future. *Int J Med Inform* 2006; 75(3-4):268–81.
24. Charles P. Friedman. *Toward Complete & Sustainable Learning Systems*. University of Michigan; 2014 [cited 2025 Feb 26]. Available from: URL: https://medicine.umich.edu/sites/default/files/2014_12_08-Friedman-IOM%20LHS.pdf.
25. Friedman CP, Wong AK, Blumenthal D. Achieving a nationwide learning health system. *Sci Transl Med* 2010; 2(57):57cm29.
26. Friedman C, Rubin J, Brown J, Buntin M, Corn M, Etheredge L et al. Toward a science of learning systems: a research agenda for the high-functioning Learning Health System. *J Am Med Inform Assoc* 2015; 22(1):43–50.
27. Grossmann C, Powers B, McGinnis JM, editors. *Digital Infrastructure for the Learning Health System: The Foundation for Continuous Improvement in Health and Health Care: Workshop Series Summary*. Washington (DC); 2011.
28. European Commission. *European Research Infrastructures: What Research Infrastructures are, what the Commission is doing, strategy areas, funding and news.*; 2020 [cited 2025 Feb 26]. Available from: URL: https://research-and-innovation.ec.europa.eu/strategy/strategy-research-and-innovation/our-digital-future/european-research-infrastructures_en.
29. Chen AT-Y. How fragmentation can undermine the public health response to Covid-19. *interactions* 2021; 28(2):64–9.

30. Dron L, Kalatharan V, Gupta A, Haggstrom J, Zariffa N, Morris AD et al. Data capture and sharing in the COVID-19 pandemic: a cause for concern. *Lancet Digit Health* 2022; 4(10):e748-e756.
31. Robert Koch-Institut. Intensivkapazitäten und COVID-19-Intensivbettenbelegung in Deutschland; 2025.
32. Verordnung zur Aufrechterhaltung und Sicherung intensivmedizinischer Krankenhauskapazitäten: DIVI IntensivRegister-Verordnung; 2020.
33. Winkelmann J, Panteli D, Berger E, Busse R, others. Have we learnt the right lessons? Intensive care capacities during the COVID-19 pandemic in Europe. *Eurohealth* 2022; 28(1):1–5.
34. Dagliati A, Malovini A, Tibollo V, Bellazzi R. Health informatics and EHR to support clinical research in the COVID-19 pandemic: an overview. *Brief Bioinform* 2021; 22(2):812–22.
35. Raab R, Küderle A, Zakreuskaya A, Stern AD, Klucken J, Kaissis G et al. Federated electronic health records for the European Health Data Space. *Lancet Digit Health* 2023; 5(11):e840-e847.
36. Bogaert P, Verschuuren M, van Oyen H, van Oers H. Identifying common enablers and barriers in European health information systems. *Health Policy* 2021; 125(12):1517–26.
37. World Health Organization. Classification of digital interventions, services and applications in health: a shared language to describe the uses of digital technology for health, 2nd ed: A shared language to describe the uses of digital technology for health,. 2nd ed.; 2023.
38. World Health Organization. Monitoring and Evaluating Digital Health Interventions: A practical guide to conducting research and assessment.
39. World Health Organization. Global strategy on digital health 2020-2025. Geneva; 2021.
40. Pommerening K, Müller T. Leitfaden zum Datenschutz in medizinischen Forschungsprojekten: Generische Lösungen der TMF 2.0. MWV Medizinisch Wissenschaftliche Verlagsgesellschaft mbH & Co. KG; 2020.
41. Rosenau L, Behrend P, Wiedekopf J, Gruendner J, Ingenerf J. Uncovering Harmonization Potential in Health Care Data Through Iterative Refinement of Fast Healthcare Interoperability Resources Profiles Based on Retrospective Discrepancy Analysis: Case Study. *JMIR Med Inform* 2024; 12:e57005.
42. Tsai CH, Eghdam A, Davoody N, Wright G, Flowerday S, Koch S. Effects of Electronic Health Record Implementation and Barriers to Adoption and Use: A Scoping Review and Qualitative Analysis of the Content. *Life (Basel)* 2020; 10(12).
43. Honavar SG. Electronic medical records – The good, the bad and the ugly. *Indian J Ophthalmol* 2020; 68(3):417–8.
44. Kim E, Rubinstein SM, Nead KT, Wojcieszynski AP, Gabriel PE, Warner JL. The Evolving Use of Electronic Health Records (EHR) for Research. *Semin Radiat Oncol* 2019; 29(4):354–61.
45. Boeckhout M, Zielhuis GA, Bredenoord AL. The FAIR guiding principles for data stewardship: fair enough? *Eur J Hum Genet* 2018; 26(7):931–6.
46. Dugas M, Blumenstock M, Dittrich T, Eisenmann U, Feder SC, Fritz-Kebede F et al. Next-generation study databases require FAIR, EHR-integrated, and scalable Electronic Data Capture for medical documentation and decision support. *NPJ Digit Med* 2024; 7(1):10.
47. Shah SM, Khan RA. Secondary Use of Electronic Health Record: Opportunities and Challenges. *IEEE Access* 2020; 8:136947–65.
48. Kahn MG, Callahan TJ, Barnard J, Bauck AE, Brown J, Davidson BN et al. A Harmonized Data Quality Assessment Terminology and Framework for the Secondary Use of Electronic Health Record Data. *EGEMS (Wash DC)* 2016; 4(1).
49. Liaw S-T, Guo JGN, Ansari S, Jonnagaddala J, Godinho MA, Borelli AJ et al. Quality assessment of real-world data repositories across the data life cycle: A literature review. *J Am Med Inform Assoc* 2021; 28(7):1591–9.

50. Lehne M, Sass J, Essenwanger A, Schepers J, Thun S. Why digital medicine depends on interoperability. *NPJ Digit Med* 2019; 2:79.
51. Hickey GL, Grant SW, Cosgriff R, Dimarakis I, Pagano D, Kappetein AP et al. Clinical registries: governance, management, analysis and applications. *Eur J Cardiothorac Surg* 2013; 44(4):605–14.
52. Brown JS, Holmes JH, Shah K, Hall K, Lazarus R, Platt R. Distributed health data networks: a practical and preferred approach to multi-institutional evaluations of comparative effectiveness, safety, and quality of care. *Med Care* 2010; 48(6 Suppl):S45-51.
53. González-García J, Estupiñán-Romero F, Tellería-Orriols C, González-Galindo J, Palmieri L, Faragalli A et al. Coping with interoperability in the development of a federated research infrastructure: achievements, challenges and recommendations from the JA-InfAct. *Arch Public Health* 2021; 79(1):221.
54. Weber GM, Murphy SN, McMurry AJ, Macfadden D, Nigrin DJ, Churchill S et al. The Shared Health Research Information Network (SHRINE): a prototype federated query tool for clinical data repositories. *J Am Med Inform Assoc* 2009; 16(5):624–30.
55. Hallock H, Marshall SE, Hoen PAC 't, Nygård JF, Hoorne B, Fox C et al. Federated Networks for Distributed Analysis of Health Data. *Front Public Health* 2021; 9:712569.
56. Semler SC, Wissing F, Heyder R. German Medical Informatics Initiative. *Methods Inf Med* 2018; 57(S 01):e50-e56.
57. Joos S, Nettelbeck DM, Reil-Held A, Engelmann K, Moosmann A, Eggert A et al. German Cancer Consortium (DKTK) - A national consortium for translational cancer research. *Mol Oncol* 2019; 13(3):535–42.
58. Kristoffersen ES, Bjorvatn B, Halvorsen PA, Nilsen S, Fossum GH, Fors EA et al. The Norwegian PraksisNett: a nationwide practice-based research network with a novel IT infrastructure. *Scand J Prim Health Care* 2022; 40(2):217–26.
59. Cuggia M, Combes S. The French Health Data Hub and the German Medical Informatics Initiatives: Two National Projects to Promote Data Sharing in Healthcare. *Yearb Med Inform* 2019; 28(1):195–202.
60. Brammen D, Greiner F, Kulla M, Otto R, Schirrmeister W, Thun S et al. AKTIN – The German Emergency Department Data Registry – real-time data from emergency medicine. *Med Klin Intensivmed Notfmed* 2020.
61. Wettstein R, Hund H, Fegeler C, Heinze O. Data Sharing in Distributed Architectures - Concept and Implementation in HiGHmed. *Stud Health Technol Inform* 2021; 283:111–8.
62. Slagman A, Pigorsch M, Greiner F, Behringer W, Bernhard M, Bienzeisler J et al. Medical and cardiovascular emergency department visits during the COVID-19 pandemic in 2020: is there a collateral damage? A retrospective routine data analysis. *Clin Res Cardiol* 2022; 111(10):1174–82.
63. Kulla M, Röhrig R, Helm M, Bernhard M, Gries A, Lefering R et al. Nationaler Datensatz "Notaufnahme": Entwicklung, Struktur und Konsentierung durch die Deutsche Interdisziplinäre Vereinigung für Intensivmedizin und Notfallmedizin. *Anaesthesist* 2014; 63(3):243–52.
64. Schranz M, Boender TS, Greiner T, Kocher T, Wagner B, Greiner F et al. Changes in emergency department utilisation in Germany before and during different phases of the COVID-19 pandemic, using data from a national surveillance system up to June 2021. *BMC Public Health* 2023; 23(1):799.
65. Boender TS, Cai W, Schranz M, Kocher T, Wagner B, Ullrich A et al. Using routine emergency department data for syndromic surveillance of acute respiratory illness, Germany, week 10 2017 until week 10 2021. *Euro Surveill* 2022; 27(27).
66. Schlump C, Thom J, Boender TS, Wagner B, Diercke M, Kocher T et al. Nutzung von Routinedaten aus Notaufnahmen zur Surveillance von Suizidversuchen und psychiatrischen Notfällen. *Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz* 2022; 65(1):30–9.
67. AKTIN Research Group. Öffentlicher Jahresbericht 2023 des AKTIN-Notaufnahmeregisters; 2024.

68. Otto R, Blaschke S, Schirrmeister W, Drynda S, Walcher F, Greiner F. Length of stay as quality indicator in emergency departments: analysis of determinants in the German Emergency Department Data Registry (AKTIN registry). *Intern Emerg Med* 2022; 17(4):1199–209.
69. Otto R, Schirrmeister W, Majeed RW, Greiner F, Lucas B, Röhrig R et al. Implementation of Emergency Department Performance Benchmarking Using R and LaTeX. *Stud Health Technol Inform* 2019; 267:238–46.
70. Ahlbrandt J, Brammen D, Majeed RW, Lefering R, Semler SC, Thun S et al. Balancing the need for big data and patient data privacy--an IT infrastructure for a decentralized emergency care research database. *Stud Health Technol Inform* 2014; 205:750–4.
71. Bienzeisler J, Kombeiz A, Ehrentreich S, Otto R, Schirrmeister W, Pegoraro M et al. Implementation report on pioneering federated data access for the German National Emergency Department Data Registry. *NPJ Digit Med* 2025; 8(1):94.
72. Seeger I, Klausen AD, Günther U, Bienzeisler J, Schnack H, Lubasch JS. Gründe für die Nichtteilnahme an einer Patientenbefragung im Kontext der prähospitalen Notfallversorgung durch Gemeindenotfallsanitäter - eine retrospektive Beobachtungsstudie. *Z Evid Fortbild Qual Gesundhwes* 2024; 187:61–8.
73. Bienzeisler J, Triefenbach L, Kombeiz A, Lottes M, Vogel C, Grabenhenrich L et al. A Federated and Distributed Data Management Infrastructure to Enable Public Health Surveillance from Intensive Care Unit Data. *Stud Health Technol Inform* 2022; 294:490–4.
74. Bienzeisler J, Becker G, Erdmann B, Kombeiz A, Majeed RW, Röhrig R et al. The Effects of Displaying the Time Targets of the Manchester Triage System to Emergency Department Personnel: Prospective Crossover Study. *J Med Internet Res* 2024; 26:e45593.
75. Kombeiz A, Bienzeisler J, Majeed RW, Röhrig R, Aktin RG. Designing a User-Friendly Data Request Management System for a Growing Health Data Network - A Case Study in the AKTIN Registry. *Stud Health Technol Inform* 2024; 321:69–73.
76. Azad M, Pandey R, Bergemann R. HPR54 The European Health Data Space (EHDS): Probable Impact, Possible Challenges and Proposed Solutions to Using Electronic Health Records (EHRs) for Research and Policy Shaping in the Region. *Value in Health* 2024; 27(6):S204.
77. Chen H, Zhao Y, Cao B, Petersen DJ, Valente MJ, Cen W. Breaking the silence of sharing data in medical research. *PLoS One* 2024; 19(5).
78. Asplin BR, Magid DJ, Rhodes KV, Solberg LI, Lurie N, Camargo CA. A conceptual model of emergency department crowding. *Ann Emerg Med* 2003; 42(2):173–80.
79. Christ M, Bingisser R, Nickel CH. Bedeutung der Triage in der klinischen Notfallmedizin. *Dtsch Med Wochenschr* 2016; 141(5):329–35.
80. Crawford SM. Goodhart's law: when waiting times became a target, they stopped being a good measure. *BMJ* 2017; 359:j5425.
81. Goodhart CAE. Problems of Monetary Management: The UK Experience. In: Goodhart CAE, editor. *Monetary Theory and Practice*. London: Macmillan Education UK; 1984. p. 91–121.
82. Sartini M, Carbone A, Demartini A, Giribone L, Oliva M, Spagnolo AM et al. Overcrowding in Emergency Department: Causes, Consequences, and Solutions—A Narrative Review. *Healthcare (Basel)* 2022; 10(9).
83. Goodacre S. Uncontrolled before-after studies: discouraged by Cochrane and the EMJ. *Emerg Med J* 2015; 32(7):507–8.
84. Bienzeisler J, Hoy W, Kombeiz A, Alhaskir M, Röhrig R, Majeed R et al. Beating the Clock: A Prediction Model for Timely Care in Emergency Departments. *Stud Health Technol Inform* 2024; 316:1657–8.
85. Antunes RS, Da André Costa C, Küderle A, Yari IA, Eskofier B. Federated Learning for Healthcare: Systematic Review and Architecture Proposal. *ACM Trans. Intell. Syst. Technol.* 2022; 13(4):1–23.
86. Li H, Singhal M. Trust Management in Distributed Systems. *Computer* 2007; 40(2):45–53.

87. Blaze M, Feigenbaum J, Ioannidis J, Keromytis AD. The Role of Trust Management in Distributed Systems Security. In: Goos G, Hartmanis J, van Leeuwen J, Vitek J, Jensen CD, editors. *Secure Internet Programming*. Berlin, Heidelberg: Springer Berlin Heidelberg; 1999. p. 185–210 [Lecture Notes in Computer Science].
88. Faguet J-P. Decentralization and Governance. *World Development* 2014; 53:2–13.
89. Foucault M. *Security, territory, population: Lectures at the Collège de France 1977-78*. Basingstoke: Palgrave Macmillan; 2009. (Lectures at the Collège de France).
90. Senellart M, Foucault M, editors. *The Birth of Biopolitics: Lectures at the Collège de France, 1978 - 79*. 1st pbk ed., [Repr.]. New York: Picador; 2010. (Lectures at the Collège de France).
91. Latour B. *Reassembling the social: An introduction to Actor-Network-Theory*. 1. publ. in pbk. Oxford: Oxford Univ. Press; 2007. (Clarendon lectures in management studies).
92. Harari YN. *Nexus: A brief history of information networks from the Stone Age to AI*. First edition. New York: Random House; 2024.
93. Bienzeisler J, Fischer H, Thiemann VS, Röhrig R. Human-Induced Errors in Networked Healthcare Research: Risk Management Under the GDPR. *Stud Health Technol Inform* 2020; 270:1128–32.
94. Kho ME, Duffett M, Willison DJ, Cook DJ, Brouwers MC. Written informed consent and selection bias in observational studies using medical records: systematic review. *BMJ* 2009; 338:b866.
95. Röhrig R, Schlünder I, Bienzeisler J, Sax U, Lipprandt M, Balzer F, Hübner U, Semler SC, Dincklage F. Das Gesundheitsdatennutzungsgesetz und seine Bedeutung für die Forschung in der Intensiv- und Notfallmedizin: Erläuterungen und erste Handlungsempfehlungen. *DIVI* 2024; 15:16–24.
96. Gehring S, Eulenfeld R. German Medical Informatics Initiative: Unlocking Data for Research and Health Care. *Methods Inf Med* 2018; 57(S 01):e46-e49.
97. Beyan O, Choudhury A, van Soest J, Kohlbacher O, Zimmermann L, Stenzhorn H et al. Distributed Analytics on Sensitive Medical Data: The Personal Health Train. *Data Intellegence* 2020; 2(1-2):96–107.
98. Triefenbach L, Otto R, Bienzeisler J, Kombeiz A, Ehrentreich S, Röhrig R et al. Establishing a Data Quality Baseline in the AKTIN Emergency Department Data Registry - A Secondary Use Perspective. *Stud Health Technol Inform* 2022; 294:209–13.
99. Weiskopf NG, Bakken S, Hripcsak G, Weng C. A Data Quality Assessment Guideline for Electronic Health Record Data Reuse. *EGEMS (Wash DC)* 2017; 5(1).
100. Weiskopf NG, Weng C. Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research. *J Am Med Inform Assoc* 2013; 20(1):144–51.
101. Nohr EA, Liew Z. How to investigate and adjust for selection bias in cohort studies. *Acta Obstet Gynecol Scand* 2018; 97(4):407–16.
102. Arts DGT, Keizer NF de, Scheffer G-J. Defining and improving data quality in medical registries: a literature review, case study, and generic framework. *J Am Med Inform Assoc* 2002; 9(6):600–11.
103. Ryu AJ, Romero-Brufau S, Qian R, Heaton HA, Nestler DM, Ayanian S et al. Assessing the Generalizability of a Clinical Machine Learning Model Across Multiple Emergency Departments. *Mayo Clin Proc Innov Qual Outcomes* 2022; 6(3):193–9.
104. Chen RJ, Wang JJ, Williamson DFK, Chen TY, Lipkova J, Lu MY et al. Algorithmic fairness in artificial intelligence for medicine and healthcare. *Nat Biomed Eng* 2023; 7(6):719–42.
105. Bienzeisler J, Bax SN, Schunk D, Wrede C, Erdmann B, Walcher F. Notfallversorgung: Die digitale Rettungskette. *Deutsches Ärzteblatt* 2024; 121(12):828-831.
106. Mehta N, Devarakonda MV. Machine learning, natural language programming, and electronic health records: The next step in the artificial intelligence journey? *J Allergy Clin Immunol* 2018; 141(6):2019-2021.e1.
107. Munoz-Gama J, Martin N, Fernandez-Llatas C, Johnson OA, Sepúlveda M, Helm E et al. Process mining for healthcare: Characteristics and challenges. *J Biomed Inform* 2022; 127:103994.

Danksagung

Eigentlich wollte ich schon vor drei Jahren fertig sein, aber das ist bei uns im Institut nichts Neues. Mein erster Dank gilt Rainer, der mir den ein oder anderen Nerv gekostet hat, aber am Ende meistens – wenn nicht sogar immer – Recht hatte. Ich danke auch Raphael, der mir mit seinem Wissen und seiner Unterstützung immer zur Seite stand.

Ein riesiges Dankeschön geht an meine Brüder Lasse und Nils. Ohne euren Input hätte ich sicher keine der Publikationen schreiben können. Genauso danke ich meiner Mama, die einfach zu allem fachlich gute Ratschläge geben kann. Ich glaube, wir alle wären ohne sie nie in der Wissenschaft gelandet, und ich bin unglaublich dankbar für ihren Wertekompass. Ihre Erfahrung aus der Wissenschaft und ihr Weitblick haben mir oft geholfen, die richtigen Entscheidungen zu treffen. Mein Dank gilt auch meiner Schwägerin Neele und meinem Schwager Timo, auf deren Hilfe ich mich genauso immer verlassen kann.

Am meisten möchte ich mich bei Caro bedanken. Du hast mich nicht nur immer unterstützt, sondern mich auch mit deinem eigenen, vor meiner abgeschlossenen Dissertation angespornt – mehr noch als die anderen. Du bist immer für mich da, unterstützt mich und hörst mir zu, selbst wenn ich zum 500. Mal dasselbe über meine Arbeit erzähle. Besonders danke ich dir auch dafür, dass du mir oft genug sagst, ich soll mal nicht so viel arbeiten und lieber zu dir auf die Couch kommen oder mit dir laufen.

Last but not least möchte ich mich bei meinen wunderbaren Kolleg:innen Lucas, Ariadna, Simon, Beatrice, Mo, William, Simon, Emily, Elmo, Dustin, Jan und Alexander bedanken. Ohne euch hätte die Arbeit nur halb so viel Spaß gemacht. Ich schätze mich glücklich, in einem Institut zu arbeiten, in dem ich euch als Kolleg:innen habe. In den letzten Jahren habe ich gelernt, dass es ein Privileg ist, Wissenschaft in einem nicht-toxischen Umfeld betreiben zu dürfen. Danke an das ganze IMI, vor allen an Frau Fuchs, Frau Huth und Frau Czichy, deren Unterstützung man so selten sieht. Danke Behrus, dessen Büro immer offenstand. Auch dem Magdeburger Team rund um AKTIN – Wiebke, Felix, Susanne, Ronny, Corinne, Kai und Saskia – gilt mein herzlicher Dank dafür, dass es so viel Spaß macht, im Team nach der Weltherrschaft zu trachten. Ebenso danke ich dem Team Notaufnahme: Miriam, Jenny und Jörg. Ich hoffe viele spannende Projekte folgen.

Danke an jede:n Einzelne:n!

Erklärung § 5 Abs. 1 zur Datenaufbewahrung

Hiermit erkläre ich, dass die dieser Dissertation zu Grunde liegenden Originaldaten im Institut für Medizinische Informatik des Universitätsklinikums Aachen hinterlegt sind.

Erklärung gemäß § 5 Abs. (1) und (2), und § 11 Abs. (3) 12. der Promotionsordnung

Hiermit erkläre ich, **Jonas Bienzeisler**, an Eides statt, dass ich den wesentlichen Anteil an der Publikation geleistet habe:

Bienzeisler J, Triefenbach L, Kombeiz A, Lottes M, Vogel C, Grabenhenrich L, Fischer M, Kocher T, Niekrenz L, Dreher M, Müller C, Röhrig R, Majeed RW; AKTIN and SPoCK Research Group.

A Federated and Distributed Data Management Infrastructure to enable public health surveillance from Intensive Care Unit Data. Stud Health Technol Inform. 2022 May 25;294:490-494. doi: 10.3233/SHTI220507.

Die Anteile an der Arbeit waren wie folgt:

	Jonas Bienzeisler	Lucas Triefenbach	Alexander Kombeiz	Matthäus Lottes	Cristopher Vogel	Linus Grabenhenrich	Martina Fischer	Theresa Kocher	Lukas Niekrenz	Michael Dreher	Christoph Müller	Rainer Röhrig	Raphael W. Majeed
Studienüberwachung	60	5	10	5		5			5		10		
Konzeption	40					20						20	20
Datenerhebung	60		20								20		
Datenauswertung	80		5	10									5
Bereitstellung von Materialien	40					20				20		20	
Interpretation der Datenauswertung	70			5								5	20
Verfassung des Manuskripts	100												
Korrektur des Manuskripts		8	8	8	8	8	8	8	8	8	8	8	12

Aus diesem wesentlichen Anteil ergibt sich selbstverständlich die Stellung als Erstautor.

Jonas Bienzeisler

Als Doktorvater bestätige ich die Angaben von Jonas Bienzeisler.

Univ.-Prof Dr. med Rainer Röhrig (Doktorvater)

Ich schließe mich der Erklärung von Rainer Röhrig als Koautor an

Lucas Triefenbach

Alexander Kombeiz

Matthäus Lottes

Christopher Vogel

Linus Grabenhenrich

Martina Fischer

Theresa Kocher

Lukas Niekrenz

Michael Dreher

Christoph Müller

Raphael W. Majeed

Erklärung gemäß § 5 Abs. (1) und (2), und § 11 Abs. (3) 12. der Promotionsordnung

Hiermit erkläre ich, **Jonas Bienzeisler**, an Eides statt, dass ich den wesentlichen Anteil an der Publikation geleistet habe:

Bienzeisler J, Kombeiz A, Ehrentreich S, Otto R, Schirrmeister W, Pegoraro M, Brammen D, Puladi B, Röhrig R, Majeed RW, AKTIN Research Group. Implementation Report on Pioneering Federated Data Access for the German National Emergency Department Data Registry. NPJ Digital Medicine 2025 doi: 10.1038/s41746-025-01481-w;

Die Anteile an der Arbeit waren wie folgt:

	Jonas Bienzeisler	Alexander Kombeiz	Saskia Ehrentreich	Ronny Otto	Wiebke Schirrmeister	Marco Pegoraro	Dominik Brammen	Behrus Puladi	Rainer Röhrig	Raphael W. Majeed
Studienüberwachung	50	10	10	10	10					10
Studiendesign/Konzeption	50						10		20	20
Datenerhebung	50	5	5	5	10		2,5	2,5	10	10
Datenauswertung	70	5	5	5		2,5		2,5		10
Statistische Auswertung	70	5	5	5		2,5		2,5		10
Bereitstellung von Materialien	20				5		5		65	5
Interpretation der Datenauswertung	70							10	10	10
Verfassung des Manuskripts	100									
Korrektur des Manuskripts	10	10	10	10	10	10	10	10	10	10

Aus diesem wesentlichen Anteil ergibt sich selbstverständlich die Stellung als Erstautor.

Jonas Bienzeisler

Als Doktorvater bestätige ich die Angaben von Jonas Bienzeisler.

Univ.-Prof Dr. med Rainer Röhrig (Doktorvater)

Ich schließe mich der Erklärung von Rainer Röhrig als Koautor an

Alexander Kombeiz

Saskia Ehrentreich

Ronny Otto

Wiebke Schirrmeister

Marco Pegoraro

Dominik Brammen

Behrus Puladi

Raphael W. Majeed

Erklärung gemäß § 5 Abs. (1) und (2), und § 11 Abs. (3) 12. der Promotionsordnung

Hiermit erkläre ich, **Jonas Bienzeisler**, an Eides statt, dass ich den wesentlichen Anteil an der folgenden Publikation geleistet habe:

Bienzeisler J, Becker G, Erdmann B, Kombeiz A, Majeed RW, Röhrig R, Greiner F, Otto R, Otto-Sobotka F, AKTIN Research Group. *The Effects of Displaying the Time Targets of the Manchester Triage System to Emergency Department Personnel: Prospective Crossover Study.* J Med Internet Res 2024;26:e45593 doi: 10.2196/45593.

Die Anteile an der Arbeit waren wie folgt:

	Jonas Bienzeisler	Guido Becker	Alexander Kombeiz	Bernadett Erdmann	Raphael W. Majeed	Rainer Röhrig	Felix Greiner	Ronny Otto	Fabian Otto-Sobotka
Studienüberwachung		10		50		35			5
Studiendesign/Konzeption	10	5		30		50			5
Datenerhebung	90	5		5					
Datenauswertung	95	1		1		1	1	1	
Statistische Auswertung	65	1		1		1	1	1	30
Bereitstellung von Materialien	60			30		10			
Interpretation der Datenauswertung	90					5			5
Verfassung des Manuskripts	100								
Korrektur des Manuskripts		10	10	10	10	15	10	10	25

Aus diesem wesentlichen Anteil ergibt sich selbstverständlich die Stellung als Erstautor.

Jonas Bienzeisler

Als Doktorvater bestätige ich die Angaben von Jonas Bienzeisler.

Univ.-Prof Dr. med Rainer Röhrig (Doktorvater)

Ich schließe mich der Erklärung von Rainer Röhrig als Koautor an

Guido Becker

Alexander Kombeiz

Bernadett Erdmann

Raphael W. Majeed

Felix Greiner

Ronny Otto

Fabian Otto-Sobotka

Erklärung gemäß § 5 Abs. (1) und (2), und § 11 Abs. (3) 12. der Promotionsordnung

Hiermit erkläre ich, **Jonas Bienzeisler**, an Eides statt, dass ich den wesentlichen Anteil an der folgenden Publikation geleistet habe:

Bienzeisler J, Triefenbach L, Kombeiz A, Lottes M, Vogel C, Grabenhenrich L, Fischer M, Kocher T, Niekrenz L, Dreher M, Müller C, Röhrig R, Majeed RW; AKTIN and SPoCK Research Group.

A Federated and Distributed Data Management Infrastructure to enable public health surveillance from Intensive Care Unit Data. Stud Health Technol Inform. 2022 May 25;294:490-494. doi: 10.3233/SHTI220507.

Bienzeisler J, Kombeiz A, Ehrentreich S, Otto R, Schirrmeister W, Pegoraro M, Brammen D, Puladi B, Röhrig R, Majeed RW, AKTIN Research Group. *Implementation Report on Pioneering Federated Data*

Access for the German National Emergency Department Data Registry. NPJ Digital Medicine 2025 doi: 10.1038/s41746-025-01481-w;

Bienzeisler J, Becker G, Erdmann B, Kombeiz A, Majeed RW, Röhrig R, Greiner F, Otto R, Otto-Sobotka F, AKTIN Research Group. *The Effects of Displaying the Time Targets of the Manchester Triage System to*

Emergency Department Personnel: Prospective Crossover Study. J Med Internet Res 2024;26:e45593 doi: 10.2196/45593

Während der Erstellung dieser Arbeiten habe ich Grammarly und das Sprachmodell ChatGPT von OpenAI ausschließlich zur sprachlichen Überarbeitung der Manuskripte genutzt. Nach der Verwendung dieser Werkzeuge habe ich den Inhalt überprüft, nach Bedarf bearbeitet und übernehme die volle Verantwortung für die endgültige Fassung der Arbeit.

Jonas Bienzeisler

Curriculum Vitae

Jonas Bienzeisler, geboren am 27.05.1991 in Bremen

Berufserfahrung

Seit 09/2019 **Institut für Medizinische Informatik, Uniklinik RWTH Aachen** Wissenschaftlicher Mitarbeiter
Forschungsschwerpunkt: Research Infrastructure

08/2018 – 08/2019 **Abteilung für Medizinische Informatik, Carl von Ossietzky Universität Oldenburg**
Wissenschaftlicher Mitarbeiter
Forschungsschwerpunkt: Research Infrastructure

Ausbildung

10/2016 – 05/2019 **Universität zu Lübeck**
M.Sc. Medizinische Ingenieurwissenschaft

09/2013 – 10/2016 **Universität zu Lübeck**
B. Sc. Medizinische Ingenieurwissenschaft

09/2003 – 07/2010 **Gymnasium Syke**
Allgemeine Hochschulreife

Publikationen

2017 **Bienzeisler J**, Landry M, Llorente A, Hüttmann G. Analysis of the in-vivo GABAB receptor relocalization and oligomerization in chronic pain conditions using spatial intensity distribution analysis. *Current Directions in Biomedical Engineering*. 2017 Sep 26;3(2):669-73

2020 **Bienzeisler J**, Fischer H, Thiemann VS, Röhrig R. Human-Induced Errors in Networked Healthcare Research: Risk Management Under the GDPR. *Stud Health Technol Inform* 2020;270:1128-1132. doi: 10.3233/SHTI200338.

2020 Drynda S, Schindler W, Slagman A, Pollmanns J, Horenkamp-Sonntag D, Schirrmeister W, Otto R, **Bienzeisler J**, Greiner F, Drösler S, Lefering R, Hitzek J, Röhrig R, Swart E, Walcher F. Evaluation of outcome relevance of quality indicators in the emergency department (ENQuIRE): study protocol for a prospective multicentre cohort study. *BMJ Open* 2020;10:e038776. doi: 10.1136/bmjopen-2020-038776.

2022 Löbe M, Bialke M, **Bienzeisler J**, Drepper J, Ganslandt T, Haderer S, Kraska D, Lablans M, Sax U, Speer R, Stäubert S, Kaulke K, Board of Trustees of the ToolPool

Gesundheitsforschung. ToolPool Gesundheitsforschung - A Repository for Software and Services Focused on Supporting Clinical and Epidemiological Research. *Stud Health Technol Inform* 2022;293:19-27. doi: 10.3233/SHTI220342.

- 2022 Triefenbach L, Otto R, **Bienzeisler J**, Kombeiz A, Ehrentreich S, Röhrig R, Majeed RW, AKTIN Research Group. Establishing a Data Quality Baseline in the AKTIN Emergency Department Data Registry - A Secondary Use Perspective. *Stud Health Technol Inform* 2022;294:209-213. doi: 10.3233/SHTI220439.
- 2022 Slagman A, Pigorsch M, Greiner F, Behringer W, Bernhard M, **Bienzeisler J**, Blaschke S, Burst V, Dechant K, Dommasch M, Ewen S, Gries A, Hans FP, Kanz KG, Klein M, Kümpers P, Napp M, Plata C, Ramshorn-Zimmer A, Risse J, Röhrig R, Somasundaram R, Schunk D, Walcher F, Möckel M. Medical and cardiovascular emergency department visits during the COVID-19 pandemic in 2020: is there a collateral damage? A retrospective routine data analysis. *Clin Res Cardiol* 2022;111:1174–1182. doi: 10.1007/s00392-022-02074-3.
- 2022 Brücken D, Unterkofler J, Pauge S, **Bienzeisler J**, Hübel C, Zechbauer S, Rossaint R, Greiner W, Aufenberg B, Röhrig R, Bollheimer LC, Optimal@NRW Research Group, Brokmann JC. Optimal@NRW: optimized acute care of nursing home residents using an intersectoral telemedical cooperation network - study protocol for a stepped-wedge trial. *Trials* 2022;23(1):814. doi: 10.1186/s13063-022-06613-1.
- 2022 **Bienzeisler J**, Triefenbach L, Kombeiz A, Lottes M, Vogel C, Grabenhenrich L, Fischer M, Kocher T, Niekrenz L, Dreher M, Müller C, Röhrig R, Majeed RW; AKTIN and SPoCK Research Group. A Federated and Distributed Data Management Infrastructure to enable public health surveillance from Intensive Care Unit Data. *Stud Health Technol Inform*. 2022 May 25;294:490-494. doi: 10.3233/SHTI22050706/2024
- 2023 Boender S, Greiner T, Kocher T, Wagner B, Greiner F, **Bienzeisler J**, Diercke M, Grabenhenrich L, AKTIN Research Group, Aigner A, Ullrich A. Changes in emergency department utilisation in Germany before and during different phases of the COVID-19 pandemic, using data from a national surveillance system up to June 2021. *BMC Public Health* 2023;23:799. doi: 10.1186/s12889-023-15375-7.06/2024
- 2023 **Bienzeisler J**, Perez-Garriga A, Brandl LC, Kock-Schoppenhauer AK, Hollenbenders Y, Kurscheidt M, Schüttler C. Report from the 68th GMDS Annual Meeting: Science. Close to People. *Methods Inf Med* 2023;62(5-06):202-205. doi: 10.1055/s-0043-1777733.
- 2024 **Bienzeisler J**, Becker G, Erdmann B, Kombeiz A, Majeed RW, Röhrig R, Greiner F, Otto R, Otto-Sobotka F, AKTIN Research Group. The Effects of Displaying the Time Targets of the Manchester Triage System to Emergency Department

- Personnel: Prospective Crossover Study. J Med Internet Res 2024;26:e45593 doi: 10.2196/45593
- 2024 Seeger I, Klausen AD, Günther U, **Bienzeisler J**, Schnack H, Lubasch JS. Gründe für die Nichtteilnahme an einer Patientenbefragung im Kontext der prähospitalen Notfallversorgung durch Gemeindenedfallsanitäter - eine retrospektive Beobachtungsstudie [Reasons for non-participation in a patient survey in the context of prehospital emergency medical care by community emergency paramedics - A retrospective observational study]. Z Evid Fortbild Qual Gesundhwes 2024;187:61-68. doi: 10.1016/j.zefq.2024.03.007.
- 2024 Heidemeyer H, Auhagen L, Majeed RW, Pegoraro M, **Bienzeisler J**, Peeva V, Beyel H, Röhrig R, van der Aalst WMP, Puladi B. A Pipeline for the Usage of the Core Data Set of the Medical Informatics Initiative for Process Mining - A Technical Case Report. Stud Health Technol Inform 2024;317:30-39. doi: 10.3233/SHTI240835.
- 2024 Kombeiz A, **Bienzeisler J**, Majeed RW, Röhrig R, AKTIN Research Group. Designing a User-Friendly Data Request Management System for a Growing Health Data Network - A Case Study in the AKTIN Registry. Stud Health Technol Inform 2024;321:69-73. doi: 10.3233/SHTI241065.
- 2024 **Bienzeisler J**, Bax SN, Schunk D, Wrede C, Erdmann B, Walcher F. Notfallversorgung: Die digitale Rettungskette. Deutsches Ärzteblatt 2024;121(12):828-831.
- 2025 **Bienzeisler J**, Kombeiz A, Ehrentreich S, Otto R, Schirrmeister W, Pegoraro M, Brammen D, Puladi B, Röhrig R, Majeed RW, AKTIN Research Group. Implementation Report on Pioneering Federated Data Access for the German National Emergency Department Data Registry. NPJ Digital Medicine 2025 doi: 10.1038/s41746-025-01481-w.

Kongressbeiträge

- 2015 **Bienzeisler J**, Lüdtke-Buzug K, Schemberg J. Magnetic flow field separation of superparamagnetic dextran coated iron oxide nanoparticles. Postervortrag, 5th International Workshop on Magnetic Particle Imaging (IWMPPI), Istanbul, Turkey, 26–28 March 2015. IEEE; 2015. doi: 10.1109/IWMPPI.2015.7107063.
- 2019 **Bienzeisler J**, Fischer H, Majeed RW, Röhrig R. Drawing upon the German National Emergency Registry for the Development of Holistic Quality Indicators: A Federated and Distributed Data Management Infrastructure. Vortrag, Proc 17th World Congress on Medical and Health Informatics, Lyon, France 25.08 - 30.08.2019.

- 2019 **Bienzeisler J**, Fischer H, Schindler W, Majeed RW, Swart E, Röhrig R, Thiemann VS. Eine datenschutzkonforme Forschungsinfrastruktur zum Verknüpfen multipler Datenquellen in der vernetzten Versorgungsforschung aufbauend auf dem Nationalen Notaufnahmeregister. Vortrag, 18. Deutscher Kongress für Versorgungsforschung (DKVF). Berlin, 09.-11.10.2019. Düsseldorf: German Medical Science GMS Publishing House; 2019. Doc19dkvf003. doi: 10.3205/19dkvf003.
- 2019 **Bienzeisler J**, B Erdmann, G Becker, D Brammen, VS Thiemann, F Otto-Sobotka, R Röhrig: Influence of the Presentation of the Target Time of the Manchester Triage System on the Real Waiting Time in Emergency Departments: A Prospective Cross-Over Study. Vortrag , 64th Annual Meeting of the German Association for Medical Informatics, Biometry and Epidemiology (GMDS), Dortmund 08.09-11.09.2019. German Medical Science GMS Publishing House; 2019. DocAbstr. 249.
- 2020 **Bienzeisler J**, Pérez Garriga A, Fortmann J, Wienströer J, Bley J, Bender B, Lutz I, Szimtenings L, Dill B, Hellmonds M, Haferkamp S, Müller-Wieland D, Cornelissen C, Röhrig R, Majeed RW, Covid-Aachen-STC. A multi-step strategy for rapid development of a research infrastructure for urgent research projects and subsequent pooling of data. Early lessons learned from SARS-CoV-2-pandemic activities. Vortrag, 65th Annual Meeting of the German Association for Medical Informatics, Biometry and Epidemiology (GMDS), Meeting of the Central European Network (CEN: German Region, Austro-Swiss Region and Polish Region) of the International Biometric Society (IBS). Berlin (online conference), 06.-09.09.2020.
- 2021 **Bienzeisler J**. Lässt sich in der Notaufnahme die stationäre Behandlungsdauer abschätzen? Vortrag, 21. Kongress der Deutschen Interdisziplinären Vereinigung für Intensiv- und Notfallmedizin. Virtueller Kongress, 01.–03.12.2021.
- 2021 Unterkofler J, **Bienzeisler J**, Laurentius T, Röhrig R, Bollheimer C. Fitness for use of routine geriatric documentation for the development of predictive models in the context of early rehabilitative geriatric complex treatment. Postervortrag, Gerontologie und Geriatrie Kongress 2022. Frankfurt, 12.09-15.09.2022. Z Gerontol Geriatr 2022;55(Suppl 1):130. doi: 10.1007/s00391-022-02091-w
- 2022 **Bienzeisler J**, A Kombeiz, RW Majeed, R Roehrig. Record Linkage with Data from the AKTIN Emergency Room

Registry: Lessons learned from the ENQUIRE Study.
Vortrag DGSMP/DGMS 2022. Magdeburg, 07.06-
09.09.2022. Gesundheitswesen 2022;84(08/09). doi:
10.1055/s-0042-1753928.

- 2022 **Bienzeisler J**, Triefenbach L, Kombeiz A, Lottes M, Vogel C, Grabenhenrich L, Fischer M, Kocher T, Niekrenz L, Dreher M, Müller C, Röhrig R, Majeed RW; AKTIN and SPoCK Research Group. A Federated and Distributed Data Management Infrastructure to enable public health surveillance from Intensive Care Unit Data. Vortrag, MIE 2022, Nice, France 27.05–30.05.2022 Stud Health Technol Inform. 2022 May 25;294:490-494. doi: 10.3233/SHTI22050706/2024
- 2023 **Bienzeisler J**, Kombeiz A, Triefenbach L, Röhrig R, Majeed RW, AKTIN-Research Group. Central monitoring of a decentralized registry – lessons learned from the AKTIN Emergency Department Data Registry. Postervortrag, 68. Jahrestagung der Deutschen Gesellschaft für Medizinische Informatik, Biometrie und Epidemiologie (GMDS). Heilbronn, 17.-21.09.2023. Düsseldorf: German Medical Science GMS Publishing House; 2023. doi: 10.3205/23gmds130.
- 2023 **Bienzeisler J**, Majeed RW, Röhrig R, Moen A, Berntsen GR, Bellika JG. Federated and distributed medical research – Fortune or misfortune? Pro and con session. Panel, MIE 2023. Gothenburg, 22.05.-25.05.2023.
- 2023 **Bienzeisler J**, Drynda S, Ganslandt T, Kombeiz A, Röhrig R, Otto R, Moen A, Ognjanovic I, Bellika JG. Caring before Sharing - Validating EHR Data in Federated and Distributed Research Infrastructures. Workshop, MIE 2023. Gothenburg, Sweden 22.05.-25.05.2023.
- 2023 **Bienzeisler J**, Bax S, Brammen D, Drynda S, Erdmann B, Röhrig R, Schunk D, Wrede C, Walcher F. Die digitale Rettungskette. Vortrag, 68. Jahrestagung der Deutschen Gesellschaft für Medizinische Informatik, Biometrie und Epidemiologie (GMDS), Heilbronn, 17.-21.09.2023. Düsseldorf: German Medical Science GMS Publishing House; 2023. DocAbstr. 210. doi: 10.3205/23gmds062.
- 2023 **Bienzeisler J**, Bax S, Brammen D, Drynda S, Erdmann B, Röhrig R, Schunk D, Wrede C, Walcher F. Effiziente Kommunikation im Rettungswesen: Konzept der Digitalen Rettungskette. Vortrag, 23. Kongress der Deutschen Interdisziplinären Vereinigung für Intensiv- und Notfallmedizin (DIVI). Hamburg, 29.11.–01.12.2023.
- 2024 **Bienzeisler J**, Hoy W, Kombeiz A, Alhaskir M, Röhrig R, Majeed R, Unterkofler J, Puladi B. Beating the Clock: A Prediction Model for Timely Care in Emergency

Departments. Postervortrag, MIE 2024 Athen, Greece, 25.08-29.08.2024 Stud Health Technol Inform. 2024 Aug 22;316:1657-1658. doi: 10.3233/SHTI240741.

- 2024 **Bienzeisler J**, Auhagen LA, Kombeiz A, Puladi B, Röhrig R, Majeed RW. Analyzing the Temporal Dynamics of the Federated Data Access Authorization Process in the AKTIN Emergency Department Data Registry. Postervortrag Kooperationstagung der GMDS, DGSMP, DGEpi, DGMS und DGPH. Dresden, 08.-13.09.2024. Düsseldorf: German Medical Science GMS Publishing House; 2024. doi: 10.3205/24gmds159.
- 2024 Röhrig R, Semler SC, **Bienzeisler J**, Bucher AM, Nienaber U, Penzkofer T, Schirmeister W, Thewes D, Windeck S. Das Gesundheitsdatennutzungsgesetz – erste Erfahrungen aus drei NUM-Infrastrukturprojekten und erste Ergebnisse der TMF-Interoperabilitätsinitiative. Workshop Kooperationstagung der GMDS, DGSMP, DGEpi, DGMS und DGPH, Dresden, Deutschland, 08.–13.09.2024. Düsseldorf: German Medical Science GMS Publishing House; 2024. DocAbstr. 190. doi: 10.3205/24gmds235.
- 2024 **Bienzeisler J**. Vorhersage der rechtzeitigen Versorgung in Notaufnahme: Machine Learning für Risikostratifizierung im Crowding-Management. Postervortrag, 24. Kongress der Deutschen Interdisziplinären Vereinigung für Intensiv- und Notfallmedizin (DIVI). Hamburg, 04.12–06.12.2024.
- 2024 **Bienzeisler J**. Was macht die Interoperabilität so kompliziert? Technische Sicht. Vortrag, 24. Kongress der Deutschen Interdisziplinären Vereinigung für Intensiv- und Notfallmedizin (DIVI). Hamburg, 04.12–06.12.2024.

Auzeichnungen

- 2022 Best Poster Award: Unterkofler J, **Bienzeisler J**, Laurentius T, Röhrig R, Bollheimer C. Fitness for use of routine geriatric documentation for the development of predictive models in the context of early rehabilitative geriatric complex treatment. Z Gerontol Geriatr 2022;55(Suppl 1):130. doi: 10.1007/s00391-022-02091-w.
- 2023 Innovationspreis Medizinische Register 2023, 3. Platz

Forschungsförderung

- 2021 AKTIN@NUM (START 124/21), Beteiligt an Antragstellung. BMBF, Förderkennzeichen 01KX2121. Bewilligungszeitraum: 01.01.2021 – 30.06.2025. Bewilligte Mittel: 6 Mio. €.

- 2021 Echtzeit-Versorgungsforschung mit dem AKTIN-Notaufnahmeregister (AKTIN-EZV), Beteiligt an Antragstellung. BMBF, Förderkennzeichen 01KX2121. Bewilligungszeitraum: 01.09.2020 – 31.03.2021. Bewilligte Mittel: 3,7 Mio. €.
- 2023 AKTIN 2.0, Beteiligt an Antragstellung. BMBF, Förderkennzeichen 01KX2121. Bewilligungszeitraum: 01.07.2023 – 30.06.2025. Bewilligte Mittel: 1,8 Mio. €
- 2023 KlimaNot, Beteiligt an Antragstellung. G-BA Innovationsfonds. Förderkennzeichen 01VSF23017. Bewilligungszeitraum: 01.01.2024 – 31.12.2026. Bewilligte Mittel: 1,8 Mio. €
- 2023 EDCareKids, Mitantragsteller. G-BA Innovationsfonds, Förderkennzeichen VSF23042. Bewilligungszeitraum: 01.01.2024 – 31.12.2026. Bewilligte Mittel: 1,9 Mio. €.
- 2024 TRANSPARENT, Beteiligt an Antragstellung, Koordinator. G-BA Innovationsfonds. Förderkennzeichen 01VSF24027. Bewilligungszeitraum: 01.01.2025 – 31.12.2027. Bewilligte Mittel: 2,2 Mio. €.
- 2024 PARALLEL (1. Stufe), Beteiligt an Antragstellung, Koordinator. G-BA Innovationsfonds. Bewilligungszeitraum: 01.01.2025 – 30.06.2025. Bewilligte Mittel: 75.Tsd. €.