AI2MED

Artificial Intelligence in Medical Care: Reducing Errors and Saving Lives

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AI2MED

Project 101140217

D4.4: Methodology on AI use-case presentations in medicine

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DISSEMINATION LEVEL		
PU	Public, fully open	X
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Executive Summary

AI2MED (Artificial Intelligence in Medical Care: Reducing Errors and Saving Lives) is an Erasmus+ project that aims to equip healthcare professionals, educators, and students with the knowledge and skills needed to integrate artificial intelligence (AI) into medical practice safely and effectively.

This deliverable presents **the methodology for developing and presenting AI use-case scenarios in medicine**. **A total of 57 use-case scenarios have been created across five MOOCs,** covering topics from data management and cybersecurity to AI ethics and practical technical skills. These cases provide practical, real-world examples that help learners understand how AI is applied in healthcare settings, the benefits it offers, and the challenges that must be addressed.

The use-case scenarios **complement the AI2MED MOOCs by bridging theoretical knowledge with applied understanding, supporting various educational formats including self-study, classroom teaching, group work, and assessment activities**.

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1 Introduction

The integration of artificial intelligence into healthcare represents **one of the most significant technological transformations in modern medicine**. From diagnostic imaging to clinical decision support, AI applications are increasingly prevalent across medical specialties. However, the effective adoption of these technologies requires healthcare professionals to understand not only the technical capabilities of AI systems but also their practical applications, limitations, and ethical implications.

The importance of practical, real-world AI examples in medical education cannot be overstated. While theoretical knowledge provides the foundation for understanding AI concepts, it is through concrete use cases that learners can truly grasp how these technologies function in clinical settings. **Use-case scenarios create a crucial link between theoretical learning and applied understanding, enabling students and professionals to contextualize AI capabilities within familiar healthcare workflows**.

The objectives of this deliverable are threefold: first, to explain the methodology used by the AI2MED consortium to develop structured AI-in-MED use-case scenarios; second, to demonstrate how these use cases can be effectively utilized in various educational contexts; and third, to provide a comprehensive collection of use-case scenarios that cover the full spectrum of AI applications in medicine.

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2 AI-in-MED Use-Case Scenarios

2.1 How We Developed the Use-Case Scenarios

The development of the AI-in-MED use-case scenarios followed a systematic methodology designed to ensure relevance, quality, and educational value. The process drew upon multiple sources and involved careful selection criteria to create a comprehensive collection of practical examples.

Sources Used

The use-case scenarios were developed using a combination of partner expertise, academic research, clinical practice observations, and market needs analysis. Each partner institution contributed domain-specific knowledge based on their areas of specialization. Scientific literature and peer-reviewed publications provided evidence-based examples of AI applications. Insights from practicing healthcare professionals ensured clinical relevance, while analysis of current trends in AI healthcare adoption informed the selection of topics.

Selection Criteria

Use cases were selected based on several key criteria: relevance to current AI applications in healthcare, diversity across medical fields and AI technologies, inclusion of ethical aspects and considerations, appropriate level of complexity for the target audience, and availability of sufficient documentation and evidence. This multi-criteria approach ensured a balanced collection that addresses various aspects of AI in medicine.

Template for Consistency

To ensure consistency across all use cases, the consortium developed a standardized Use Case Card Template. This template includes eleven key fields that capture essential information about each AI application: Use case name, Use case description, Stakeholders, Inputs, Process, Results/Output, Benefits, Limitations and challenges, Application examples, Sources, and Additional information. This structured approach ensures that all use cases provide comparable information and can be easily integrated into educational materials.

2.2 How to Use the Use-Case Scenarios

The AI-in-MED use-case scenarios are designed to complement the AI2MED MOOCs and can be used in multiple educational contexts:

Complementing AI2MED MOOCs

Each use-case is aligned with specific modules and units within the five AI2MED MOOCs. Learners can reference relevant use cases while progressing through the course material to see practical applications of the concepts being taught.

Understanding Practical AI Applications

The use cases help learners understand how AI technologies function in real healthcare settings, including the types of data required, the processes involved, and the expected outcomes.

Educational Formats

The use cases can be utilized in self-study for individual learning and reflection, classroom teaching as illustrative examples and discussion starters, group work for collaborative analysis and problem-solving exercises, and assessment as case studies for evaluation of learning outcomes.

Adaptability and Reusability

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The standardized format makes the use cases adaptable to different educational contexts and reusable across various programs. Educators can modify or extend the use cases to meet specific learning objectives or local requirements.

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3 List of AI-in-MED Use-Case Scenarios

This section presents all 57 use-case scenarios developed for the AI2MED project, organized by MOOC. Each use case follows the standardized template format to ensure consistency and completeness.

3.1 MOOC 1: Data Management and Cybersecurity

This MOOC contains 8 use-case scenarios covering various aspects of data management and cybersecurity.

3.1.1 Using a AI-powered tool to help healthcare professional with preventing antibiotic resistance (Antimo)

Module: Developing a healthcare data management strategy

Unit: Assessing Healthcare Data Needs and Challenges

Use case name	Using a AI-powered tool to help healthcare professional with preventing antibiotic resistance (Antimo)
Use case description	AntiMo is a tool designed to support healthcare professionals in preventing antibiotic resistance. It accomplishes this by optimizing antibiotic prescriptions and continuously monitoring resistance patterns within hospital settings. Utilizing artificial intelligence, AntiMo analyzes clinical data to identify patients at risk for antibiotic-resistant infections. The platform features a digital antibiogram that predicts antibiotic resistance hours before traditional laboratory results, allowing clinicians to select appropriate therapies proactively. By adhering to the World Health Organization's AWaRe guidelines, AntiMo promotes responsible antibiotic use and reduces unnecessary prescriptions.
Stakeholders	• Healthcare Professionals • Microbiologists • Hospital managers
Inputs	Patient data (medical history, clinical symptoms)
Process	• The healthcare professional adds patient's data • Antimo analyzes patients data and predicts antibiotic resistance • The healthcare professional proactively selects the appropriate therapy using the AWaRE guidelines
Results/Output	• Digital antibiogram • Data aggregation • Data visualization

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Benefits	• Simplified data analysis • Time saving • Antibiotic resistance prevention
Limitations and challenges	• Data entry within the tool is required • Some hospital tools might not be compatible yet with the tool • Need for staff training on the new platform.
Application examples	• Visualization of data trends • Prevention of antibiotic resistance • Analysis of clinical data trends by researchers • Enhanced patient management.
Sources	AntiMO Kelyon
Additional information	• Article by ANSA (Italian): Nasce AntiMo, la nuova piattaforma IA contro l'antibiotico-resistenza • Medicina • Ansa.it

3.1.2 Developing a framework for stronger healthcare data management

Module: Developing a healthcare data management strategy

Unit: Designing and implementing a Comprehensive Data Management Framework

Use case name	Developing a framework for stronger healthcare data management
Use case description	Development of a framework that uses IoT products, such as sensors, and services to manage healthcare data in order to support remote monitoring and improve clinical responsiveness.
Stakeholders	• Patients • Healthcare professionals • Hospital managers
Inputs	• Patient data

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	• Stakeholder knowledge
Process	1. Communication with stakeholders to evaluate feature importance 2. Incorporation of existing tools 3. Data collection 4. Data analysis 5. Creation of a framework
Results/Output	• Structured data • Reatime data
Benefits	• Better analytics • Enhanced data management • Organizational performance • Personalized intervention for patients • Cost control • Greater patient satisfaction
Limitations and challenges	• Potential resistance to change • Need for training and support • Collaboration between stakeholders is crucial: need for a communication protocol between stakeholders • Data should have high quality: fragmentation should be avoided
Application examples	• Hospitals utilizing analytics to enhance decision-making • Institutions enhancing data compliance frameworks.
Sources	• Negash, Y. T., & Hanum, F. (2025). An analytical framework for improving healthcare data management and organizational performance. Healthcare Analytics, 8, 100415. https://doi.org/10.1016/j.health.2025.100415 • Javed, A. R., Sarwar, M. U., Beg, M. O., Asim, M., Baker, T., & Tawfik, H. (2020). A collaborative healthcare framework for shared healthcare plan with ambient intelligence. Human-Centric Computing and Information Sciences, 10(1). https://doi.org/10.1186/s13673-020-00245-7
Additional information	• Palanisamy, V., & Thirunavukarasu, R. (2019). Implications of big data analytics in developing healthcare frameworks – A review. Journal of King Saud University • Computer and Information Sciences, 31(4), 415–425. https://doi.org/10.1016/j.jksuci.2017.12.007

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	• Oliva, S. Z., & Felipe, J. C. (2018). Optimizing public healthcare management through a data warehousing analytical framework. IFAC-PapersOnLine, 51(27), 407–412. https://doi.org/10.1016/j.ifacol.2019.02.004

3.1.3 Managing Big Data in healthcare

Module: Developing a healthcare data management strategy

Unit: Evaluating and Optimizing Data Management Strategies

Use case name	Managing Big Data in healthcare
Use case description	Management of a large volume of data in the healthcare environment, including hospital records, patient medical records, and exam results, in order to derive meaningful results.
Stakeholders	• IT specialists • Hospital managers
Inputs	• Large amount of data
Process	• Evaluate the problem of big data management with mathematicians, computer scientists, and biologists • Select a tool to work with big data such as Hadoop or Apache Spark to distribute data between multiple machines • Extract data from documents, use OCR to recognize the characters from print documents if required or analyze images to extract data • Use Artificial Intelligence to organize data
Results/Output	• Structured data
Benefits	• Better management of large data • Easy access to large data • Data querying • Data visualization
Limitations and challenges	• Large storage might require cloud solutions, which might raise data privacy concerns • Initial high costs • Data might require some cleaning in preparation

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	• A unique format is needed to store data • Data sharing between various hospitals might be useful
Application examples	• Storing data for large hospitals • Querying data collected from multiple healthcare facilities
Sources	• Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: management, analysis and future prospects. Journal of Big Data, 6(1). https://doi.org/10.1186/s40537-019-0217-0
Additional information	-

3.1.4 Easy management of electronic medical records in resource-constrained settings by using a free and open source solution (OpenMRS)

Module: Developing a healthcare data management strategy

Unit: Fundamentals of a data management strategy

Use case name	Easy management of electronic medical records in resource-constrained settings by using a free and open source solution (OpenMRS)
Use case description	OpenMRS is an open-source electronic medical record (EMR) platform designed to manage patient data in resource-constrained settings. It allows healthcare providers to collect, manage, and analyze patient information efficiently, facilitating improved patient care and record-keeping.
Stakeholders	• Healthcare professionals • Patients • Data analysts • IT technicians
Inputs	• Patient medical history • Clinical notes • Laboratory results • Imaging data • Treatment plans
Process	1. Data is collected from various sources

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	2. Healthcare providers access the records for clinical decisions 3. Data can be used for analytics and research
Results/Output	• Electronic patient health records • Real-time data accessibility for healthcare providers
Benefits	• Better management of patient health records • Real-time data accessibility for healthcare providers • Improved patient care through informed decision-making • Simplified analysis of data
Limitations and challenges	• Need for training staff to utilize the system effectively • Potential issues with data interoperability with other healthcare systems • Maintenance and support challenges
Application examples	• Hospitals in developing countries using OpenMRS for patient record management • Community health programs utilizing OpenMRS for tracking health interventions and patient follow-ups • Research initiatives leveraging OpenMRS data for public health studies
Sources	OpenMRS
Additional information	• Introduction to OpenMRS and Open Source Software (OSS) EMR • Mohammed-Rajput NA, Smith DC, Mamlin B, Biondich P, Doebbeling BN; Open MRS Collaborative Investigators. OpenMRS, a global medical records system collaborative: factors influencing successful implementation. AMIA Annu Symp Proc. 2011;2011:960-8. Epub 2011 Oct 22. PMID: 22195155; PMCID: PMC3243141. • Mamlin, B. W., Shivers, J. E., Glober, N. K., & Dick, J. J. (2021). OpenMRS as an emergency EMR—How we used a global good to create an emergency EMR in a week. International Journal of Medical Informatics, 149, 104433. https://doi.org/10.1016/j.ijmedinf.2021.104433 • Kerr, K. A., Norris, T., & Stockdale, R. (2008). The strategic management of data quality in healthcare. Health Informatics Journal, 14(4), 259–266. https://doi.org/10.1177/1460458208096555 • Healthcare Management: Strategies for Optimizing Efficiency and Patient Outcomes https://www.proquest.com/openview/f94d138b95bbb1ca6af903f75fbd2030

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3.1.5 Data compliance in applications using IoT

Module: Healthcare Data Governance

Unit: Data compliance in healthcare

Use case name	Data compliance in applications using IoT
Use case description	When offering data services in the European Union, strict adherence to data compliance regulations is crucial for protecting patients' privacy. This involves aligning with the General Data Protection Regulation (GDPR), implementing security measures, and ensuring transparency in data handling.
Stakeholders	• Healthcare professionals • Patients • Hospital managers • Lawyers
Inputs	• Sensor or device data • Patient data • Regulations
Process	• Make sure that communication between sensor or device data and services takes place over a securely paired channel • Encrypt data before storage • Store encrypted data
Results/Output	• Data GDPR compliance
Benefits	• More privacy for patients • Reduced security risks
Limitations and challenges	• Slower implementation • Higher upfront costs
Application examples	• Privacy-respecting Electronic Health Register • Privacy-respecting remote visit
Sources	• Kammüller, F., Ogunyanwo, O. O., & Probst, C. W. (2019). Designing Data Protection for GDPR Compliance into IoT Healthcare Systems (Version 1). arXiv. https://doi.org/10.48550/ARXIV.1901.02426

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Additional information	• van Kolfschooten, H., & van Oirschot, J. (2024). The EU Artificial Intelligence Act (2024): Implications for healthcare. Health Policy (Amsterdam, Netherlands), 149(105152), 105152. https://doi.org/10.1016/j.healthpol.2024.105152

3.1.6 Ensuring data governance in healthcare services

Module: Healthcare Data Governance

Unit: Foundations of Healthcare Data Governance

Use case name	Ensuring data governance in healthcare services
Use case description	Healthcare data includes sensitive personal information such as medical histories, diagnoses, treatments, prescriptions, test results and home addresses, making it both valuable and at risk for misuse and theft. Protecting data privacy and security is crucial for safeguarding patient rights, preventing identity theft and cyber-attacks, maintaining trust in the healthcare system, ensuring continuity of care, and adhering to legal and ethical standards.
Stakeholders	• Patients • Legal experts • Software engineers
Inputs	• Data compliance laws • Data governance techniques • Patient data
Process	• Establish policies for privacy and security • Define responsibilities and roles • Assess employee training • Create accountability measures for all stakeholders • Ensure simple communication between stakeholders • Make communication between stakeholders secure • Guarantee data safety to avoid theft of sensitive data
Results/Output	Healthcare management that prioritizes privacy to reduce data theft and safeguard patient information
Benefits	• More privacy for patient

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	• Less risks for patients • More security for healthcare data
Limitations and challenges	• Communication between stakeholders is required • Need for staff training • Healthcare data needs to be carefully managed to avoid data thefts • Staff should work abiding to regulations
Application examples	
Sources	A. Faridoon, and M.T. Kechadi, "Healthcare Data Governance, Privacy, and Security - A Conceptual Framework," 2024 https://arxiv.org/pdf/2403.17648
Additional information	Winter, J. S., & Davidson, E. (2018). Big data governance of personal health information and challenges to contextual integrity. The Information Society, 35(1), 36–51. https://doi.org/10.1080/01972243.2018.1542648

3.1.7 Creation of a healthcare data life cycle

Module: Healthcare Data Governance

Unit: Healthcare data life cycle

Use case name	Creation of a healthcare data life cycle
Use case description	With the digitalization of healthcare, health services managers must improve data life cycles to manage data and produce high quality datasets.
Stakeholders	• Healthcare professionals • IT specialists • Hospital managers
Inputs	• Patient data • Hospital data
Process	• Analyze current data • Get new data • Clean or transform data • Ensure data quality • Manage data access, data security and distribution • Manage data analysis

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Results/Output	Clinical data management
Benefits	• Better data quality • Better data management • Better analytics • Data standardization
Limitations and challenges	• Need to enforce the data strategy
Application examples	• Hill Physicians Medical Group commissioned a work to manage healthcare data life cycle, see additional information
Sources	• Zhang, J., Symons, J., Agapow, P., Teo, J. T., Paxton, C. A., Abdi, J., Mattie, H., Davie, C., Torres, A. Z., Folarin, A., Sood, H., Celi, L. A., Halamka, J., Eapen, S., & Budhdeo, S. (2022). Best practices in the real-world data life cycle. PLOS Digital Health, 1(1), e0000003. https://doi.org/10.1371/journal.pdig.0000003
Additional information	• Verma, Ravi, and Jeannette Harper. "Life cycle of a data warehousing project in healthcare." Journal of healthcare information management 15.2 (2001): 107-118. https://webdocs.cs.ualberta.ca/~zaiane/courses/cmput605/2008/pdf/Life_Cycle.pdf

3.1.8 Data quality issues in healthcare and simple solutions

Module: Healthcare Data Governance

Unit: Introduction to Data Governance Strategies

Use case name	Data quality issues in healthcare and simple solutions
Use case description	Data quality issues present a major challenge for healthcare databases. High-quality data is essential for effective data analysis. Therefore, prioritizing data quality assessment is crucial in healthcare data management.
Stakeholders	• Data analysts • Healthcare professionals • IT specialists
Inputs	• Patient data

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Process	• Establish a team for quality management • Create a standard for data • Modernize legacy systems • Actively manage data integrity • Find and manage duplicate data
Results/Output	Better data quality
Benefits	• Better data quality • Better data standards • Better analysis
Limitations and challenges	• Need for qualified staff • Higher initial costs • Need for a defined standard • Need for trained staff • Resistance to change from the staff
Application examples	
Sources	• Strong, D. M., Lee, Y. W., & Wang, R. Y. (1997). Data quality in context. Communications of the ACM, 40(5), 103–110. https://doi.org/10.1145/253769.253804 • Botsis T, Hartvigsen G, Chen F, Weng C. Secondary Use of EHR: Data Quality Issues and Informatics Opportunities. Summit Transl Bioinform. 2010 Mar 1;2010:1-5. PMID: 21347133; PMCID: PMC3041534. https://pmc.ncbi.nlm.nih.gov/articles/PMC3041534/
Additional information	• Sukumar, Sreenivas R., Ramachandran Natarajan, and Regina K. Ferrell. "Quality of Big Data in health care." International journal of health care quality assurance 28.6 (2015): 621-634. https://www.osti.gov/servlets/purl/1193181

3.2 MOOC 2: Advanced Digital Competencies

This MOOC contains 20 use-case scenarios covering various aspects of advanced digital competencies.

3.2.1 Patient Vital Signs Monitoring with Device Calibration Inconsistencies

Module: Data Visualization

Unit: Data Cleaning & Preprocessing for Visualization

Use case name	Patient Vital Signs Monitoring with Device Calibration Inconsistencies
Use case description	Vital signs monitoring systems in hospitals generate massive volumes of continuous patient data, yet device calibration inconsistencies, systematic measurement errors, and data quality issues can significantly compromise clinical decision-making. This use case addresses the implementation of comprehensive data quality assessment and cleaning protocols to identify and correct measurement artifacts, value preferences, and calibration drift across multiple monitoring devices. The system detects logically inconsistent readings, identifies systematic rounding patterns, validates physiological plausibility, and implements automated quality control checks to ensure reliable vital signs data for clinical dashboards and early warning systems.
Stakeholders	• Clinical Engineering: Medical device calibration and maintenance oversight • Nursing Staff: Front-line vital signs documentation and patient monitoring • Quality Assurance: Hospital-wide data quality monitoring and improvement • IT Department: Electronic health record system management and integration • Rapid Response Teams: Early warning score calculation and deterioration detection • Hospital Administration: Patient safety compliance and resource allocation
Inputs	Continuous vital signs data streams from bedside monitors (blood pressure, heart rate, respiratory rate, temperature, oxygen saturation) Device metadata, including model, calibration dates, maintenance records, and serial numbers Historical baseline measurements and patient demographic information Clinical reference ranges and physiological plausibility thresholds Manual nursing documentation and spot-check measurements Device calibration protocols and manufacturer specifications
Process	1. Data Quality Assessment and Pattern Detection Statistical profiling analyses vital signs distributions to identify value preferences such as temperature clustering at 36.0°C or blood pressure rounded to the nearest 10. Maximum likelihood estimation quantifies the excess prevalence of

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	preferred values, while pattern recognition detects temporal inconsistencies coinciding with device changes. 2. Outlier Detection and Validation Combines statistical methods (z-scores, IQR) with clinical plausibility checks to distinguish physiological extremes from artifacts. Identifies logically inconsistent readings like diastolic exceeding systolic pressure, and validates vital signs combinations against medical possibility thresholds. 3. Device Calibration Monitoring Tracks individual device accuracy over time using Bland-Altman analysis to quantify systematic bias. Correlates quality issues with calibration schedules to identify devices requiring maintenance or replacement. 4. Automated Quality Control Real-time monitoring triggers alerts when devices exceed error thresholds or when systematic quality issues emerge. Quality dashboards provide hospital-wide visibility into measurement reliability across units and device types. 5. Data Cleaning Implementation Flags potentially unreliable measurements, removes confirmed artifacts with documentation, and applies forward-fill imputation for short monitoring gaps. All cleaning actions are logged in detailed audit trails for traceability
Results/Output	Quality-assured vital signs dataset with validated measurements Device performance reports identifying monitors requiring calibration Quality metrics dashboard showing measurement accuracy across units Automated alerts for device malfunction and systematic quality issues
Benefits	Enhanced Patient Safety: Prevents missed deterioration and false alarms through reliable vital signs monitoring Proactive Device Management: Early detection enables scheduled maintenance before devices produce misleading data Resource Optimisation: Reducing false alarms allows clinical staff to focus on genuine patient care needs Regulatory Compliance: Quality documentation demonstrates adherence to medical device safety standards
Limitations and challenges	Clinical Context Dependency: Automated checks cannot always distinguish artifacts from genuine physiological extremes in critically ill patients Retrospective Detection: Many quality issues identified after data collection, limiting real-time clinical utility Imputation Uncertainty: Filling missing values introduces assumptions that may not reflect true patient status Resource Requirements: Comprehensive monitoring demands significant computational infrastructure and clinical engineering expertise
Application examples	Oxford University Hospitals NHS Trust (2016-2019) Analysis of 4,375,654 vital signs records from 135,173 patients revealed 11.3% of temperature measurements inappropriately recorded as 36.0°C (480,000+ inaccurate readings). Blood pressure and heart rate showed 2.0-2.4% rounding to nearest 10. Quality issues varied significantly by patient age, sex, length of stay, and between medical versus surgical specialties, demonstrating need for tailored quality control approaches. ICU Vital Signs Quality Study (PSNet/AHRQ) Automated analysis of 50,000 ICU patient stays found >33%

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	omission rates in required hourly measurements. Study identified numerous logically inconsistent blood pressure readings with diastolic exceeding systolic values—physiological impossibilities indicating systematic errors. Significant proportion of outlier values required clinical review to distinguish genuine extremes from measurement artifacts.
Sources	https://www.nature.com/articles/s41598-023-30691-z https://psnet.ahrq.gov/issue/errors-omissions-and-outliers-hourly-vital-signs-measurements-intensive-care https://pubmed.ncbi.nlm.nih.gov/38551079/
Additional information	Comprehensive data quality assessment employs statistical profiling to identify measurement distributions and anomalies, validates clinical plausibility through domain-specific constraint checking, and implements systematic outlier detection using both univariate and multivariate methods. Preprocessing workflows incorporate automated quality monitoring with real-time alerts, systematic validation rules aligned with physiological boundaries, and detailed audit trail documentation ensuring full traceability of all cleaning decisions while maintaining separation between raw measurements and quality-assured datasets for analytical use.

3.2.2 Population Health Management Dashboard for Chronic Disease Monitoring

Module: Data Visualization

Unit: Design Principles in Medical Contexts

Use case name	Population Health Management Dashboard for Chronic Disease Monitoring
Use case description	Interactive visualisation dashboard for monitoring chronic disease prevalence and outcomes across patient populations. The system integrates data from EHRs, laboratory systems, and pharmacy records to display geographic disease distribution, demographic breakdowns, risk stratification, and care quality metrics. Design emphasises color-coded geographic heat maps, time-series trend analysis, and hierarchical information display following clinical decision-making workflows.
Stakeholders	• Population health managers, • Primary care physicians, • Health system administrators, • Quality improvement teams, • Public health officials,

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	• Care coordinators, • Policymakers
Inputs	EHR data: ICD-10 diagnosis codes, patient demographics, encounter histories. Laboratory data: HbA1c levels, lipid panels, blood pressure readings. Pharmacy data: Medication adherence, prescription patterns. Quality metrics: Care gap indicators, screening completion rates. Geographic data: Patient locations, social determinants of health by zip code
Process	1. Data Integration: Extract patient data from multiple sources using standardised queries 2. Geographic Mapping: Apply color-coded heat maps (green=low prevalence, yellow=moderate, red=high) showing disease distribution across regions 3. Risk Stratification: Group patients using visual encoding—bar chart lengths represent risk levels, color intensity indicates urgency 4. Trend Analysis: Display time-series line charts with reference range bands showing disease progression over months/years 5. Dashboard Layout: Organise information hierarchically—critical metrics (high-risk patients) positioned upper-left, detailed breakdowns accessible via progressive disclosure 6. Accessibility Design: Implement colorblind-friendly palettes, high contrast ratios, redundant encoding (color symbols)
Results/Output	Interactive dashboard providing: • Geographic heat maps showing chronic disease hotspots • Demographic breakdowns by age, gender, race/ethnicity using grouped bar charts • Risk-stratified patient lists with color-coded severity indicators • Time-series charts tracking population health metrics over time • Quality measure compliance displays with alert systems • Drill-down capabilities from population to individual patient level
Benefits	Addresses 90% of $4.1 trillion annual healthcare costs attributed to chronic disease management Supports monitoring of 129 million Americans with chronic conditions (42% with 2+ conditions) Reduced cognitive load through proper visual hierarchy and information organisation Rapid pattern recognition via color-coded alerts (red=critical, yellow=warning, green=normal) Improved care coordination through clear visualisation of patient risk categories Accessible design ensures all clinicians can interpret critical information regardless of color perception

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Limitations and challenges	Data quality variability across different EHR systems requires careful color selection for clinical environments with variable lighting conditions. Risk of information overload if the dashboard design is not properly hierarchical. Alert fatigue if warning thresholds are not carefully calibrated. Requires ongoing validation that visualisations accurately represent underlying data. Need for staff training to interpret visual encodings correctly
Application examples	CDC Chronic Disease Indicators (CDI) Web Tool: Interactive dashboard system tracking 113 indicators across 21 topic areas with state-level data. Features geographic maps, bar graphs, and trend analysis for conditions including hypertension (32% adult prevalence), diabetes (13.2%), and obesity (42%). System received over 1 million page views since its 2015 launch. Princeton Health Affiliated Physicians (PHAP): Integrated Lightbeam Health Solutions population health software with EHR to monitor chronic disease patients. Dashboard enables providers to identify care gaps, risk-stratify patients, and assign high-risk individuals to care managers. System replaced the manual pivot table process, providing seamless access to performance metrics and patient needs. Design Implementation: Both systems apply Unit 3 principles—hierarchical information layout, color-coded risk stratification, time-series trending, geographic heat mapping, and accessible visual encodings supporting rapid clinical decision-making.
Sources	https://www.cdc.gov/pcd/issues/2024/24_0109.htm https://www.cdc.gov/chronic-diseas e/data-research/facts-stats/index.html https://www.healthit.gov/success-story/using-population-health-data-chronic-behavioral-disease-management
Additional information	Dashboard design applies evidence-based visualisation principles, including hierarchical information layout with critical metrics positioned upper-left, standardised medical color conventions (red for high-risk alerts, yellow for warnings, green for normal ranges), redundant encoding strategies for accessibility, and progressive disclosure supporting both rapid assessment and detailed analysis. Geographic heat maps, time-series trend charts, and demographic comparison displays follow clinical decision-making workflows while maintaining high contrast ratios suitable for variable hospital lighting conditions.

3.2.3 Emergency Department Patient Flow Real-Time Tracking Dashboard

Module: Data Visualization

Unit: Interactive Visualizations & Dashboards

Use case name	Emergency Department Patient Flow Real-Time Tracking Dashboard

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Use case description	Real-time dashboard systems utilise AI and data analytics to continuously monitor and optimise patient flow in emergency departments. These systems automatically track patients from arrival to discharge, analyse bottlenecks, predict wait times, and provide actionable insights to healthcare staff. The dashboard displays a geographical ED layout with patient locations, real-time wait times, bed availability, and staff assignments, enabling proactive management of ED operations and significantly reducing patient waiting times.
Stakeholders	• Emergency physicians and nurses • ED administrators and managers • Triage staff and care coordinators • Patients and their families • Hospital quality improvement teams • IT and informatics departments
Inputs	• Real-time patient registration and triage data • Electronic health records (EHR) timestamps • Bed occupancy and availability status • Laboratory and imaging order status • Staff assignments and schedules • Historical ED performance metrics
Process	1. Automatic data collection from hospital information systems without manual input 2. Real-time processing and analysis of patient flow metrics 3. AI algorithms identify bottlenecks and predict wait times 4. Visual representation of ED status on wall-mounted monitors and workstations 5. Generation of automated alerts for critical delays or capacity issues 6. Continuous updating of performance indicators and predictive analytics
Results/Output	• Real-time geographical ED layout with patient locations • Live wait time displays and predictions • Automated alerts for time-sensitive tasks • Performance metrics dashboard (door-to-doctor time, length of stay, LWBS rates) • Bed turnover and availability forecasts • Throughput optimisation recommendations

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Benefits	• 35% reduction in ED length of stay (from 204 to 132 minutes at Cambridge Hospital) • 71% decrease in door-to-provider time (from 63 to 18 minutes) • 78% reduction in patients leaving without being seen (from 4.1% to 0.9%) • Elimination of ambulance diversion (148 hours to 0 hours per quarter) • 20% reduction in the average length of stay at Massachusetts General Hospital • Improved patient satisfaction scores (12th to 59th percentile) • Enhanced situational awareness for clinical staff
Limitations and challenges	• Integration complexity with existing hospital information systems • Data quality and completeness issues affecting accuracy • Staff training requirements and change management • Initial implementation costs and infrastructure requirements • Need for customisation to match specific ED workflows • Privacy and security concerns with patient data display
Application examples	Cambridge Health Alliance (USA): Implemented a comprehensive ED dashboard, resulting in a 35% reduction in length of stay and elimination of ambulance diversions. Massachusetts General Hospital (USA): A Custom dashboard providing real-time patient flow information achieved a 20% reduction in average ED length of stay. Royal Melbourne Hospital (Australia): Real-time dashboard system improved bed turnover time by 15% and reduced waiting times for incoming patients. Seoul National University Hospital (Korea): 5-year implementation of an autonomous dashboard with a geographical layout, achieving high usability scores from clinical staff.
Sources	https://pmc.ncbi.nlm.nih.gov/articles/PMC4009311/ https://pubmed.ncbi.nlm.nih.gov/30467100/
Additional information	Key performance indicators commonly tracked: Door-to-doctor time, ED length of stay, left without being seen (LWBS) rate, bed occupancy rate, patient throughput per hour, and time to disposition decision. Technologies utilised: Real-time locating systems (RTLS), predictive analytics, machine learning algorithms, streaming data platforms, change data capture (CDC), and continuous query processing. Industry benchmarks: Average ED length of stay target <4 hours, LWBS rate target <2%, door-to-provider time target <30 minutes.

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3.2.4 Interactive Dashboard for Hospital Infection Control Metrics

Module: Data Visualization

Unit: Introduction to Visualization Tools & Techniques

Use case name	Interactive Dashboard for Hospital Infection Control Metrics
Use case description	An AI-powered business intelligence dashboard that visualises hospital infection data in real-time, integrating with Electronic Health Records to automatically track Healthcare-Associated Infections (HAIs). The system uses algorithm-based selection to identify patients at risk and provides automated alerts to quality managers. Using platforms like Tableau or Power BI with direct EHR connections, it transforms infection surveillance data into actionable insights through dashboards, trend analysis, and automated reporting.
Stakeholders	• Hospital quality managers • Infection control teams • ICU directors • Department heads • Hospital administrators • Nursing staff • Epidemiologists
Inputs	Patient admission data, infection diagnosis codes, laboratory test results, antibiotic prescription records, environmental cultures, hand hygiene compliance data, staffing schedules, ward location data
Process	1. Data extraction from EHR systems (Epic, Cerner, Allscripts) via direct API connections 2. Real-time data processing and cleaning to identify infection events 3. Pattern recognition algorithms detect anomalies and emerging trends 4. Geographic and temporal mapping of infection clusters 5. Automated calculation of infection rates and quality metrics 6. Dashboard visualisation with interactive filtering and drill-down capabilities 7. Automated alerts sent to relevant stakeholders when thresholds are exceeded
Results/Output	Real-time infection rate dashboards, trend analysis charts, geographic heat maps showing infection hotspots, comparative benchmarking reports, automated alert notifications, regulatory compliance reports for CMS and HEDIS measures, and executive summary reports

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Benefits	National surveillance data show significant HAI reductions between 2022-2023: MRSA decreased by 16%, central line-associated bloodstream infections by 13%, C. difficile infections by 13%, catheter-associated urinary tract infections by 11%, and ventilator-associated events by 5%. Electronic surveillance systems show high sensitivity (>0.8) for infection detection. Automated systems enable faster outbreak identification, reduce manual surveillance workload, improve regulatory compliance, and support data-driven infection prevention decisions.
Limitations and challenges	Dependence on data quality and completeness from EHR systems requires technical staff for initial setup and maintenance, integration challenges with legacy hospital systems, potential alert fatigue from false positives, need for staff training on dashboard interpretation, and ongoing costs for platform licensing
Application examples	Hospital-wide surveillance systems using algorithm-based patient selection followed by infection control practitioner confirmation. ICU-focused systems for ventilator-associated pneumonia and central line-associated bloodstream infections. Surgical site infection tracking across multiple procedure types. Multi-facility health systems using standardised surveillance across their networks. Systems integrating microbiology data, antibiotic prescriptions, and clinical chemistry for comprehensive HAI detection.
Sources	https://www.cdc.gov/healthcare-associatedinfections/php/data/index.html https://doi.org/10.2807/1560-7917.ES.2020.25.2.1900321
Additional information	According to a systematic review of 78 studies on electronically assisted surveillance systems, most successful implementations use a semi-automated approach: algorithm-based patient selection followed by infection control practitioner confirmation. CDC data from the National Healthcare Safety Network shows approximately one in 31 hospital patients has at least one healthcare-associated infection on any given day. Surveillance systems typically integrate microbiology data, antibiotic prescriptions, and clinical chemistry to achieve high detection sensitivity while maintaining workflow efficiency.

3.2.5 Developing a Clinical Decision Support System Using Multiple Data Sources

Module: Data Visualization

Unit: Types of Medical Data & Formats

Use case name	Developing a Clinical Decision Support System Using Multiple Data Sources

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Use case description	Development of an AI-powered clinical decision support system that integrates multiple heterogeneous Electronic Health Record data sources to predict emergency department outcomes. The system processes structured clinical data (vital signs, laboratory results, ICD-coded diagnoses), unstructured clinical documentation (physician notes, medication reconciliation), and temporal data (medication administration records, triage information) through a multi-stream architecture. Each data type is processed independently before integration via self-attention mechanisms, enabling accurate predictions for patient disposition, ICU admission requirements, and mortality risk.
Stakeholders	• AI/ML developers and data scientists • Clinical informaticians, • EHR system architects, • Healthcare IT teams, • Clinical domain experts (emergency physicians, nurses), • Hospital administrators, • Research institutions, • Health system CIOs, • Regulatory compliance officers
Inputs	Structured data: Vital signs (heart rate, blood pressure, respiratory rate, temperature, SpO2), laboratory results (Complete Blood Count, chemistry panels), ICD-9/10 diagnostic codes, patient demographics Unstructured data: Clinical notes, medication reconciliation records Temporal data: Timestamped medication administration (pyxis), triage information, periodic vital measurements All data sources linked via unique hospital admission identifiers
Process	1. Data Extraction: Build ETL pipelines to extract data from laboratory information systems, pharmacy dispensing systems, triage systems, and clinical documentation platforms 2. Data Classification: Categorise data by type (structured numerical, coded diagnoses, unstructured text, temporal sequences) and biological scale (laboratory, physiological, clinical) 3. Text Serialisation: Convert structured data into clinical pseudo-notes using standardised templates that preserve clinical meaning 4. Multi-Stream Processing: Generate separate embeddings for each data type using pre-trained medical language models (MedBERT) 5. Attention-Based Integration: Apply self-attention mechanisms to learn optimal weighting across data sources 6. Model Training: Train on 70% of data, validate on 15%, test on 15%

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	7. Cross-Institutional Validation: Deploy few-shot learning adaptation for new institutions
Results/Output	Validated clinical decision support system providing: • ED disposition predictions (admission vs discharge) • ICU admission risk assessment • Mortality risk stratification • Discharge planning recommendations Performance metrics: • 95% accuracy in ED disposition prediction • Superior F1, AUROC, and AUPRC scores vs traditional ML models • Successful cross-institutional deployment (400,019 MIMIC visits; 947,028 UCLA visits) • Rapid adaptation capability: 128-512 examples needed for new sites
Benefits	Reduced data harmonisation requirements through a text serialisation approach. Modular architecture enables the addition of new data sources without system redesign. Leverages pre-trained models (MedBERT, BioBERT), reducing development costs. Few-shot learning enables rapid deployment: 128-512 examples vs thousands typically required. Outperforms GPT-4 (95% vs 86% accuracy) and traditional ML approaches. Interpretable: self-attention reveals which data sources influenced predictions
Limitations and challenges	Requires multidisciplinary expertise (clinical informatics, NLP, ML, healthcare operations). Privacy regulations (HIPAA, GDPR) complicate training data access. Computationally intensive: requires GPU resources for training. Poor direct cross-institutional transfer without fine-tuning due to population and practice variations. Temporal data synchronisation across systems with different timestamps. Missing data handling strategies are required for incomplete records. Ongoing maintenance is needed for EHR system updates
Application examples	Beth Israel Deaconess Medical Center: MEME system developed using MIMIC-IV database (400,019 ED visits). Integrated six data modalities: triage vitals, medication reconciliation, ICD-9/10 codes, periodic vitals, and medication administration records. Dataset split: 280,013 training, 60,003 validation, 60,003 testing. UCLA Health: Cross-institutional validation across 947,028 ED visits. Few-shot learning protocol achieved near-maximal performance with 128-512 labeled examples, demonstrating rapid deployment methodology. German Medical Informatics Initiative (HELP Study): Multi-center framework across 38 university hospitals for privacy-preserving CDSS development using standardised EHR data integration.
Sources	https://www.nature.com/articles/s41746-025-01777-x

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	https://www.nature.com/articles/s41597-022-01782-9
Additional information	Technical Architecture: Multiple Embedding Model for EHR (MEME) uses frozen pre-trained encoders to generate embeddings for each data stream, concatenates vectors, and applies self-attention for contextual integration before final classification. Data Types Integrated: • Structured clinical data: Quantitative vital signs with reference ranges, laboratory panels (hematology, chemistry), coded diagnoses • Unstructured clinical documentation: Progress notes, medication reconciliation • Temporal sequences: Time-series vital signs, medication administration timestamps • Demographics: Patient characteristics linked across systems. Model Flexibility: Compatible with evolving language models—performance improves as newer medical NLP models become available (tested with ClinicalBERT, Bio_ClinicalBERT, BioBERT, MedBERT).

3.2.6 Introduction to Visualization Tools and Techniques

Module: 1. Data Visualisation

Unit: 1. Introduction to Visualization Tools & Techniques

Use case name	Introduction to Visualization Tools and Techniques
Use case description	This use case focuses on demonstrating how artificial intelligence (AI) can enhance the visualisation of complex health and medical data using widely adopted eHealth and data science tools. AI-supported visualisation techniques allow large, heterogeneous datasets—such as electronic health records (EHRs), clinical outcomes, population health statistics, and sensor data—to be transformed into intuitive, interactive, and interpretable visual formats. By integrating AI with established platforms such as Tableau, Power BI, R, and Python-based libraries (e.g., Matplotlib and Seaborn), users can move beyond static charts toward dynamic, adaptive, and insight-driven visual analytics. In clinical, research, and educational contexts, AI-enhanced data visualisation supports sense-making, pattern recognition, and evidence-based decision-making. Machine learning algorithms can assist with feature selection, anomaly detection, clustering, and trend identification, which are then presented visually to support human interpretation. This approach bridges the gap between raw data and actionable knowledge, enabling clinicians, researchers, students, and health administrators to better understand complex systems, identify risks, monitor outcomes, and communicate findings effectively across multidisciplinary healthcare teams.

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Stakeholders	• Clinicians and healthcare professionals • Medical students and health sciences learners • Health data scientists and analysts • Hospital administrators and health system managers • Public health professionals • Health informatics teams • Policy makers and healthcare planners • Patients (indirect beneficiaries through improved insights)
Inputs	• Electronic Health Records (EHRs) • Clinical datasets (labs, imaging metadata, outcomes) • Population health data • Wearable and IoT health sensor data • Registry data • Research datasets • Administrative and operational health system data • Structured and semi-structured datasets (CSV, SQL, APIs)
Process	• Data ingestion from multiple healthcare data sources • Data cleaning, normalization, and preprocessing • AI-assisted feature extraction and pattern detection • Application of machine learning models for clustering, classification, and trend analysis • Integration with visualisation platforms (Tableau, Power BI, R, Python libraries) • Generation of dashboards, charts, heatmaps, networks, and interactive visual outputs • User interaction, filtering, and exploratory analysis • Iterative refinement based on stakeholder feedback
Results/Output	• Interactive dashboards • Automated visual reports • Predictive trend visualisations • Risk and outcome maps • Pattern and anomaly detection displays • Population health visual analytics •Clinical performance monitoring tools

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	• Research-ready visual datasets
Benefits	• Improved interpretability of complex medical data • Faster insight generation and decision support • Enhanced communication across clinical and non-clinical teams • Support for evidence-based medicine • Improved educational understanding of data science concepts • Scalability across datasets and institutions • Democratization of data access and understanding • Improved transparency in healthcare analytics
Limitations and challenges	• Data quality and completeness issues • Risk of visual misinterpretation • Algorithmic bias in AI-supported pattern detection • Technical skill requirements • Interoperability challenges between systems • Data privacy and governance constraints • Infrastructure and computational resource needs • Over-reliance on automated insights
Application examples	• Visualising hospital performance metrics • Monitoring disease outbreaks and trends • Clinical pathway analysis • Predictive modelling dashboards • Patient flow and capacity planning • Population health mapping • Educational training dashboards for students • Research data exploration platforms
Sources	1. Data Visualization – An Introduction: Statistics Canada https://youtu.be/gewM4balOek?si=9EfXPtIldJcGU8hb 2. Data Visualization and Misrepresentation https://youtu.be/x-rDVXVwW9s?si=HDhZEi5HQLd80yVh
Additional information	

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3.2.7 Types of Medical Data & Formats

Module: 1. Data Visualisation

Unit: 2. Types of Medical Data & Formats

Use case name	Types of Medical Data & Formats
Use case description	This use case focuses on introducing the diverse types of medical and healthcare data and the formats in which these data are commonly generated, stored, and managed across digital health ecosystems. It covers structured, semi-structured, and unstructured data sources, including Electronic Health Records (EHRs), medical imaging data, laboratory and pathology results, genomic data, and real-time patient monitoring streams. Understanding these data types and formats is essential for effective data visualisation, analytics, and AI integration within modern healthcare systems. The use case emphasizes how AI and data science tools can support the interpretation and visual representation of heterogeneous medical data by standardising formats, extracting meaningful features, and enabling interoperability across systems. By linking data formats to visualisation techniques, learners and professionals develop the capacity to transform raw clinical data into meaningful visual insights. This foundation supports advanced applications such as clinical decision support, predictive modelling, population health analytics, and real-time monitoring dashboards, while also strengthening digital literacy in medical, clinical, and health informatics education contexts.
Stakeholders	• Clinicians and allied health professionals • Medical and health sciences students • Health informatics specialists • Hospital IT and data management teams • Health data scientists and analysts • Researchers • Healthcare administrators • Digital health system developers
Inputs	• Electronic Health Records (EHR) • Medical imaging data (DICOM, PACS systems) • Laboratory and pathology data (LIS) • Genomic and omics datasets • Real-time monitoring data (ICU, wearables, IoT devices) • Clinical notes and unstructured text • Administrative and billing data • Interoperability standards (FHIR, HL7, SNOMED CT)

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Process	• Identification of data types and sources • Classification of data formats and structures • Data extraction and ingestion pipelines • Standardisation and harmonisation of datasets • AI-supported data preprocessing and feature extraction • Mapping of data types to appropriate visualisation methods • Integration into visualisation and analytics platforms • Validation and quality assurance processes
Results/Output	• Categorised medical data repositories • Structured datasets for visualisation • Interoperable data models • Standardised data pipelines • Visual-ready clinical datasets • Data dictionaries and metadata frameworks • Integrated multi-source dashboards
Benefits	• Improved understanding of healthcare data ecosystems • Enhanced data literacy among clinicians and students • Better interoperability across systems • More effective data visualisation design • Improved data quality and consistency • Support for AI and machine learning applications • Foundation for digital transformation in healthcare
Limitations and challenges	• Data fragmentation across systems • Lack of standardisation between vendors • Interoperability constraints • Data governance and regulatory barriers • Privacy and security risks • Technical complexity of integration • Resource and infrastructure limitations
Application examples	• Visualising multimodal patient records • Integrated imaging and clinical dashboards • ICU monitoring data visualisation

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	• Longitudinal patient journey mapping • Population health data integration • Clinical research data harmonisation • Education platforms for data literacy training
Sources	1. Health Information Formats, Leitlinie Gesundheitsinformation https://www.leitlinie-gesundheitsinformation.de/guideline/health-information-formats/?lang=en 2. Data Formats, NIH Pragmatic trials Collaboratory https://rethinkingclinicaltrials.org/chapters/conduct/acquiring-real-world-data/data-formats/
Additional information	

3.2.8 Design Principles in Medical Contexts

Module: 1. Data Visualisation

Unit: 3. Design Principles in Medical Contexts

Use case name	Data Visualisation Design Principles in Medical Contexts
Use case description	This use case focuses on understanding the critical design considerations required when creating effective data visualisations for medical and clinical environments. Unlike general-purpose visualisation, medical data visualisation must account for high-stakes decision-making, cognitive load, time pressure, and the need for accuracy, clarity, and interpretability. The use case explores how design principles such as visual encoding, colour theory, chart selection, and layout structure directly influence clinical understanding, safety, and decision quality. The use case emphasises the translation of complex clinical data into intuitive, clinically meaningful visual representations. It addresses the selection of appropriate chart types (e.g., bar charts, heat maps, line graphs, radial plots, network diagrams), the use of colour to encode risk, urgency, and categorisation, and the design of dashboards that align with clinical workflows. By integrating AI-supported analytics with strong visual design principles, this approach ensures that insights are not only computationally accurate but also human-centred, usable, and trustworthy within real-world healthcare settings.
Stakeholders	• Clinicians and healthcare professionals • Nurses and allied health staff • Medical and health sciences students • Health informatics specialists

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	• UX/UI designers in healthcare • Health data scientists • Hospital administrators • Clinical system developers
Inputs	• Clinical datasets (EHRs, lab results, imaging metadata) • Real-time monitoring data • Population health data • Clinical workflow data • User requirements and clinical task analyses • Human–computer interaction (HCI) principles • Design frameworks and guidelines
Process	• Identification of clinical use contexts and workflows • Analysis of user needs and cognitive load • Selection of appropriate visual encoding methods • Application of colour theory and accessibility principles • Chart and visual format selection • Dashboard layout and information hierarchy design • Integration with AI-generated insights • Usability testing and clinical validation • Iterative design refinement
Results/Output	• Clinically optimised dashboards • High-clarity visual interfaces • Risk-aware visual representations • Workflow-aligned visual systems • Interactive clinical visualisation tools • AI-integrated decision support displays
Benefits	• Improved clinical comprehension • Reduced cognitive overload • Faster and safer decision-making • Enhanced usability of AI systems • Better communication across care teams • Increased trust in digital systems • Improved patient safety outcomes

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Limitations and challenges	• Complexity of clinical workflows • Risk of visual misinterpretation • Colour accessibility issues (e.g., colour blindness) • Design standardisation difficulties • Resistance to interface change • Resource and training requirements • Regulatory and compliance constraints
Application examples	• ICU monitoring dashboards • Emergency department triage displays • Clinical decision support interfaces • Patient risk stratification tools • Population health dashboards • Clinical pathway visualisations • Medical education training platforms
Sources	1. Data Design Principles – WHO https://data.who.int/about/datadot/data-design-principles 2. Principles of Effective Data Visualization - NIH https://pmc.ncbi.nlm.nih.gov/articles/PMC7733875/
Additional information	

3.2.9 Data cleaning and pre-processing for visualisation

Module: 1. Data Visualisation

Unit: 4. Data Cleaning & Preprocessing for Visualization

Use case name	Data visualisation Data cleaning and pre-processing for visualisation
Use case description	This use case focuses on the technical foundations required to prepare medical and healthcare data for effective visualisation through robust data cleaning and pre-processing practices. In clinical and eHealth contexts, raw data are often incomplete, inconsistent, noisy, and heterogeneous, making direct visualisation unreliable or misleading. This use case introduces systematic approaches to handling missing values, detecting and correcting errors, managing outliers, normalising variables, and transforming data into formats suitable for meaningful visual representation. The use case also highlights how AI-supported tools and data science techniques can

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	automate and enhance pre-processing workflows. Machine learning methods can assist with anomaly detection, imputation of missing data, feature scaling, and dimensionality reduction, ensuring that visual outputs accurately reflect underlying clinical realities. By establishing high-quality data pipelines prior to visualisation, this use case strengthens the reliability, interpretability, and trustworthiness of dashboards, analytics platforms, and AI-driven decision support systems across clinical, research, and educational settings.
Stakeholders	• Health data scientists and analysts • Clinicians and clinical researchers • Health informatics professionals • Medical and health sciences students • Hospital IT and data engineering teams • Digital health developers • Public health analysts
Inputs	• Raw clinical datasets (EHRs, lab data, monitoring data) • Imaging metadata and registries • Research and trial datasets • Administrative health system data • Unstructured and semi-structured data sources • Data standards and ontologies • Interoperability frameworks
Process	• Data extraction from source systems • Identification of missing, inconsistent, and erroneous values • Handling missing data (imputation, deletion, modelling) • Outlier detection and treatment • Data normalisation and scaling • Data transformation and feature engineering • Format harmonisation and standardisation • AI-assisted preprocessing automation • Validation and quality control
Results/Output	• Cleaned and validated datasets • Normalised and standardised data structures • Visual-ready datasets • High-integrity data pipelines

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	• Feature-engineered datasets • Preprocessing workflows and protocols
Benefits	• Improved accuracy of visualisations • Increased reliability of insights • Enhanced interpretability of data • Reduced bias and noise • Stronger foundations for AI analytics • Better decision support quality • Increased trust in digital health systems
Limitations and challenges	• Complexity of healthcare data structures • Risk of inappropriate imputation • Loss of clinically relevant information • Algorithmic bias in preprocessing methods • Technical skill requirements • Resource and infrastructure demands • Data governance and compliance constraints
Application examples	• Preparing EHR data for dashboards • Cleaning ICU monitoring data • Preprocessing research datasets • Population health analytics pipelines • Clinical trial data preparation • AI model training data pipelines • Educational data science labs
Sources	1. Normal Workflow and Key Strategies for Data Cleaning Toward Real-World Data: Viewpoint https://pmc.ncbi.nlm.nih.gov/articles/PMC10557005/
Additional information	

3.2.10 Interactive Visualisations and Dashboard

Module: 1. Data Visualisation

Unit: 5. Interactive Visualizations & Dashboards

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Use case name	Interactive Visualisations and Dashboard
Use case description	This use case focuses on the design and development of interactive data visualisations and multi-layer dashboards that support clinical decision-making and patient care. It introduces the key techniques required to build dynamic visual systems that allow users to explore data at multiple levels of detail, enabling clinicians and healthcare professionals to move seamlessly from high-level overviews to granular, patient-specific insights. Interactive dashboards transform static data displays into responsive analytical tools that support real-time exploration, filtering, and contextual interpretation of complex medical data. The use case also links theoretical design and technical principles to real-world clinical applications, highlighting existing interactive dashboard systems currently used in hospitals, clinics, and public health institutions. These systems support activities such as patient monitoring, risk stratification, capacity management, disease surveillance, and clinical performance tracking. By integrating AI-driven analytics with interactive visualisation frameworks, this approach enables adaptive, intelligent dashboards that respond to user behaviour, clinical priorities, and evolving data streams, enhancing both situational awareness and clinical workflow efficiency.
Stakeholders	• Clinicians and healthcare professionals • Nurses and allied health staff • Health informatics specialists • Health data scientists and analysts • Hospital administrators • Clinical system developers • Medical and health sciences students • Digital health innovation teams
Inputs	• Electronic Health Records (EHRs) • Real-time patient monitoring data • Clinical and operational datasets • Population health data • Imaging and laboratory data • AI-generated analytics outputs • User interaction and workflow data
Process	• Identification of clinical use cases and user needs • Data integration from multiple sources • Design of interactive visual components • Development of multi-layer dashboard architectures

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	• Implementation of drill-down and filtering mechanisms • Integration of AI-driven insights and predictions • User interface and experience design • Clinical validation and usability testing • Continuous system refinement
Results/Output	• Interactive clinical dashboards • Multi-layer visual analytics platforms • Drill-down patient insight tools • Real-time monitoring interfaces • Adaptive AI-powered visual systems • Integrated decision-support displays
Benefits	• Enhanced clinical situational awareness • Faster access to patient insights • Improved decision-making quality • Better workflow integration • Increased efficiency in care delivery • Improved communication across teams • Greater trust in digital health systems
Limitations and challenges	• Technical complexity of system integration • Interoperability constraints • Data quality and latency issues • Risk of information overload • Training and adoption barriers • Infrastructure and maintenance costs • Privacy and security concerns
Application examples	• ICU patient monitoring dashboards • Emergency department command centres • Hospital capacity management systems • Clinical risk stratification tools • Public health surveillance dashboards • Predictive analytics platforms • Educational clinical simulation dashboards

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Sources	1. Reflections on interactive visualization of electronic health records: past, present, future https://pmc.ncbi.nlm.nih.gov/articles/PMC11491741/ 2. Interactive data visuals Institute for Health Metrics and Evaluation https://www.healthdata.org/data-tools-practices/interactive-data-visuals
Additional information	

3.2.11 Fundamentals of predictive modelling

Module: 2. Predictive Analytics

Unit: 1. Fundamentals of Predictive Modelling

Use case name	Fundamentals of predictive modelling
Use case description	This use case provides a foundational introduction to predictive analytics and the core concepts that underpin predictive modelling in medical and healthcare contexts. It focuses on building conceptual understanding of key terminology and principles, including dependent and independent variables, model training and testing, overfitting and underfitting, regularization, bias–variance trade-offs, and model generalisability. These concepts form the theoretical backbone for understanding how AI and machine learning systems generate predictions from health data. The use case also introduces the main categories of predictive models commonly used in healthcare, particularly regression and classification approaches. Learners explore how these models are applied to real-world medical problems such as risk prediction, diagnosis support, outcome forecasting, and patient stratification. By linking theory to practical clinical applications, this unit builds essential AI literacy for clinicians, students, and health professionals, enabling them to critically interpret predictive outputs, understand model limitations, and engage safely with AI-driven decision support systems in clinical and research environments.
Stakeholders	• Clinicians and healthcare professionals • Medical and health sciences students • Health data scientists and analysts • Health informatics specialists • Clinical researchers • Digital health developers • Hospital administrators
Inputs	• Clinical datasets (EHRs, lab results, outcomes data) • Population health datasets

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	• Research and trial datasets • Structured and semi-structured data • Feature variables and target variables • Domain knowledge and clinical expertise
Process	• Identification of prediction objectives • Definition of dependent and independent variables • Data preprocessing and feature selection • Model selection (regression, classification) • Model training and validation • Regularisation and overfitting control • Model evaluation and performance testing • Interpretation of predictive outputs • Clinical contextualisation
Results/Output	• Trained predictive models • Risk prediction outputs • Classification predictions • Regression forecasts • Performance metrics (accuracy, sensitivity, specificity) • Interpretable model outputs
Benefits	• Improved AI literacy in healthcare • Better understanding of predictive systems • Safer use of AI in clinical settings • Enhanced decision support capabilities • Support for evidence-based practice • Stronger interdisciplinary collaboration • Foundation for advanced AI learning
Limitations and challenges	• Risk of model overfitting • Data quality and bias issues • Limited interpretability of some models • Misuse or overreliance on predictions • Ethical and accountability concerns • Skill gaps in AI education • Integration into clinical workflows

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Application examples	• Disease risk prediction models • Readmission prediction systems • Diagnostic classification tools • Treatment outcome forecasting • Population health risk models • Predictive triage systems • Educational predictive modelling labs
Sources	Predictive Modeling in Medicine, Encyclopedia 2023, 3(2), 590-601; https://doi.org/10.3390/encyclopedia3020042, https://www.mdpi.com/2673-8392/3/2/42?utm_source=researchgate.net&utm_medium=article
Additional information	e.g. photos, graphs, scientific articles, additional links

3.2.12 Statistical techniques and risk scores

Module: 2. Predictive Analytics

Unit: 2. Statistical Techniques & Risk Scores

Use case name	Statistical techniques and risk scores
Use case description	This use case focuses on the traditional statistical techniques that form the foundation of modern predictive analytics in medicine and healthcare. It introduces core methods such as logistic regression and Cox proportional hazards modelling, which remain central to clinical research, epidemiology, and risk prediction despite the rise of advanced machine learning approaches. These statistical models provide interpretable, mathematically grounded methods for understanding relationships between clinical variables and health outcomes. The use case also explores the development and application of clinical risk scores, such as CHA_2DS_2-VASc used for scoring stroke risk, and similar scoring systems, which translate statistical models into practical tools for everyday clinical decision-making. These risk scores are widely embedded in clinical guidelines, decision support systems, and routine practice. By linking statistical modelling theory to real-world clinical tools, this unit enables learners and professionals to understand how predictive analytics has historically evolved in medicine and how modern AI-based systems build upon these established foundations.
Stakeholders	• Clinicians and healthcare professionals • Clinical researchers • Medical and health sciences students

	• Biostatisticians • Health data scientists and analysts • Health informatics specialists • Policy makers and guideline developers
Inputs	• Clinical datasets (EHRs, outcomes data, registries) • Longitudinal patient data • Population health datasets • Research and trial datasets • Clinical variables and biomarkers • Epidemiological data
Process	• Definition of clinical outcomes and endpoints • Selection of predictor variables • Statistical model development • Logistic regression modelling • Cox proportional hazards modelling • Model validation and calibration • Risk score derivation • Clinical translation and guideline integration • Evaluation of predictive performance
Results/Output	• Statistical prediction models • Risk stratification outputs • Clinical risk scores • Survival analysis models • Predictive probability estimates • Interpretable prediction tools
Benefits	• High interpretability and transparency • Strong clinical trust and acceptance • Integration into clinical guidelines • Evidence-based risk stratification • Support for clinical decision-making • Educational clarity for learners • Foundation for AI model development

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Limitations and challenges	• Limited ability to model complex non-linear relationships • Assumptions of model structures • Sensitivity to data quality and missing values • Population-specific validity issues • Static nature of traditional risk scores • Updating and recalibration challenges • Integration with dynamic AI systems
Application examples	• Stroke risk prediction (CHA_2DS_2-VASc) • Cardiovascular risk modelling • Cancer survival analysis • Readmission risk modelling • Mortality risk prediction • Clinical guideline decision tools • Population risk stratification programmes
Sources	Predictive Analytic Techniques and Big Data for Improved Health Outcomes in the Context of Value Based Health Care and Coverage Decisions: A Scoping Review – The London School of Economics and Political Science https://www.lse.ac.uk/business/consulting/assets/documents/Predictive-Analytic-Techniques-and-Big-Data-for-Improved-Health-Outcomes-Final-Report.pdf
Additional information	e.g. photos, graphs, scientific articles, additional links

3.2.13 Data mining and pattern recognition

Module: 2. Predictive Analytics

Unit: 3. Data Mining & Pattern Recognition

Use case name	Data mining and pattern recognition
Use case description	This use case focuses on the application of data mining and pattern recognition techniques to large-scale clinical and health datasets in order to identify meaningful trends, structures, and hidden relationships. In modern healthcare environments, vast volumes of data are generated from sources such as hospital admission systems, electronic health records, imaging repositories, and real-time wearable and sensor technologies. Data mining methods enable these complex datasets to be systematically explored and transformed into actionable knowledge. The use case emphasises how AI and machine learning techniques support automated pattern detection,

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	trend analysis, clustering, and anomaly identification across high-dimensional medical data. By applying these methods to domains such as hospital utilisation, disease progression, population health trends, and continuous patient monitoring, healthcare systems can move from reactive analysis to proactive, predictive insight generation. This approach strengthens predictive analytics capabilities by revealing patterns that are not easily detectable through traditional statistical methods, enabling more informed planning, early intervention, and data-driven clinical and operational decision-making.
Stakeholders	• Clinicians and healthcare professionals • Health data scientists and analysts • Health informatics specialists • Public health professionals • Hospital administrators • Clinical researchers • Digital health developers • Medical and health sciences students
Inputs	• Hospital admission and discharge data • Electronic Health Records (EHRs) • Real-time wearable and sensor data • ICU and monitoring system data • Population health datasets • Longitudinal patient records • Operational and administrative datasets
Process	• Data aggregation from large-scale sources • Data preprocessing and cleaning • Feature extraction and dimensionality reduction • Application of data mining algorithms • Pattern recognition and clustering • Trend detection and temporal analysis • AI-assisted anomaly detection • Validation and clinical interpretation • Integration into predictive analytics systems
Results/Output	• Identified clinical patterns • Trend analysis reports

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	• Predictive insights • Risk pattern visualisations • Behavioural and physiological profiles • Early warning indicators • Knowledge discovery outputs
Benefits	• Early detection of emerging risks • Improved population health management • Enhanced predictive modelling • Proactive clinical intervention • Better operational planning • Discovery of hidden data relationships • Stronger evidence-based decision-making
Limitations and challenges	• Data quality and noise • Algorithmic bias • Interpretability challenges • High computational requirements • Privacy and data governance risks • Integration complexity • Skills and training gaps
Application examples	• Hospital admission trend analysis • Disease outbreak detection • Wearable sensor data monitoring • Chronic disease pattern analysis • Patient behaviour modelling • Resource utilisation forecasting • Population health surveillance systems
Sources	Islam MS, Hasan MM, Wang X, Germack HD, Noor-E-Alam M. A Systematic Review on Healthcare Analytics: Application and Theoretical Perspective of Data Mining. Healthcare (Basel). 2018 May 23;6(2):54. doi: 10.3390/healthcare6020054. PMID: 29882866; PMCID: PMC6023432. https://pmc.ncbi.nlm.nih.gov/articles/PMC6023432/
Additional information	e.g. photos, graphs, scientific articles, additional links

3.2.14 Validation methods

Module: 2. Predictive Analytics

Unit: 4. Validation Methods

Use case name	Validation methods
Use case description	This use case focuses on the critical role of model validation in predictive analytics within healthcare and clinical contexts. Validation methods are essential for ensuring that predictive models are safe, reliable, accurate, and clinically meaningful before they are used in real-world medical decision-making. In healthcare, poorly validated models can lead to misdiagnosis, inappropriate treatment decisions, and patient harm, making rigorous validation processes a core requirement of ethical and responsible AI deployment. The use case introduces key validation techniques used in healthcare predictive modelling, including cross-validation methods, Receiver Operating Characteristic (ROC) curves, confusion matrices, sensitivity, specificity, precision, and related performance metrics. These methods allow clinicians, data scientists, and health informaticians to assess model accuracy, robustness, generalisability, and clinical relevance. By embedding validation within clinical and regulatory contexts, this unit supports the development of trustworthy AI systems that align with evidence-based medicine, clinical governance standards, and patient safety principles.
Stakeholders	• Clinicians and healthcare professionals • Clinical researchers • Health data scientists and analysts • Health informatics specialists • Hospital quality and safety teams • Digital health developers • Medical and health sciences students • Regulatory and governance bodies
Inputs	• Clinical datasets (EHRs, outcomes data, registries) • Predictive model outputs • Training and testing datasets • Validation datasets • Clinical outcome labels • Ground-truth reference standards
Process	• Dataset partitioning (training, validation, testing) • Application of cross-validation techniques

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	• Model performance testing • Construction of confusion matrices • ROC curve generation and analysis • Sensitivity and specificity evaluation • Calibration assessment • Clinical relevance assessment • Model refinement and revalidation
Results/Output	• Validated predictive models • Performance metrics reports • ROC curves and AUC values • Confusion matrices • Sensitivity and specificity profiles • Calibration plots • Clinical validation summaries
Benefits	• Improved patient safety • Increased trust in AI systems • Higher clinical reliability • Evidence-based deployment of models • Regulatory compliance support • Better clinical decision support quality • Ethical and responsible AI use
Limitations and challenges	• Limited availability of high-quality labelled data • Population bias and dataset shift • Overfitting to validation datasets • Generalisability across institutions • Complexity of clinical validation • Resource and infrastructure demands • Regulatory and governance complexity
Application examples	• Validation of diagnostic AI models • Risk prediction system testing • Clinical decision support tool evaluation • Predictive triage model validation • Readmission prediction models

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	• Population health risk model assessment • Wearable health prediction system testing
Sources	Van Calster B, Wynants L, Timmerman D, Steyerberg EW, Collins GS. Predictive analytics in health care: how can we know it works? J Am Med Inform Assoc. 2019 Dec 1;26(12):1651-1654. doi: 10.1093/jamia/ocz130. PMID: 31373357; PMCID: PMC6857503. https://pmc.ncbi.nlm.nih.gov/articles/PMC6857503/ Van Calster, B., McLernon, D.J., van Smeden, M. et al. Calibration: the Achilles heel of predictive analytics. BMC Med 17, 230 (2019). htt ps://doi.org/10.1186/s12916-019-1466-7 https://www.springermedizin.de/calibration-the-achilles-heel-ofpredictiveanalytics/51675328
Additional information	e.g. photos, graphs, scientific articles, additional links

3.2.15 Clinical Applications and Case Studies

Module: 2. Predictive Analytics

Unit: 5. Clinical Applications & Case Studies

Use case name	Clinical Applications and Case Studies
Use case description	This use case focuses on real-world clinical applications of predictive analytics across multiple domains of healthcare, demonstrating how predictive models are used to support decision-making, planning, and patient care. It explores practical examples in disease progression modelling, hospital readmission prediction, healthcare resource allocation, and population health management. These applications illustrate how predictive analytics moves beyond theory into operational and clinical impact. The use case highlights how AI-driven predictive systems support early intervention, risk stratification, system optimisation, and proactive care delivery. By examining concrete case studies and real-world deployments, learners and professionals gain insight into how predictive analytics is embedded in clinical workflows, hospital systems, and public health infrastructures. This applied perspective strengthens understanding of both the clinical value and implementation challenges of predictive analytics, supporting evidence-based, data-driven healthcare transformation.
Stakeholders	• Clinicians and healthcare professionals • Hospital administrators and managers • Public health professionals

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	• Health informatics specialists • Health data scientists and analysts • Clinical researchers • Policy makers • Patients and communities
Inputs	• Electronic Health Records (EHRs) • Hospital admission and discharge data • Clinical outcomes data • Population health datasets • Wearable and monitoring data • Resource utilisation and operational data • Social determinants of health data
Process	• Identification of clinical and operational prediction goals • Data integration from multiple healthcare sources • Feature selection and modelling • Predictive model development • Model validation and calibration • Clinical workflow integration • Monitoring and performance evaluation • Continuous model improvement
Results/Output	• Disease progression prediction models • Readmission risk scores • Resource demand forecasts • Population risk stratification outputs • Predictive dashboards • Early warning systems
Benefits	• Earlier clinical interventions • Reduced hospital readmissions • Optimised resource allocation • Improved population health planning • Enhanced patient outcomes • Cost efficiency in healthcare delivery • Evidence-based system management

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Limitations and challenges	• Data quality and interoperability issues • Algorithmic bias and fairness concerns • Model generalisability • Ethical and governance challenges • Clinical trust and adoption barriers • Infrastructure requirements • Regulatory constraints
Application examples	• Predicting sepsis progression in hospitalised patients • Readmission prediction in chronic heart failure • ICU capacity forecasting • Emergency department demand prediction • Population-level diabetes risk prediction • Pandemic trend modelling • Chronic disease management systems
Sources	• Sepsis prediction systems (e.g., early warning score models in hospital care) • Hospital readmission prediction models (e.g., CMS Hospital Readmission Reduction Program analytics) • Population health risk stratification platforms (e.g., NHS population health management systems) • ICU resource forecasting models • COVID-19 predictive modelling platforms • Wearable-based disease monitoring studies • Chronic disease predictive management programmes
Additional information	Scientific Articles and Case Studies Rajkomar A. et al. (2018). Scalable and accurate deep learning with electronic health records. Nature Digital Medicine. https://www.nature.com/articles/s41746-018-0029-1 Esteva A. et al. (2019). A guide to deep learning in healthcare. Nature Medicine. https://www.nature.com/articles/s41591-018-0316-z Obermeyer Z., Emanuel E.J. (2016). Predicting the Future — Big Data, Machine Learning, and Clinical Medicine. New England Journal of Medicine. https://www.nejm.org/doi/full/10.1056/NEJMp1606181 Clinical Systems and Platforms NHS Population Health Management: https://www.england.nhs.uk/integratedcare/population-health-management/ MS Predictive Analytics Programs: https://www.cms.gov/data-research

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	Visual Resources (Dashboards and Graphs) WHO Global Health Observatory Visualisations: https://www.who.int/data/gho

3.2.16 Overview of machine learning algorithms

Module: 3. Machine Learning

Unit: 1. Overview of Machine Learning Algorithms

Use case name	Overview of machine learning algorithms
Use case description	This use case provides a comprehensive introduction to the core categories of machine learning algorithms and processes, with a specific focus on their relevance to medicine and healthcare. It introduces the fundamental paradigms of supervised learning (including regression and classification), unsupervised learning (including clustering and dimensionality reduction), and reinforcement learning. Together, these approaches form the conceptual foundation for most modern AI systems used in clinical, research, and operational healthcare environments. The use case emphasises how these machine learning approaches are applied to real-world medical problems such as diagnosis support, risk prediction, patient stratification, disease discovery, workflow optimisation, and adaptive clinical systems. By building a structured conceptual framework, learners and professionals gain the ability to understand how different algorithmic approaches are selected, trained, validated, and deployed in healthcare settings. This foundational knowledge supports safe, ethical, and effective engagement with AI technologies, enabling clinicians and health professionals to interpret machine learning outputs, understand limitations, and participate meaningfully in AI-enabled healthcare transformation.
Stakeholders	• Clinicians and healthcare professionals • Medical and health sciences students • Health data scientists and analysts • Health informatics specialists • Clinical researchers • Digital health developers • Hospital administrators • Policy makers and regulators
Inputs	• Clinical datasets (EHRs, lab results, imaging metadata) • Population health datasets • Research and clinical trial data • Real-time monitoring and wearable data

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	• Structured and unstructured health data • Domain knowledge and clinical expertise
Process	• Identification of clinical and analytical objectives • Data preparation and preprocessing • Feature selection and engineering • Model selection (supervised, unsupervised, reinforcement learning) • Algorithm training and optimisation • Model validation and evaluation • Clinical interpretation of outputs • Integration into healthcare systems
Results/Output	• Trained machine learning models • Predictive and classification outputs • Clustering and pattern discovery results • Dimensionality-reduced data representations • Adaptive learning systems • Clinical decision support outputs
Benefits	• Improved diagnostic and predictive capabilities • Enhanced clinical decision support • Discovery of hidden clinical patterns • Automation of complex analytical tasks • Support for personalised medicine • Increased healthcare system efficiency • Strong foundation for advanced AI applications
Limitations and challenges	• Data quality and bias • Interpretability and transparency issues • Ethical and governance concerns • Model generalisability • Integration into clinical workflows • Technical skill requirements • Infrastructure and resource demands
Application examples	• Disease risk prediction models • Diagnostic classification systems

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	• Patient clustering for care pathways • Imaging analysis and triage systems • Clinical workflow optimisation tools • Adaptive treatment recommendation systems • Research discovery platforms
Sources	Ting Sim JZ, Fong QW, Huang W, Tan CH. Machine learning in medicine: what clinicians should know. Singapore Med J. 2023 Feb;64(2):91-97. doi: 10.11622/smedj.2021054. Epub 2021 May 19. PMID: 34005847; PMCID: PMC10071847. https://pmc.ncbi.nlm.nih.gov/articles/PMC10071847/
Additional information	e.g. photos, graphs, scientific articles, additional links

3.2.17 Neural networks and deep learning basics

Module: 3. Machine Learning

Unit: 2. Neural Networks & Deep Learning Basics

Use case name	Neural networks and deep learning basics
Use case description	This use case introduces the foundational concepts of neural networks and deep learning, with a specific focus on their applications in medicine and healthcare. It explores how artificial neural networks mimic aspects of human learning through layered architectures, enabling complex pattern recognition, feature learning, and representation modelling from large-scale medical datasets. Deep learning forms the core of many modern AI systems in healthcare, particularly in areas such as medical imaging, clinical prediction, and digital diagnostics. The use case provides a conceptual understanding of key neural network architectures, including Convolutional Neural Networks (CNNs) for imaging data and Recurrent Neural Networks (RNNs) for sequential and time-series data such as Electronic Health Records (EHRs) and physiological monitoring streams. It also introduces other relevant deep learning models, such as transformers for clinical text analysis, autoencoders for feature extraction and anomaly detection, and graph neural networks for modelling biological and clinical networks. Together, these approaches demonstrate how deep learning supports advanced clinical analytics, decision support, and intelligent healthcare systems.
Stakeholders	• Clinicians and healthcare professionals • Medical and health sciences students • Health data scientists and analysts • Health informatics specialists

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	• Clinical researchers • Digital health developers • Imaging specialists and radiologists • Hospital IT teams
Inputs	• Medical imaging data (X-ray, CT, MRI, ultrasound) • Electronic Health Records (EHRs) • Time-series physiological data • Clinical text and notes • Genomic and omics datasets • Wearable and sensor data • Research and clinical trial data
Process	• Data collection and preprocessing • Data annotation and labelling • Model architecture selection (CNNs, RNNs, transformers, autoencoders) • Feature learning through deep architectures • Model training and optimisation • Validation and evaluation • Interpretability and explainability analysis • Clinical integration and deployment
Results/Output	• Trained deep learning models • Image classification and segmentation outputs • Time-series prediction models • Clinical text analytics outputs • Pattern recognition results • Predictive clinical insights • AI-assisted diagnostic tools
Benefits	• High-performance pattern recognition • Improved diagnostic accuracy • Automation of complex analysis tasks • Enhanced clinical decision support • Support for precision medicine • Scalability across data modalities • Discovery of complex clinical relationships

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Limitations and challenges	• High data and computational requirements • Limited interpretability of deep models • Risk of algorithmic bias • Data privacy and governance issues • Model generalisability challenges • Integration into clinical workflows • Ethical and regulatory concerns
Application examples	• CNN-based radiology image analysis • Automated pathology slide interpretation • RNN-based EHR time-series prediction • ICU patient deterioration prediction • Clinical text mining using transformers • Genomic pattern analysis • Wearable sensor analytics
Sources	Choi, R.Y., Coyner, A.S., Kalpathy-Cramer, J., Chiang, M.F., & Campbell, J.P. (2020). Introduction to Machine Learning, Neural Networks, and Deep Learning. Translational Vision Science & Technology, 9(2), 14. doi: 10.1167/tvst.9.2.14. PMID: 32704420; PMCID: PMC7347027. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC7347027/
Additional information	e.g. photos, graphs, scientific articles, additional links

3.2.18 Algorithmic complexity and model optimization

Module: 3. Machine Learning

Unit: 3. Algorithmic Complexity & Model Optimization

Use case name	Algorithmic complexity and model optimization
Use case description	This use case introduces the fundamental concepts of algorithmic complexity and model optimisation in machine learning, with a specific focus on healthcare and medical AI applications. It explores how model performance, efficiency, scalability, and reliability depend not only on data quality and model architecture, but also on optimisation processes such as hyperparameter tuning, gradient descent, and backpropagation. These mechanisms are central to how learning algorithms improve their performance during training. The use case also examines ensemble learning methods, including random forests and gradient boosting approaches such

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	as XGBoost, which combine multiple models to improve predictive accuracy, robustness, and generalisability. In medical contexts, optimisation is critical for ensuring that AI systems are not only accurate but also stable, efficient, interpretable, and safe for clinical deployment. By linking optimisation theory to real-world healthcare use cases, this unit builds essential understanding of how machine learning systems are refined for reliable performance in high-stakes clinical environments.
Stakeholders	• Health data scientists and analysts • Clinicians and healthcare professionals • Health informatics specialists • Clinical researchers • Digital health developers • Medical and health sciences students • Hospital IT and AI engineering teams
Inputs	• Training and validation datasets • Clinical and population health data • Model architectures and configurations • Feature sets and engineered variables • Performance metrics and evaluation criteria • Computational resources
Process	• Definition of model objectives and constraints • Selection of optimisation strategies • Hyperparameter tuning and search strategies • Gradient descent optimisation • Backpropagation in neural networks • Ensemble model construction • Model evaluation and benchmarking • Performance optimisation and refinement • Clinical validation and testing
Results/Output	• Optimised machine learning models • Improved model performance metrics • Robust ensemble models • Efficient training pipelines • Scalable AI systems • Clinically deployable models

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Benefits	• Improved predictive accuracy • Increased model robustness • Better generalisability • Reduced overfitting • Improved computational efficiency • Safer clinical deployment • Higher trust in AI systems
Limitations and challenges	• High computational costs • Risk of over-optimisation • Complexity of tuning processes • Reduced interpretability in ensembles • Infrastructure and resource demands • Skills and training requirements • Validation complexity in healthcare contexts
Application examples	• Optimised diagnostic prediction models • Ensemble-based disease risk prediction • Clinical outcome forecasting systems • Imaging AI model optimisation • ICU risk prediction tools • Population health predictive platforms • AI model deployment pipelines
Sources	Understanding Optimization Algorithms in Machine Learning. Towards Data Science. Available at: https://towardsdatascience.com/understanding-optimization-algorithms-in-machine-learning-edfdb4df766b/
Additional information	e.g. photos, graphs, scientific articles, additional links

3.2.19 Workflow and Pipelines for healthcare

Module: 3. Machine Learning

Unit: 4. Workflow & Pipelines for Healthcare ML Projects

Use case name	Workflow and Pipelines for healthcare
Use case description	This use case provides a structured overview of the end-to-end workflows and data pipeline processes required to support machine learning in healthcare environments. It focuses on how raw clinical and health data are transformed into reliable, deployable AI systems through coordinated stages of data sourcing, cleaning, feature engineering, model training,

	validation, and deployment. In medical contexts, these workflows must operate within complex regulatory, ethical, and clinical governance frameworks, making robust pipeline design essential for safe AI implementation. The use case emphasises the integration of technical machine learning processes with clinical workflows and healthcare infrastructures. It highlights how well-designed pipelines support reproducibility, scalability, transparency, and accountability in AI systems. By understanding the full lifecycle of machine learning systems in healthcare, learners and professionals gain insight into how AI models move from data collection to real-world clinical impact, supporting trustworthy, sustainable, and clinically aligned AI deployment across hospitals, research institutions, and health systems.
Stakeholders	• Clinicians and healthcare professionals • Health data scientists and analysts • Health informatics specialists • Hospital IT and data engineering teams • Digital health developers • Clinical researchers • Hospital administrators • Governance and compliance teams
Inputs	• Electronic Health Records (EHRs) • Clinical and operational datasets • Imaging and laboratory data • Population health data • Wearable and sensor data • Data standards and interoperability frameworks • Clinical domain knowledge
Process	• Data sourcing and acquisition • Data cleaning and preprocessing • Data integration and harmonisation • Feature engineering and selection • Model development and training • Model validation and testing • Regulatory and governance review • Deployment in clinical systems • Monitoring, maintenance, and updating

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Results/Output	• End-to-end ML pipelines • Deployable clinical AI models • Automated data workflows • Integrated AI services • Continuous learning systems • Clinical decision support tools
Benefits	• Reproducible AI development Scalable deployment of models • Improved data quality and consistency • Safer clinical AI systems • Faster translation from research to practice • Better integration into clinical workflows • Strong governance and accountability
Limitations and challenges	• Interoperability barriers • Data governance and privacy constraints • Technical complexity • Infrastructure requirements • Skills and workforce gaps • Regulatory compliance challenges • Maintenance and lifecycle management
Application examples	• Hospital AI deployment pipelines • Clinical decision support system integration • Imaging AI workflow systems • Predictive analytics pipelines • Research-to-clinic translation platforms • Population health ML systems • Continuous monitoring AI services
Sources	Kanbar, L.J., Wissel, B., Ni, Y., Pajor, N., Glauser, T., Pestian, J., & Dexheimer, J.W. (2022). Implementation of Machine Learning Pipelines for Clinical Practice: Development and Validation Study. JMIR Medical Informatics, 10(12), e37833. doi: 10.2196/37833. PMID: 36525289; PMCID: PMC9804095. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC9804095/

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	Yan, A.P., Guo, L.L., Inoue, J., Arciniegas, S.E., Vettese, E., Wolochacz, A., Crellin-Parsons, N., Purves, B., Wallace, S., Patel, A., Roshdi, M., Jessa, K., Cardiff, B., & Sung, L. (2025). A roadmap to implementing machine learning in healthcare: From concept to practice. Frontiers in Digital Health, 7 (2025). doi: 10.3389/fdgth.2025.1462751 Available at: https://doi.org/10.3389/fdgth.2025.1462751
Additional information	e.g. photos, graphs, scientific articles, additional links

3.2.20 Real World Machine Learning Applications in Medicine

Module: 3. Machine Learning

Unit: 5. Real-World ML Applications in Medicine

Use case name	Real World Machine Learning Applications in Medicine
Use case description	This use case surveys real-world, deployed machine learning applications in medicine, focusing on how models are translated from development to clinical use and embedded into workflows. It highlights four high-impact domains where machine learning has moved beyond prototypes into routine or near-routine practice: diagnostic imaging analysis, predictive pathology, genomics-enabled analytics, and personalised treatment recommendations. Across these domains, machine learning methods help clinicians manage information overload, reduce time-to-insight, and improve consistency in pattern recognition tasks. The unit emphasises the practical realities of deployment in clinical environments, including data quality and interoperability, model validation and governance, human factors (trust, usability, workflow fit), and ongoing performance monitoring. Learners explore how these applications are evaluated (e.g., clinical validation, regulatory authorisations where relevant), how outputs are presented to clinicians (e.g., alerts, prioritisation, decision support), and how limitations (bias, generalisability, false alarms) are mitigated. The goal is to develop a grounded understanding of where machine learning is already delivering measurable value in medicine, and what is required to implement these systems safely and sustainably.
Stakeholders	• Clinicians (radiology, pathology, oncology, primary care) • Patients and patient advocacy groups • Hospital administrators and operational leaders • Health informatics and IT teams • Health data scientists / ML engineers • Clinical researchers and trial teams • Quality & safety, clinical governance, and compliance teams

	• Regulators and health technology assessment bodies
Inputs	• Diagnostic imaging (e.g., CT, MRI, X-ray, fundus photographs) • Digital pathology whole-slide images (WSI) • Electronic Health Records (EHR) and clinical time-series • Genomic sequencing data (FASTQ/BAM/CRAM/VCF) and variant annotations • Clinical outcomes data and registries • Treatment protocols, guidelines, and knowledge bases • Real-world evidence datasets (claims, outcomes, utilisation)
Process	• Define clinical use case and outcome (what decision is supported and when) • Data sourcing and governance (consent, privacy, security, access control) • Data cleaning and preprocessing (standardisation, quality checks, missingness) • Feature engineering / representation learning (including imaging and sequence encodings) • Model development (supervised learning, deep learning, ensemble methods) • Validation (internal and external; calibration; subgroup analysis; safety checks) • Deployment (integration with PACS/LIS/EHR; UI/UX design; clinical workflow alignment) • Monitoring (drift detection, auditing, incident review, periodic recalibration) • Change management (training, documentation, governance, and continuous improvement)
Results/Output	• AI-assisted triage and prioritisation alerts • Diagnostic support outputs (classification, detection, segmentation) • Pathology screening assistance (suspicious foci marking, case prioritisation) • Variant calling and genomic interpretation outputs • Patient stratification and risk prediction outputs • Treatment and trial-matching suggestions (decision support, not autonomous prescribing) • Dashboards for quality, workflow performance, and model monitoring
Benefits	• Faster time-to-diagnosis and improved clinical throughput

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	• More consistent detection of subtle patterns (supporting human review) • Earlier identification of deterioration or high-risk patients • Enhanced precision medicine via integrated clinical molecular insights • Improved resource allocation and prioritisation in high-demand services • Standardisation of decision support across teams and sites
Limitations and challenges	• Dataset shift and generalisability across sites, scanners, protocols, and populations • Bias and inequity risk (performance differences across demographic subgroups) • False positives/negatives and downstream workflow impacts (alarm fatigue) • Interpretability and explanation needs in high-stakes decisions • Integration complexity (EHR/PACS/LIS interoperability) • Regulatory, legal, and accountability considerations • Maintenance burden: monitoring, updates, and recalibration over time
Application examples	• Diagnostic imaging analysis: AI triage for suspected stroke, autonomous retinal screening, imaging prioritisation • Predictive pathology: AI assistance for prostate biopsy review, lymph node metastasis detection support • Genomics: ML-enhanced variant calling pipelines and secondary analysis at scale • Personalised treatment recommendations: precision oncology decision support combining molecular profiling, guidelines, and trial matching
Sources	A) Diagnostic imaging analysis Viz.ai – Viz LVO (large vessel occlusion) workflow triage product overview: https://www.viz.ai/large-vessel-occlusion IDx-DR (autonomous diabetic retinopathy screening): https://www.healthvisors.com/en/idx-dr/ B) Predictive pathology (digital pathology broader lab/pathology context) Paige – FDA-approved Paige Prostate (assistive AI for prostate biopsy diagnosis): https://info.paige.ai/prostate Steiner, D.F., et al. (2018). Impact of deep learning assistance on histopathologic review (LYNA). American Journal of Surgical Pathology. https://pubmed.ncbi.nlm.nih.gov/30312179/ C) Genomics

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	Poplin, R., et al. (2018). A universal SNP and small-indel variant caller using deep neural networks (DeepVariant). Nature Biotechnology. https://www.nature.com/articles/nbt.4235 Illumina DRAGEN – Machine learning for variant calling documentation (DRAGEN-ML): https://help.dragen.illumina.com/ D) Personalised treatment recommendations Tempus Oncology – AI-enabled precision oncology solutions (trial matching and care pathway intelligence): https://www.tempus.com/oncology/
Additional information	

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3.3 MOOC 3: Interpersonal and Cross-Disciplinary Communication

This MOOC contains 10 use-case scenarios covering various aspects of interpersonal and cross-disciplinary communication.

3.3.1 AI-Powered Brain CT Analysis for Stroke and Hemorrhage Detection

Module: AI's Role in Reducing Errors and Improving Decision-Making in Healthcare

Unit: Case Studies on AI's Impact on Medical Errors

Use case name	AI-Powered Brain CT Analysis for Stroke and Hemorrhage Detection
Use case description	AI-powered imaging systems for brain CT and MRI use deep learning algorithms to identify acute ischemic stroke, intracerebral hemorrhage (ICH), and large vessel occlusion (LVO). These systems act as intelligent triage tools, automatically prioritizing urgent cases and alerting radiologists or neurologists in real time. By reducing interpretation delays and minimizing oversight errors, they enhance diagnostic accuracy, workflow efficiency, and time-to-treatment (e.g., for thrombolysis or thrombectomy), supporting improved decision-making and coordination of care.
Stakeholders	• Radiologists / Neuroradiologists – Primary users and validators of AI output. • Neurologists / Emergency physicians / Stroke teams – Recipients of AI alerts and primary treatment decision-makers. • Radiology technicians – Operate imaging hardware and initiate data transfer to PACS. • Health IT & PACS administrators – Maintain technical infrastructure and integration. • Hospital management & QA – Oversee performance, compliance, and adoption. • Patients & families – Indirect stakeholders benefiting from faster diagnosis and reduced errors.
Inputs	• MRI or CT brain scans (DICOM (Digital Imaging and Communications in Medicine) standard format) • Patient demographic and clinical data (onset time, symptoms, vital signs) • Radiology Information System (RIS) and Picture Archiving and Communication System (PACS) access • Annotations or ground-truth datasets for AI model training, used during model development and validation

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	• Integration metadata (timestamps, modality type, study priority)
Process	• Image Acquisition: Brain imaging (non-contrast CT, CTA, or MRI) performed in emergency or inpatient settings. • Automated Preprocessing: The AI system standardizes and segments scan data to enhance contrast and suppress noise. • AI Detection: Deep convolutional neural networks (CNNs) analyze scans to identify acute ischemic stroke, intracranial hemorrhage (ICH), or large vessel occlusion (LVO). • Alert Generation: The system issues real-time notifications and annotated images to clinicians or PACS dashboards, highlighting suspected findings. • Clinical Review: Radiologists verify and finalize results within the standard reporting workflow. • Model Updating: System performance is refined periodically using new data and clinician feedback, under regulatory oversight.
Results/Output	• AI-generated heatmaps or overlays indicating lesion locations. • Automatic case prioritization in the radiology worklist. • Structured findings appended to radiology reports. • Timestamped alerts that shorten "door-to-needle" time in stroke care. • Audit trails documenting AI-human decision concordance for quality monitoring.
Benefits	• Reduced diagnostic errors: Decrease in missed or misclassified stroke and hemorrhage cases. • Faster treatment decisions: Time-to-notification reductions of 15–60 minutes reported in clinical studies. • Improved inter-rater reliability: AI standardizes image interpretation across readers. • Enhanced workflow efficiency: Automated triage reduces radiologist workload and reporting delays. • Evidence-based outcomes: Multi-center studies demonstrate improved workflow metrics and treatment timeliness in stroke networks using AI triage systems.
Limitations and challenges	• Dependence on high-quality, artifact-free imaging for accurate analysis. • Variability across scanner models and imaging protocols affecting generalizability. • Occasional false positives or negatives requiring radiologist verification. • Integration and interoperability issues with existing PACS/RIS systems. • Clinician acceptance and explainability challenges for AI decisions.

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	• Ongoing regulatory and liability considerations for autonomous decision support.
Application examples	Viz.ai FDA De Novo-cleared and CE-marked platform for automated detection and triage of large vessel occlusion (LVO) strokes. It integrates into hospital imaging workflows and has been shown to reduce specialist notification times by about 52 minutes, improving coordination of care. RapidAI CE- and FDA-cleared software suite for stroke imaging analysis, detecting ischemic core and perfusion mismatch within minutes. It supports faster imaging-to-treatment decisions and greater diagnostic consistency in emergency stroke management. Avicenna.AI (CINA-ICH) FDA-cleared and CE-marked tool for automated intracranial hemorrhage detection on non-contrast CT scans. It integrates with PACS systems and achieves around 90% sensitivity and specificity in multicenter validation studies. Aidoc FDA-cleared AI platform for radiology triage, including stroke and intracranial hemorrhage detection. Studies report high diagnostic accuracy and improved workflow efficiency through automated case prioritization.
Sources	Seyam, M., Weikert, T., Saut, A., Brehm, A., Psychogios, M-N. & Blackham, K. (2022) 'Utilization of Artificial Intelligence–based Intracranial Hemorrhage Detection on Emergent Noncontrast CT Images in Clinical Workflow', Radiology: Artificial Intelligence. doi: 10.1148/ryai.210168. Available at: https://pubs.rsna.org/doi/10.1148/ryai.210168 Villringer, K., Sokiranski, R., Opfer, R., Spies, L., Hamann, M., Bormann, A., Brehmer, M., Galinovic, I., & Fiebach, J.B. (2025) An Artificial Intelligence Algorithm Integrated into the Clinical Workflow Can Ensure High Quality Acute Intracranial Hemorrhage CT Diagnostic. Clinical Neuroradiology, 35(1), 115–122. doi: 10.1007/s00062-024-01461-9. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC11832613/ Soun, J.E., Chow, D.S., Nagamine, M., Takhtawala, R.S., Filippi, C.G., Yu, W. & Chang, P.D. (2021) Artificial Intelligence and Acute Stroke Imaging. American Journal of Neuroradiology, 42(1), pp. 2–11. doi: 10.3174/ajnr.A6883. Available at: https://www.ajnr.org/content/42/1/2 Jiang, B., Pham, N. et al. Deep Learning Applications in Imaging of Acute Ischemic Stroke: A Systematic Review and Narrative Summary. Radiology. doi: 10.1148/radiol.240775. Available at: https://pubs.rsna.org/doi/10.1148/radiol.240775 Al-Janabi, O.M.; El Refaei, A.; Elgazzar, T.; Mahmood, Y.M.; Bakir, D.; Gajjar, A.; Alateya, A.; Jha, S.K.; Ghozy, S.; Kallmes, D.F.; et al. (2024) Current Stroke Solutions Using Artificial Intelligence: A Review of the

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Additional information	

3.3.2 AI-Enabled Cardiac Diagnostics and Decision Support

Module: AI's Role in Reducing Errors and Improving Decision-Making in Healthcare

Unit: Designing AI Solutions for Safe and Effective Healthcare Communication

Use case name	AI-Enabled Cardiac Diagnostics and Decision Support
Use case description	AI-assisted cardiac imaging and electrocardiogram (ECG) analysis tools combine deep learning, computer vision, and signal processing to support clinicians in detecting complex cardiovascular conditions, including arrhythmias, left ventricular dysfunction, and heart failure. Systems such as Caption AI, Ultromics EchoGo Core, and Mayo Clinic's ECG-AI guide clinicians during echocardiography or interpret ECG data in real time. These tools enhance diagnostic consistency and communication by generating explainable visual feedback and structured summaries that fit seamlessly into clinical workflows. In emergency and critical care settings, such AI support improves decision-making speed, reduces inter-operator variability, and provides reliable triage information — while ensuring clinicians retain final oversight.
Stakeholders	• Cardiologists / Echocardiographers – Primary interpreters of AI-processed results • Emergency and critical care physicians – Use AI-assisted findings to guide immediate interventions

	• Sonographers and technicians – Operate ultrasound devices and ensure data quality • Nurses and allied staff – Communicate AI-guided findings to care teams • Health IT teams and biomedical engineers – Manage integration with EHR and imaging systems • Patients and families – Benefit from faster, more accurate diagnoses and clearer communication of results
Inputs	• Ultrasound (echo) or ECG signal data in DICOM (Digital Imaging and Communications in Medicine) or compatible formats • Patient demographic and clinical history data (age, sex, risk factors) • Integration with EHR, PACS (Picture Archiving and Communication Systems), and cardiology information systems • Annotated datasets used for algorithm training and ongoing validation • Metadata: timestamps, device type, study protocol, acquisition quality
Process	• Data Acquisition: Real-time ultrasound or ECG signals are captured via connected devices • Automated Preprocessing: AI system standardizes signal quality, filters noise, and verifies image orientation • Guided Acquisition (for echocardiography): The AI provides real-time visual cues ("move probe left", "increase depth") ensuring optimal image capture even by non-experts. • AI Analysis: Deep learning models assess cardiac chamber size, wall motion, ejection fraction, and rhythm abnormalities • Explainable Output: Annotated images, graphs, and heatmaps highlight abnormal patterns or regions of interest • Clinical Review: Cardiologists review AI findings, confirm or adjust interpretation, and finalize the report • Continuous Validation: Outcomes and user feedback are used to refine models and improve reliability across populations.
Results/Output	• Automated quantification of cardiac function (e.g., ejection fraction, wall motion score) • Color-coded overlays showing regions of abnormality • Real-time feedback during image acquisition ("adequate view achieved") • Structured reports integrated directly into the EHR • Timely alerts for high-risk findings (e.g., severe dysfunction or arrhythmia)
Benefits	• Improved diagnostic accuracy: Detects subtle patterns that may be missed by human observers, improving early detection of dysfunction

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	• Enhanced workflow efficiency: Reduces scanning time and the need for rescans • Explainable communication: Visual feedback supports clinician confidence and aids patient education • Increased access: Enables high-quality echo imaging in rural or resource-limited settings through guided acquisition • Validated outcomes: Multiple studies confirm high correlation between AI and expert cardiologist measurements
Limitations and challenges	• Dependence on high-quality signal acquisition and device calibration • Risk of alert fatigue if AI sensitivity is set too high • Limited performance in patients with atypical anatomy or comorbidities • Need for external validation across diverse populations and care settings • Legal and ethical considerations for liability when AI advice influences urgent treatment decisions.
Application examples	Caption AI (Caption Health / GE HealthCare) https://www.captionhealth.com Regulatory Status: FDA De Novo-cleared for real-time echocardiography guidance (2020; updated integration with GE HealthCare, 2024). Function: Enables non-expert clinicians (e.g., nurses, general practitioners) to capture diagnostic-quality cardiac images with real-time AI feedback on probe positioning and view adequacy. Key Validation Study: Asch F.M. et al. (2022). Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use. JAMA Cardiology, 7(6), 597–603. https://jamanetwork.com/journals/jamacardiology/fullarticle/2776714 In this clinical trial, AI-guided operators achieved diagnostic-quality imaging in 98.8% of cases for left-ventricular assessment compared with expert sonographers. Supporting Industry Source: Caption Health Press Release (2022): "JAMA Cardiology Publication Shows Effectiveness of AI-Guided Ultrasound Software." https://www.caption-care.com/press/caption-health-announces-jama-cardiology-publication-showing-effectiveness-of-ai-guided-ultrasound-software Ultromics EchoGo Core / EchoGo Amyloidosis (Ultromics) https://www.ultromics.com/ Regulatory Status: CE-marked and FDA-cleared software for automated quantification of cardiac function; granted "Breakthrough Device" designation for heart-failure detection (HFpEF module, 2023). Function: Uses deep-learning models on echocardiograms to calculate ventricular strain, ejection fraction, and tissue characterization. The EchoGo Amyloidosis module supports early detection of cardiac amyloid disease.

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	Key Clinical Evidence: Jeremy A Slivnick et al. (2025). Cardiac amyloidosis detection from a single echocardiographic video clip: a novel artificial intelligence-based screening tool, European Heart Journal, ehaf387. https://doi.org/10.1093/eurheartj/ehaf387 Reported sensitivity 85% and specificity 93% for AI-assisted amyloidosis detection versus expert interpretation. Supporting Regulatory Announcement: Ultromics Receives FDA Clearance for EchoGo Heart Failure: An AI-Based Platform for Precision Detection of HFpEF (2023). https://www.prnewswire.com/news-releases/ultromics-receives-fda-clearance-for-its-breakthrough-device-echogo-heart-failure-301695862.html Research Collaboration: Mayo Clinic News Network (2025): "AI-Enhanced Echocardiography Improves Early Detection of Amyloid Build-Up in the Heart." https://newsnetwork.mayoclinic.org/discussion/ai-enhanced-echocardiography-improves-early-detection-of-amyloid-buildup-in-the-heart Mayo Clinic AI-ECG Algorithms https://www.mayoclinic.org/departments-centers/ai-cardiology/overview/ovc-20486648 Regulatory Status: The AI-ECG algorithm for low ejection fraction (LEF) received U.S. FDA 510(k) clearance in October 2023. It is deployed for clinical decision support within Mayo Clinic and partner institutions, and additional models for pulmonary hypertension and cardiac amyloidosis carry FDA Breakthrough Device Designation while undergoing expanded validation (Anumana Press Release, 2023). Function: Uses convolutional neural networks trained on >2 million ECGs to identify asymptomatic left-ventricular dysfunction, atrial fibrillation risk, and cardiac amyloidosis. Key Research Publications: Attia Z.I. et al. (2019). Screening for Cardiac Contractile Dysfunction Using an Artificial Intelligence–Enabled Electrocardiogram. Nature Medicine, 25, 70–74. https://www.nature.com/articles/s41591-018-0240-2 Siontis, K.C., Noseworthy, P.A., Attia, Z.I. et al. (2021). Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. Nature Reviews Cardiology, 18, 465–478. https://doi.org/10.1038/s41569-020-00503-2 Performance: Original AI-ECG achieved AUC 0.93 (sensitivity 86%, specificity 85%) for detecting LV dysfunction; validated externally with AUC 0.82 in independent cohorts. Institutional Overview: Mayo Clinic Platform Blog (2023): "Bringing AI-Assisted Cardiology into the Future." https://www.mayoclinicplatform.org/2023/08/03/bringing-ai-assisted-cardiology-into-the-future
Sources	See above for links related to specific examples

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Additional information	

3.3.3 Oxford Medical Simulation (OMS): AI-Supported Reflective Simulation and Feedback

Module: Continuous Learning and Professional Development in AI-Healthcare Communication

Unit: Lifelong Learning in AI and Healthcare Communication

Use case name	Oxford Medical Simulation (OMS): AI-Supported Reflective Simulation and Feedback
Use case description	Oxford Medical Simulation (OMS) delivers immersive, interactive virtual-reality (VR) and desktop simulations that enable healthcare learners to practise clinical decision-making, communication, and teamwork in a safe, repeatable environment. Learners engage with realistic virtual patients using voice and hand interaction to take histories, request investigations, and manage care. Following each scenario, OMS provides personalized feedback that identifies actions taken or missed, highlights strengths and areas for improvement, and encourages self-directed reflective thinking. The feedback enables learners to review what went well and what could be improved before or during a facilitated debrief. The platform logs user actions during the scenario and aligns performance to competency frameworks, generating dashboards that visualize individual and cohort progress. By integrating immersive simulation with structured, data-driven feedback, OMS helps learners transform experience into insight — reinforcing reflective practice, supporting continuous improvement, and strengthening confidence in real-world clinical communication and teamwork.
Stakeholders	• Healthcare and nursing students / clinicians • Engage in immersive VR or desktop simulations and review feedback for self-reflection • Clinical educators and mentors • Facilitate debriefs using AI-generated feedback reports and dashboards • Curriculum designers / simulation leads • Incorporate AI-supported metrics and reflective activities into institutional competency frameworks • Academic and healthcare institutions • Implement scalable, standardized reflective-learning programs supported by simulation and AI technologies

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Inputs	• Library of 250 evidence-based VR and desktop scenarios covering acute, chronic, and communication-focused cases. • Learner interaction data: actions taken, requests made, and decisions logged in real time. • Performance metrics aligned to institutional competency standards. • Integration with Learning Management Systems (LMS) and analytics dashboards for educators and administrators. • Optional voice-controlled and hand-gesture AI modules for more natural interaction with virtual patients.
Process	• Scenario Engagement – The learner enters an interactive clinical simulation through VR headset or desktop platform. • Action Logging – The system records the learner's decisions and actions throughout the encounter • Automated Feedback – At scenario completion, OMS generates individualized feedback identifying strengths and improvement areas • Competency Mapping – Logged actions are linked to established learning outcomes or institutional frameworks • Reflection and Debrief – Learners use feedback to reflect independently or as part of a facilitator-led discussion • Iteration and Re-practice – Scenarios can be repeated, enabling learners to apply insights and track improvement
Results/Output	• Personalized feedback reports summarizing performance against scenario objectives • Competency dashboards tracking learner progress across cases • Standardized reflective opportunities integrated into clinical education workflows • Aggregated analytics for educators to identify training gaps or curriculum needs
Benefits	• Encourages structured reflection and self-assessment through data-driven feedback • Improves communication and teamwork skills in realistic, safe environments • Enhances accessibility and scalability — learners can practise anywhere via VR or desktop • Reduces educator burden, offering consistent automated formative feedback • Supports continuous professional growth and confidence in complex decision-making.

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Limitations and challenges	• Current feedback primarily evaluates logged learner actions and scenario outcomes rather than offering full conversational or emotional analysis • Effectiveness depends on hardware availability, institutional digital literacy, and active educator facilitation to guide reflection • Integration with learning management systems (LMS) and compliance with data-privacy standards (e.g., GDPR) require institutional oversight • As with all simulation-based education, the long-term impact on real-world patient outcomes remains an area of ongoing study
Application examples	• Oxford Medical Simulation (OMS) Website: https://oxfordmedicalsimulation.com • Used across academic and healthcare institutions globally (UK NHS Trusts, US and EU universities) • Deployed for competency-based assessment and reflective-skill development in professional curricula
Sources	Published findings and organizational reports on the efficacy, usability, and cost effectiveness of virtual-reality simulation in healthcare education from OMS site: https://oxfordmedicalsimulation.com/research/ Stamer, T., Steinhäuser, J., & Flägel, K. (2023). Artificial Intelligence Supporting the Training of Communication Skills in the Education of Health Care Professions: Scoping Review. Journal of medical Internet research, 25, e43311. https://doi.org/10.2196/43311
Additional information	

3.3.4 AI-Powered Clinical Documentation Assistants

Module: Effective Strategies for Communicating AI Solutions in Healthcare

Unit: AI Tools for Enhancing Healthcare Communication

Use case name	AI-Powered Clinical Documentation Assistants
Use case description	AI-powered Clinical Documentation Assistants (CDAs) utilize ambient listening, speech recognition, and natural language processing (NLP) to automatically transcribe and summarize clinician-patient interactions into structured electronic health record (EHR) entries. These tools aim to alleviate administrative burdens, enhance documentation accuracy, and allow clinicians to focus more on patient care.

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Stakeholders	• Physicians and specialists • Nurse practitioners and physician assistants • Medical scribes • Health IT departments • Hospital administrators • Health insurance providers
Inputs	• Audio recordings of clinician-patient conversations • EHR system access (e.g., patient history, medications) • Clinical terminologies and ontologies (e.g. Systematized Nomenclature of Medicine • Clinical Terms (SNOMED CT), International Classification of Diseases (ICD-10)) • Metadata such as appointment type and care context
Process	• Audio Capture: Secure recording of clinical encounters • Speech Recognition: Transcription of spoken language into text • NLP Processing: Identification of clinical entities and context • Summarization & Structuring: Generation of structured clinical notes • Integration & Review: Population of notes into the EHR for clinician review • Adaptive Learning: Continuous improvement through user feedback
Results/Output	• Structured clinical notes generated automatically, including standardized formats such as SOAP notes (Subjective, Objective, Assessment, and Plan) and discharge summaries • Intelligent suggestions for diagnostic and procedural coding using recognized classifications (e.g. ICD • International Classification of Diseases) • Direct integration of structured data into electronic health record (EHR) systems • Time-stamped documentation supporting traceability for audit and billing purposes • Optional voice-controlled navigation and data entry within EHR environments
Benefits	• Reduction in documentation time • Decreased clinician burnout and improved job satisfaction • Enhanced accuracy and completeness of medical records • Accelerated billing cycles and improved coding precision

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	• Increased patient-clinician interaction time • Scalability across various specialties and care settings
Limitations and challenges	• Dependence on high-quality audio input • Learning curve for clinicians adapting to new workflows • Ensuring data privacy and compliance with regulations (e.g. HIPAA, GDPR) • Potential NLP errors requiring manual verification • Variability in performance across different languages and accents • Integration challenges with existing EHR systems
Application examples	• Nuance DAX Copilot (Microsoft): Utilized by over 400 U.S. healthcare organizations, DAX Copilot ambiently records clinician-patient visits and generates draft notes for EHR integration • Suki AI: An AI assistant that streamlines clinical documentation through ambient note generation, dictation, and coding capabilities, integrating seamlessly with major EHRs • Augmedix: Offers ambient AI medical documentation technology that alleviates administrative burdens, allowing doctors more time for patient care • Abridge: Transforms clinical conversations into structured notes in real-time, integrated directly into EHR workflows, and supports-multiple languages. • Amazon Transcribe Medical: Provides HIPAA-eligible speech-to-text transcription services tailored for medical use, supporting various specialties (foundational technology)
Sources	Nuance DAX Copilot (Microsoft), https://daxcopilot.ai/ Suki AI, https://www.suki.ai/ Augmedix, https://www.augmedix.com/ Abridge, https://www.abridge.com/ Amazon Transcribe Medical, https://aws.amazon.com/transcribe/medical/ Bracken, A., Reilly, C., Feeley, A. et al. Artificial Intelligence (AI), Powered Documentation Systems in Healthcare: A Systematic Review. J Med Syst 49, 28 (2025). https://doi.org/10.1007/s10916-025-02157-4
Additional information	

3.3.5 IBM Watson for Oncology – A Cautionary Tale

Module: Effective Strategies for Communicating AI Solutions in Healthcare

Unit: Communicating AI Concepts to Medical Professionals

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Use case name	IBM Watson for Oncology – A Cautionary Tale
Use case description	IBM Watson for Oncology was developed as an AI-powered decision support tool to recommend cancer treatments based on clinical guidelines and medical literature. Trained with expert input from US hospital Memorial Sloan Kettering, it aimed to deliver personalized, evidence-based therapy options. However, the system faced serious criticism for unsafe recommendations, lack of transparency, limited data training, and unmet promises. Its eventual discontinuation reflects the ethical risks of deploying inadequately validated AI in clinical care.
Stakeholders	• Oncologists and care teams (primary users) • Cancer patients • Hospitals and health systems • Medical regulators and policymakers • Insurers and healthcare payers
Inputs	• Patient clinical records (diagnosis, biomarkers, comorbidities) • Oncology literature and clinical guidelines • Curated synthetic training cases • Optional genomic profiles or clinical trial data • Clinician queries
Process	• Clinicians input patient data into the platform • AI matches case features with treatment options • Treatment options are ranked: "Recommended," "For Consideration," "Not Recommended" • Each option includes supporting evidence • Clinician reviews suggestions and makes the final decision
Results/Output	• Ranked treatment recommendations with confidence scores • References to supporting journal articles or guidelines • Optional clinical trial matches or genomic insights
Benefits	• Accelerated access to global cancer research • Attempted standardization of oncology care across settings • Aspirational support for clinicians in resource-limited environments • Early successes in matching expert consensus in certain cases

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Limitations and challenges	• Unsafe recommendations: Suggested harmful treatments in real scenarios • Overhyped performance: Marketing outpaced real-world efficacy • Training bias: Data derived from a narrow expert base (Memorial Sloan Kettering only) • Lack of transparency: Clinicians couldn't evaluate AI logic or confidence • Limited adaptability: Poor performance in global contexts with different drug access • Erosion of trust: Failed deployments damaged confidence in AI healthcare • Unclear accountability: Legal ambiguity in clinician–AI decision dynamics
Application examples	• IBM Watson for Oncology: Deployed in 15+ countries; discontinued after serious performance concerns and project cancellations (e.g. MD Anderson). • Watson Health sold in 2022, effectively ending the oncology AI product line
Sources	Henrico Dolfing (2024) 'Case Study: The $4 Billion AI Failure of IBM Watson for Oncology', HenricoDolfing.com https://www.henricodolfing.com/2024/12/case-study-ibm-watson-for-oncology-failure.html This detailed case study outlines how unrealistic promises, lack of clinician input, and weak clinical integration led to Watson's downfall, positioning it as a cautionary tale in medical AI. David D. Luxton (2019) 'Should Watson be consulted for a second opinion?', AMA Journal of Ethics, 21(2) https://journalofethics.ama-assn.org/article/should-watson-be-consulted-second-opinion/2019-02 This article critically examines the ethical implications of using AI like Watson as a second opinion in clinical care, highlighting concerns about trust, transparency, and the limits of algorithmic reasoning in high-stakes decisions. Konam, S. (2022) 'Where did IBM go wrong with Watson Health?', Quartz. https://qz.com/ibm-watson-health-failure-ai-1850313791 This article analyzes how IBM Watson for Oncology failed due to limited training data, overreliance on synthetic cases, and poor generalizability, offering key lessons in ethical AI deployment. Ross, C. and Swetlitz, I. (2017) IBM pitched its Watson supercomputer as a revolution in cancer care. It's nowhere close. STAT News. https://www.statnews.com/2017/09/05/watson-ibm-cancer/ This early exposé reveals how Watson for Oncology failed to meet its ambitious claims, citing insiders and clinicians who reported mismatch

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	between the AI's suggestions and clinical reality, and highlighting a growing gap between marketing and medical effectiveness.
Additional information	Modern alternatives: • Paige AI: FDA-cleared for cancer pathology detection, with transparent training and clear human oversight • LLM Oncology Assistants: Emerging GPT-like models emphasize traceability, feedback loops, and narrow task focus • Collaborative clinical AI platforms (the "human-in-the-loop" approach): Systems that blend AI insights with clinician oversight in oncology For example: Fountzilas, E., Pearce, T., Baysal, M.A. et al. Convergence of evolving artificial intelligence and machine learning techniques in precision oncology.npj Digit. Med. 8, 75 (2025). This peer-reviewed paper contrasts early expert-rule systems like Watson with modern precision oncology tools, emphasizing the importance of rigorous validation and real-world performance. https://doi.org/10.1038/s41746-025-01471-y Bristow, H. (2024). "Cancer Diagnostics in the Age of AI." – The Pathologist This interview highlights how current AI tools like Paige succeed by focusing on narrow tasks, undergoing FDA validation, and maintaining clinician control—addressing the ethical gaps Watson left behind. https://thepathologist.com/inside-the-lab/cancer-diagnostics-in-the-age-of-ai

3.3.6 AI Chatbots in Mental Health Support

Module: Ethical, Legal, and Patient-Centered Considerations in AI Communication

Unit: Ethical and Legal Frameworks in AI-Driven Communication

Use case name	AI Chatbots in Mental Health Support
Use case description	AI chatbots are designed to deliver mental health support using natural language processing (NLP). These systems simulate human-like conversations and provide Cognitive Behavioral Therapy (CBT)-based responses. They aim to offer timely, accessible support for individuals struggling with anxiety, depression, or stress. However, this raises ethical concerns around privacy, misdiagnosis, and the replacement of human care.
Stakeholders	• Patients seeking mental health support (users) • Employers concerned about mental health issues • Mental health professionals • Health service providers and insurers

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Inputs	• User chat messages • Self-reported symptoms • Behavioral patterns (e.g. usage frequency, sentiment changes) • Optional biometric or device data
Process	• Users interact with the chatbot through text-based conversations • The chatbot analyzes inputs using natural language processing to identify emotional cues and mental health indicators • Based on CBT principles, the chatbot provides responses aimed at reframing negative thoughts and promoting coping strategies • In some cases, the chatbot may suggest seeking professional help or provide resources for crisis situations
Results/Output	• Real-time, personalized conversational support • Delivery of CBT-based exercises and coping mechanisms • Suggestions for self-care routines • Recommendations for further mental health resources or professional consultation
Benefits	• Accessibility: Available 24/7, providing immediate support without the need for appointments • Anonymity: Users may feel more comfortable discussing sensitive issues anonymously • Scalability: Can serve a large number of users simultaneously, addressing gaps in mental health service availability • Cost-Effectiveness: Offers a low-cost alternative or supplement to traditional therapy sessions
Limitations and challenges	• Privacy Concerns: Sensitive user data may be vulnerable to breaches or misuse (especially if not protected under health privacy laws like HIPAA in the US) • Data Handling Practices: Investigations reveal that some mental health apps may share user data with third parties, raising questions about consent and transparency • Efficacy: While some studies show short-term benefits, there is limited evidence on long-term effectiveness compared to traditional therapy • Lack of Human Empathy: Chatbots cannot replicate the nuanced understanding and empathy of human therapists • Risk Management: Potential inability to appropriately handle crisis situations or recognize signs of severe mental health issues

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Application examples	• Woebot: A chatbot developed to deliver CBT-based support, showing promise in reducing symptoms of depression and anxiety in short-term studies • Wysa: An AI chatbot offering mental health support, used in various settings including by the UK's National Health Service. • Tess: A psychological AI chatbot designed to support mental health through text-based conversations.
Sources	Krakower, D. (2025). When your therapist is an algorithm: Risks of AI counseling. Psychology Today https://www.psychologytoday.com/us/blog/the-human-algorithm/202503/when-your-therapist-is-an-algorithm-risks-of-ai-counseling The article discusses the emotional risks and ethical concerns of using AI chatbots as therapy substitutes, warning about user dependency and insufficient oversight. Rana, M., Jameel, S., & Akram, A. (2024). Enhancing mental health with artificial intelligence. Discover Mental Health, 4(1) https://www.sciencedirect.com/science/article/pii/S2949916X24000525 This article highlights the potential of AI to address global mental health challenges by enhancing access and reducing costs, while stressing the importance of ethical integration. Psychreg. (2023). How mental health chatbots are changing the way we get support https://www.psychreg.org/how-mental-health-chatbots-are-changing-way-we-get-support/ Chatbots are making mental health support more accessible by offering anonymous, affordable, and stigma-free assistance to users. Stanford HAI. (2023). Exploring the dangers of AI in mental health care https://hai.stanford.edu/news/exploring-the-dangers-of-ai-in-mental-health-care The article outlines key risks of mental health AI, including bias, poor regulation, and the danger of misdiagnosis or inadequate care in critical scenarios. Kaur, A. et al. (2024). AI chatbots for mental health: Exploring user perspectives and potential harms. Frontiers in Psychiatry. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC11514308/ This article presents insights from users with depression on mental health chatbot use, revealing both helpful features and concerns about personalization and safety.
Additional information	

3.3.7 AI-Powered Conversational Agents for Diabetes Self-Management Education

Module: Ethical, Legal, and Patient-Centered Considerations in AI Communication

Unit: Patient-Centered AI Communication Strategies

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Use case name	AI-Powered Conversational Agents for Diabetes Self-Management Education
Use case description	AI-powered conversational agents (including chatbots) are increasingly utilized to support patients with Type 2 Diabetes Mellitus (T2DM) in understanding and managing their condition. These systems provide personalized education, medication reminders, lifestyle guidance, and real-time responses to patient inquiries. By reinforcing structured education and increasing engagement, these tools assist patients in applying self-care practices in daily life.
Stakeholders	• Patients with T2DM • Diabetes educators • Primary care providers & endocrinologists • Hospital administrators • Public health organizations
Inputs	• Patient medical data (e.g. glucose levels, medication history) • Lifestyle data (diet, activity, sleep) • Patient interactions (messages, queries) • Educational content (validated diabetes education guidelines)
Process	• The AI chatbot ingests patient-specific data and contextual preferences • Utilizing Natural Language Processing (NLP) and Machine Learning (ML) models, it interprets questions, generates responses, and adapts over time • Based on patient responses and health data, it tailors educational content, sends reminders, and answers questions • Conversations are continuously updated to match the patient's learning and behavior patterns
Results/Output	• Real-time, tailored patient education messages • Behavioral nudges and reminders (e.g., check blood sugar, take medication) • Daily/weekly progress summaries • Reports to caregivers or clinicians if integrated
Benefits	• Improved patient engagement and knowledge retention • Reduced burden on healthcare professionals • Enhanced adherence to treatment and self-care routines • Scalable and cost-effective for healthcare systems • 24/7 support availability, beneficial in underserved areas

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Limitations and challenges	• Requires patient trust and buy-in • Challenges in AI explainability and validation in clinical settings • Variability in literacy and digital access among patients • Compliance with data privacy and security regulations (e.g., GDPR, HIPAA) • Risk of misinformation if content is not properly curated
Application examples	• Lark Health: Offers AI health coaching for diabetes management, providing personalized guidance and monitoring • My Diabetes Coach (Australia): Utilizes an embodied conversational agent named "Laura" to deliver diabetes self-management education and support via a smartphone app • AIDA Project: Features a text-based chatbot and a speech-based dialog system providing information about diabetes and dietary recommendations • mPulse Mobile: Implements conversational AI to drive behavior change and improve diabetes self-management among patients
Sources	Wu, Y., et al. (2024) Application of Chatbots to Help Patients Self-Manage Diabetes: Systematic Review and Meta-Analysis https://www.jmir.org/2024/1/e60380 This systematic review and meta-analysis evaluated the effectiveness of chatbot interventions in supporting diabetes self-management, analyzing 25 studies from 14 countries and finding that chatbots can improve patient engagement and glycemic control Baptista, S., et al. (2020) Acceptability of an Embodied Conversational Agent for Type 2 Diabetes Self-Management Education and Support via a Smartphone App: Mixed Methods Study https://mhealth.jmir.org/2020/7/e17038 This mixed methods study assessed the acceptability of an embodied conversational agent named "Laura" in the My Diabetes Coach app, finding high user engagement and perceived usefulness among adults with type 2 diabetes Bot MD (2024) How AI is Transforming Diabetes Care: A Comprehensive Guide https://www.botmd.io/en/blog/how-ai-is-transforming-diabetes-care-a-comprehensive-guide This article discusses how AI-driven tools are enhancing diabetes care by improving education, adherence, and patient engagement through personalized solutions and targeted messaging Alloatti, F., et al. (2021) Diabetes and Conversational Agents: The AIDA Project Case Study https://link.springer.com/article/10.1007/s44163-021-00005-1 This case study describes the development and implementation of the AIDA Chatbot and AIDA Cookbot, the first Italian-language conversational agents designed to support diabetes patients, clinicians, and caregivers with information and dietary guidance mPulse Mobile (2020) Conversational AI Drives Behavior Change to Improve Diabetes Self-Management. https://go.mpulse.com/hubfs/2023%20-%20Case%20Studies/mPulseMobile-CaseStudy-Diabetes.pdf This case study illustrates how mPulse Mobile's conversational AI solutions effectively

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	engage individuals in diabetes self-management, leading to improved health outcomes and behavior change through tailored and meaningful dialogue
Additional information	

3.3.8 Resolving misunderstandings in AI-healthcare team discussions

Module: Foundations of Interpersonal and Cross-Disciplinary Communication

Unit: Common Barriers and Challenges in Interdisciplinary Communication

Use case name	Resolving misunderstandings in AI-healthcare team discussions
Use case description	In modern healthcare settings, interdisciplinary teams comprising clinicians, data scientists, IT professionals, and administrators collaborate to integrate AI technologies into clinical workflows. However, these collaborations often encounter misunderstandings due to differences in professional languages, varying levels of AI literacy, and distinct priorities. For instance, clinicians may prioritize patient safety and ethical considerations, while data scientists focus on algorithm performance and data integrity. Such misunderstandings can lead to conflicts, hinder the effective implementation of AI solutions, and compromise patient care. Addressing these challenges requires structured communication strategies, mutual education, and the establishment of shared goals. By fostering an environment of open dialogue and continuous learning, interdisciplinary teams can bridge gaps in understanding, align their objectives, and collaboratively harness AI's potential to enhance healthcare outcomes.
Stakeholders	Clinicians (physicians, nurses, allied health professionals) Data scientists and AI developers Healthcare administrators and managers IT support staff Patients and patient advocacy groups Ethicists and legal advisors
Inputs	Clinical data (e.g., patient records, imaging results) AI model outputs and performance metrics Feedback from clinical staff and patients Organizational policies and protocols Training materials on AI tools and applications
Process	Identification of misunderstandings: Regular interdisciplinary meetings are held to discuss AI integration, during which misunderstandings are identified through feedback and observation. Structured communication: Implement communication frameworks such as SBAR (Situation, Background, Assessment, Recommendation) to standardize information exchange. Mutual education sessions: Organize workshops where clinicians learn about AI basics, and data scientists gain insights into clinical workflows and patient care priorities. Establishment of shared goals: Facilitate sessions to define common objectives, ensuring all stakeholders have aligned expectations regarding AI implementation. Feedback mechanisms: Develop

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	channels for continuous feedback, allowing team members to express concerns and suggestions regarding AI tools and processes. Conflict resolution protocols: Establish clear protocols for addressing and resolving conflicts arising from misunderstandings, possibly involving neutral mediators when necessary.
Results/Output	Enhanced mutual understanding among interdisciplinary team members Improved integration and utilization of AI tools in clinical settings Reduction in conflicts and implementation delays Elevated patient care quality and safety Increased staff satisfaction and collaboration
Benefits	Improved collaboration: Fosters a collaborative environment where diverse expertise is valued and integrated. Effective AI implementation: Ensures AI tools are effectively tailored to meet clinical needs, enhancing their utility and acceptance. Enhanced patient outcomes: By aligning AI applications with clinical priorities, patient care quality and safety are improved. Professional development: Encourages continuous learning and professional growth among team members. Organizational efficiency: Reduces delays and resource wastage associated with miscommunications and conflicts.
Limitations and challenges	Resource constraints: Allocating time and resources for training and meetings can be challenging. Resistance to change: Some team members may be resistant to adopting new communication frameworks or AI tools. Complexity of AI tools: The technical complexity of AI systems may still pose understanding challenges despite training efforts. Maintaining engagement: Sustaining active participation from all stakeholders over time requires ongoing motivation and reinforcement.
Application examples	Addressing misunderstandings in AI tool deployment In a healthcare facility, the deployment of an AI scheduling tool faced resistance due to misunderstandings about its functionality. By organizing joint training sessions and feedback meetings, the team resolved misconceptions, leading to improved scheduling efficiency and staff satisfaction. Enhancing interdisciplinary communication in AI implementation A hospital introduced regular interdisciplinary workshops to facilitate better understanding between clinicians and AI developers. These sessions led to the successful integration of an AI-based diagnostic tool, with clinicians reporting increased confidence in using the system and developers gaining valuable insights into clinical needs.
Sources	Simbo AI Blog: Navigating Conflicts Among Healthcare Professionals LinkedIn Article: AI Workplace Conflict Resolution: Effective Strategies ScienceDirect: Artificial intelligence and multidisciplinary team meetings Frontiers in Big Data: Interdisciplinary Research in Artificial Intelligence: Challenges and Opportunities

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Additional information	How to prepare supporting information for your article Provides comprehensive guidelines on preparing supplementary materials, including acceptable file formats and content types. How to Prepare Supporting Information for Your Article A free full-text archive of biomedical and life sciences journal literature, useful for sourcing relevant articles and images. PubMed Central (PMC) Provides access to a vast collection of biomedical literature, including articles, reviews, and clinical guidelines. Europe PMC

3.3.9 Interactive workflow optimization

Module: Foundations of Interpersonal and Cross-Disciplinary Communication

Unit: Communication Models in AI and Healthcare

Use case name	Interactive workflow optimization
Use case description	In emergency clinics and hospitals, AI tools—such as triage assistants and documentation bots—are being deployed to automate repetitive administrative tasks, support clinical decision-making, and streamline workflows. For instance, a custom AI triage assistant designed with machine learning and Bayesian networks can reduce triage times by around 40% and identify critical patients 25% faster. Similarly, AI-powered documentation assistants like Heidi Health's scribe or GPT-4–based systems can save clinicians 2 hours daily by transcribing consultations and drafting notes, significantly reducing burnout and improving patient interaction quality. These AI applications transform static, one-way alert workflows into interactive, real-time communication among clinicians, AI specialists, and support staff—turning passive alerts into collaborative discussions and documentation into shared knowledge. The result: faster decision-making, reduced errors, and better clinician engagement and patient care through transactional communication-enhanced workflows.
Stakeholders	Clinicians (Physicians, Nurses and Allied Staff) • Provide frontline patient care and interact directly with AI alerts and documentation tools. • Primary users who rely on AI to support decision-making, reduce administrative burden, and improve clinical workflows. AI Developers and Data Scientists • Design, validate, and maintain AI models (e.g., triage systems, ambient scribes) used in clinical settings. • Responsible for ensuring model accuracy, transparency, and integration into daily workflows. Health IT Staff and System Integrators • Implement AI tools in hospital information systems (EHRs, dashboards). • Ensure system compatibility, data flow, and usability. Healthcare Managers and Administrators • Oversee implementation strategy, resource allocation, and quality monitoring. • Facilitate stakeholder engagement and align AI with institutional priorities. Patients and Carers

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	• Beneficiaries of improved care coordination, accuracy, and reduced clinician burden. • Their consent and expectations shape the acceptability and ethical use of AI. Regulators and Policy-Makers • Govern data privacy, AI safety, accountability, and clinical standards. • Provide frameworks for ethical deployment and long-term monitoring. Researchers and Academics • Conduct qualitative and quantitative evaluations of AI impacts on workflows, safety, and communication. • Contribute evidence to improve design and implementation models.
Inputs	Patient vital signs • Heart rate, respiratory rate, oxygen saturation, and blood pressure are continuously monitored and serve as key indicators for risk scoring (e.g., sepsis, acute deterioration). Electronic health record (EHR) data Real-time clinical observations Medical Imaging and Diagnostic Tests Audio transcription of consultations Environmental and contextual data
Process	1. Data ingestion and preprocessing 2. Feature extraction and pattern recognition 3. Classification and predictive modeling 4. Contextual aggregation and scoring 5. Alert generation and rationale explanation 6. Real-time dashboard display and interaction
Results/ Output	Triage prioritization alerts • The AI system generates real-time risk scores and priority flags (e.g., sepsis, critical deterioration risk), enabling clinicians to act promptly. Studies report faster triage decisions by up to 40% and enhanced accuracy, with triage prediction accuracy ranging from 80.5% to 99.1%. Clinical documentation and summaries • AI scribes transcribe consultations and produce structured clinical notes like SOAP notes, discharge summaries, and referrals. Clinicians using ambient AI reports note a 20–30% reduction in documentation time and better after-hours work-life balance. Error detection and quality control • The AI flags documentation inconsistencies, missing data, or coding errors in real-time, improving compliance, coding accuracy, and quality of medical records. Clinician engagement metrics • Mixed quantitative and qualitative feedback shows that about half of users report improvements in documentation workflows, while studies highlight increased clinician satisfaction, reduced burnout, and enhanced trust. Computational outputs • For imaging models (e.g., Aidoc), outputs include segmented lesion regions and diagnosis probabilities, with high performance metrics, 93% sensitivity and 95% specificity for pulmonary embolism and intracranial hemorrhage detection
Benefits	Increased diagnostic accuracy Time savings and efficiency Reduced clinician burnout and improved job satisfaction Operational and economic impact Enhanced patient–clinician interaction

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Limitations and challenges	Data quality and availability • Healthcare datasets are often incomplete, inconsistent, or siloed, hindering model training and reliability Bias and Fairness • AI models may perpetuate systemic bias (e.g., underdiagnosing minority groups) due to skewed historical data. • Ensuring fairness demands continuous monitoring and algorithmic adjustments. Explainability • Many AI systems (especially deep learning) lack transparency, making their decisions hard to interpret or justify. • Without explainability, clinicians may hesitate to rely on AI outputs. Privacy & Data Security • AI requires access to sensitive patient records, raising concerns around GDPR/HIPAA compliance and potential data breaches. Workflow Integration & Usability • Technical tools often don't fit existing clinical workflows, causing disruptions or underutilization. • Requires significant redesign and clinician engagement to embed real-time communication. Implementation Costs & Infrastructure • Deployment needs advanced IT infrastructure, skilled staff, and sustained funding, barriers for smaller healthcare organizations. Regulatory & Ethical Compliance • AI in healthcare is subject to stringent regulatory pathways (e.g., FDA, CE marking), requiring lengthy validation and approvals. • Raises complex questions of accountability, who's responsible if AI makes a harmful decision? Human Factors & Trust • Clinicians may fear loss of autonomy, mistrust AI results, or resist new technologies. • Building trust requires transparency, training, and ongoing human oversight.
Application examples	1. Duke University: Sepsis Watch AI monitors patient data in real time and flags potential sepsis cases. 2. City Hospital: Patient Flow Optimization System Combines predictive analytics, real-time dashboards, and dynamic staffing suggestions. 3. Regional Medical Center Network: AI Triage AI triages 350 ED beds across multiple hospitals; early-warning alerts integrated into nurse-physician conversations. 4. Memorial Healthcare (South Florida): AI Chatbots Implemented across six hospitals to manage appointments, triage, and discharge follow-up. 5. Kaiser Permanente: NLP Inbox Triage & Mammography Risk Scoring AI sorts ~1.2M patient messages monthly, cutting physician inbox workload by 50%.
Sources	https://dihi.org/project/sepsiswatch https://pubmed.ncbi.nlm.nih.gov/39657021/ https://www.wired.com/stor y/ai-help-patients-doctors-understand/ https://common-sense.com/blog/2025/05/ca se-study-how-ai-reduced-patient-wait-t imes-by-30-at-city-hospital/index.html

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	https://www.triageiq.com/quantifying-the-impact-of-ai-triage-on-patient-outcomes https://www.researchgate.net/publication/389177823_Artificial_Intelligence_in_Healthcare_Transformative_Opportunities_and_Policy_Implications
Additional information	

3.3.10 Explaining AI diagnostics to non-technical medical staff

Module: Foundations of Interpersonal and Cross-Disciplinary Communication

Unit: Fundamentals of Communication in Healthcare and AI

Use case name	Explaining AI diagnostics to non-technical medical staff
Use case description	In modern healthcare settings, artificial intelligence (AI) systems are increasingly employed to assist in diagnostics by analyzing complex medical data such as imaging, laboratory results, and patient histories. While these systems can enhance diagnostic accuracy and efficiency, their outputs often lack transparency, making it challenging for non-technical medical staff, such as nurses, general practitioners, and administrative personnel, to comprehend and trust the AI-generated conclusions. This use case addresses the implementation of Explainable AI (XAI) techniques to bridge the understanding gap between complex AI diagnostics and non-technical medical staff. By incorporating user-friendly explanations, such as visual annotations on medical images, simplified textual summaries, and confidence scores, XAI aims to make AI decisions more interpretable. For instance, in radiology, AI systems can highlight specific areas on an X-ray that influenced a diagnosis, allowing staff to visually grasp the rationale behind the AI's conclusion. The primary objective is to foster trust and facilitate informed decision-making among non-technical staff by providing clear, concise, and accessible explanations of AI diagnostics. This not only enhances interdisciplinary communication but also ensures that AI tools are effectively integrated into clinical workflows, ultimately improving patient care outcomes.
Stakeholders	Nurses General practitioners Medical administrative staff Radiologists AI System Developers Hospital administrators Patients
Inputs	Patient medical records Diagnostic images (e.g., X-rays, MRIs) Laboratory test results Clinical notes
Process	The process of implementing Explainable AI (XAI) to elucidate AI diagnostics for non-technical medical staff involves several key steps: • Data

	acquisition and preprocessing Collect relevant patient data, including medical images (e.g., X-rays, MRIs), laboratory results, and clinical notes. Preprocess the data to ensure quality and consistency, addressing issues such as missing values or image artifacts. • AI model analysis Utilize AI algorithms to analyze the preprocessed data, identifying patterns and generating diagnostic predictions. Employ models capable of providing interpretable outputs, such as decision trees or models augmented with explanation techniques. • Generation of explanations Apply XAI techniques (e.g., SHAP, LIME) to the AI model's outputs to determine the contributing factors to each prediction. Translate these factors into understandable explanations, highlighting key variables or image regions influencing the diagnosis. • Visualization and communication Present the explanations through intuitive visualizations, such as annotated images or bar charts indicating feature importance. Provide concise textual summaries that contextualize the AI's findings in clinical terms familiar to medical staff. • Integration into clinical workflow Incorporate the explanatory outputs into existing clinical systems, ensuring accessibility for non-technical staff. Facilitate training sessions to familiarize staff with interpreting and utilizing the AI-generated explanations effectively.
Results/Output	Diagnostic recommendations with accompanying explanations Visual aids (e.g., highlighted areas on medical images) Simplified textual summaries Confidence scores indicating the AI's certainty
Benefits	Improved understanding of AI diagnostics among non-technical staff XAI aids non-technical medical personnel in making informed decisions by elucidating the rationale behind AI outputs. This clarity supports better patient care and reduces reliance on opaque "black-box" AI systems. Enhanced trust in AI systems by providing clear explanations of AI-driven decisions, XAI fosters transparency, enabling non-technical staff to understand and trust AI recommendations. This transparency is crucial for the ethical adoption of AI in healthcare settings. Facilitated interdisciplinary communication: clear explanations of AI diagnostics bridge the communication gap between technical and non-technical staff, promoting collaborative decision-making and cohesive patient care strategies. Identification and mitigation of bias: XAI enables the detection of potential biases within AI models by highlighting the factors influencing decisions. This capability is essential for ensuring equitable and fair treatment across diverse patient populations. Regulatory compliance and ethical standards: Providing explainable outputs aligns AI systems with healthcare regulations and ethical standards, facilitating compliance with policies that mandate transparency in clinical decision-making processes. More informed and timely clinical decisions
Limitations and challenges	Potential oversimplification of complex AI decisions Risk of misinterpretation of AI explanations Need for continuous training and education of staff Ensuring explanations are tailored to varying levels of medical knowledge

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Application examples	Use of annotated X-rays to explain AI-detected anomalies to nurses Simplified reports generated by AI systems for general practitioners Training sessions for administrative staff on interpreting AI outputs Breast Cancer detection with Explainable AI An AI system capable of detecting breast cancer with accuracy comparable to radiologists. The system provides visual explanations, such as highlighting areas of concern on mammograms, aiding clinicians in understanding and trusting the AI's decisions.
Sources	BMC Medical Informatics and Decision Making: Explainability for artificial intelligence in healthcare Nature Scientific Reports: Non-task expert physicians benefit from correct explainable AI SpringerOpen: Explainability, transparency and black box challenges of AI in healthcare Quantori: Explainable AI for Medical Image Analysis, a Case Study ScienceDirect: Application of explainable artificial intelligence in medical health
Additional information	Case Study: enhancing diagnostic transparency in radiology A study conducted by Quantori demonstrated the application of Explainable AI in medical image analysis. By integrating XAI techniques, radiologists could better understand AI-driven diagnostic suggestions, leading to improved trust and collaboration between AI systems and medical professionals. Survey of explainable AI techniques in healthcare An extensive survey published in the Journal of Healthcare Engineering provides a comprehensive overview of current XAI techniques used in healthcare. The paper discusses various methods to increase interpretability in medical imaging and text analysis, offering guidelines for developing better AI models in clinical settings.

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3.4 MOOC 4: AI Ethics and Oversight

This MOOC contains 6 use-case scenarios covering various aspects of ai ethics and oversight.

3.4.1 ChestLink (Oxipit AI) Under EU Legal Frameworks for AI in Healthcare

Module: AI Healthcare Ethics and Law

Unit: EU Legal Frameworks for AI in Healthcare

Use case name	ChestLink (Oxipit AI) Under EU Legal Frameworks for AI in Healthcare
Use case description	ChestLink is an autonomous radiology AI system that analyzes chest X-ray DICOM images and issues final reports for clearly normal scans without requiring radiologist review. Only cases with any indication of abnormality or uncertainty are forwarded to a radiologist. This approach reduces the burden on radiologists by filtering out a significant portion of routine examinations. Developed in Lithuania, ChestLink became the first CE-marked autonomous diagnostic imaging AI in Europe in 2022 under the EU Medical Devices Regulation (MDR) as a Class IIb software medical device. This approval demonstrates that a system capable of issuing diagnostic conclusions without direct physician oversight can meet EU regulatory standards for safety and performance. Clinical deployments and pilots across several EU countries (Netherlands, Finland, Spain, Lithuania) show that ChestLink autonomously reports a portion of normal exams—typically 10–40% depending on the setting—with more than 99% precision in distinguishing normal from abnormal exams, allowing radiologists to concentrate on complex cases. The system provides a practical example of how emerging AI-driven autonomous diagnostic tools intersect with EU MDR, the upcoming EU AI Act, and GDPR obligations in health data processing.
Stakeholders	• Radiologists • Primary care physicians • Hospital directors and clinical managers • PACS/RIS administrators • Patients undergoing chest X-ray examinations • Oxipit (AI provider) under the AI Act terminology • Healthcare institutions deploying the system (AI Act "deployers") • National competent authorities for medical devices and AI oversight • Data Protection Officers (DPOs) and supervisory authorities (GDPR)
Inputs	Chest X-ray images in standard DICOM format Examination metadata (patient ID/pseudonym, date, clinical request) System configuration parameters (confidence thresholds, normal-case definitions) Technical

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	documentation, logs, and performance metrics required for MDR and AI Act compliance
Process	1. The chest X-ray image is acquired and automatically forwarded from PACS/RIS to ChestLink. 2. The model, trained on more than 500,000 X-ray images, analyzes the scan and classifies it as "normal" or "potentially abnormal." 3. If the model's confidence exceeds predefined high-assurance thresholds (targeting >99% sensitivity), it generates a final normal report without radiologist intervention. 4. Any scan with uncertainty, atypical pattern, poor image quality, or possible abnormality is routed to a radiologist. 5. The system generates audit logs on inputs, outputs, decisions, and model versions fulfilling MDR and AI Act obligations. 6. Data processing occurs within hospital infrastructure or a secure cloud environment, supported by appropriate GDPR safeguards such as pseudonymisation and strict access controls.
Results/Output	Final normal radiology report generated autonomously by the AI system A queue of cases forwarded to radiologists for manual review Performance dashboards (percentage automated, override rates, accuracy metrics) System logs, documentation, and monitoring data necessary for MDR post-market surveillance and future AI Act supervision
Benefits	Clinical & Operational • Automation of 10–40% of chest X-ray workload (primarily routine normal scans) • More radiologist time for complex, urgent, and diagnostically challenging cases • Increased patient throughput and more efficient use of imaging resources • Potential reduction of reporting delays in busy radiology departments Legal & Regulatory (EU Perspective) • Demonstrates successful MDR Class IIb conformity assessment for autonomous diagnostic AI • Represents a real-world example of a future high-risk AI system under the EU AI Act (Annex I) • Shows how MDR safety and performance requirements can align with AI Act obligations, including logging, risk management, and human oversight protocols • Incorporates GDPR-compliant processing of health data with safeguards supporting confidentiality, security, and lawful medical-use grounds

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Limitations and challenges	Clinical and Technical • Automation applies only to clearly normal chest X-ray exams; coverage is limited • Residual risk of false negatives (very small but clinically serious) requiring extremely conservative operating thresholds • Model generalizability may vary across populations, devices, and atypical conditions • Inability to process low-quality or non-standard images, which must be redirected to radiologists Legal, Ethical, and Governance • Complex questions regarding liability if an autonomous system fails to detect pathology Compliance with upcoming AI Act high-risk obligations, including: • continuous post-market monitoring • incident reporting • model updates • human oversight instructions • extensive logging requirements • GDPR challenges: lawful grounds for processing health data, DPIA requirements, allocation of roles and responsibilities (controller/processor), and ensuring proportionality of data processing.
Application examples	Hospitals using ChestLink to speed up reporting of routine chest X-rays. Primary care clinics adopting ChestLink to clear normal cases faster and reduce workload on radiologists. Radiology departments integrating ChestLink into triage workflows to prioritise scans with suspected findings. Healthcare systems piloting autonomous imaging AI to stabilise reporting times in areas with staff shortages. Research teams studying ChestLink to evaluate autonomous diagnostics, performance monitoring, and EU regulatory compliance.
Sources	
Additional information	https://oxipit.ai/news/first-autonomous-ai-medical-imaging-application/ https://startupreporter.eu/chestlink-ai-will-see-you-now/ https://artificialintelligenceact.eu/ https://link.springer.com/chapter/10.1007/978-3-031-41264-6_11 https://www.acadrad.org/wp-content/uploads/2024/02/brady-et-al-2024-multisociety-stmt.pdf https://pubs.rsna.org/doi/full/10.1148/ryai.230513 https://www.jmir.org/2025/1/e56306/PDF

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3.4.2 AI-Assisted Diagnosis and Medical Liability in Clinical Decision-Making

Module: AI Risks

Unit: Societal and professional risks of AI

Use case name	AI-Assisted Diagnosis and Medical Liability in Clinical Decision-Making
Use case description	This use case explores the integration of AI-based diagnostic algorithms in clinical settings and the resulting implications for medical liability. AI systems are increasingly used to support or autonomously perform diagnostic tasks, offering improved accuracy and efficiency. However, their use introduces complex legal challenges, particularly when errors occur. This use case examines how liability is distributed among stakeholders – clinicians, developers, and institutions – when AI contributes to patient harm.
Stakeholders	• Physicians and radiologists • AI developers and software vendors • Hospital administrators • Patients
Inputs	Patient health records Medical imaging (e.g., radiographs, ECGs) Laboratory test results Demographic and epidemiological data AI model training datasets
Process	1. AI algorithms analyse patient data to detect patterns or anomalies. 2. The system generates diagnostic suggestions or risk stratifications. 3. Clinicians review AI outputs and integrate them into clinical decision-making. 4. In some cases, AI may operate autonomously (e.g., in screening programs). 5. Outcomes are documented and communicated to patients.
Results/Output	Diagnostic reports Risk scores or stratification Alerts for abnormal findings Recommendations for further testing or treatment
Benefits	Enhanced diagnostic accuracy and speed Reduced clinician workload Improved access to care in underserved areas Early detection of diseases Cost savings through optimised resource allocation
Limitations and challenges	Liability ambiguity: Difficulty in assigning fault when AI errors occur Black box problem: Lack of transparency in AI decision-making Bias and fairness: Risk of health disparities due to unrepresentative training data Informed

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	consent: Challenges in explaining AI use and limitations to patients Over-reliance: Risk of clinicians deferring too much to AI outputs Regulatory gaps: Absence of unified legal frameworks for AI liability Data privacy and cybersecurity: Concerns over large-scale data use
Application examples	AI-ECG algorithms for rhythm detection in cardiology AI-assisted mammography in breast cancer screening Autonomous AI tools for diabetic retinopathy detection Clinical decision support systems in emergency departments
Sources	Cestonaro C, Delicati A, Marcante B, Caenazzo L and Tozzo P (2023) Defining medical liability when artificial intelligence is applied on diagnostic algorithms: a systematic review. Front. Med. 10:1305756. doi: 10.3389/fmed.2023.1305756
Additional information	

3.4.3 Parkinson's Disease Pathology Prediction using Colourimetry and Machine Learning

Module: Foundations of AI in Healthcare

Unit: Current AI applications in diagnostics, treatment, and administration

Use case name	Parkinson's Disease Pathology Prediction using Colourimetry and Machine Learning
Use case description	The project used the Parkinson’s UK Brain Bank images to explore the viability of using AI to identify Parkinson’s Disease. Detailed images from 400 brains with or without Parkinson’s were taken using microscopes capable of magnifying at 200x what an eye can normally see. The project produced a two-step solution. Firstly, an algorithm is applied to the existing images to highlight alpha-synuclein proteins that are indicative of Parkinson’s Disease being present. The second step was to use a trained neural network model that takes in the synthetically stained images to give a classification for whether Parkinson’s Disease is present in the image. The results seen using this method were excellent and could match (and exceed) the performance of experts in some aspects.
Stakeholders	Neurologists AI researchers Patients with suspected neurodegenerative conditions Academic institutions and research hospitals
Inputs	Digitized whole-slide images (WSIs) of post-mortem brain tissue Annotated datasets with Lewy body locations Metadata including patient demographics and disease stage

Process	Preprocessing: WSIs are tiled into smaller patches for analysis. Model Training: A convolutional neural network (CNN) is trained on annotated patches to detect Lewy bodies. Inference: The trained model scans new slides to identify and quantify Lewy bodies. Post-processing: Results are aggregated and visualized to support interpretation.
Results/Output	Heatmaps showing Lewy body distribution Quantitative metrics (e.g., count, density) of pathology Visual overlays for validation by pathologists Structured data for research and clinical decision-making
Benefits	Objective and reproducible pathology assessments Significant time savings in slide review Scalable analysis for large datasets and trials Support for biomarker discovery and disease staging
Limitations and challenges	Limited generalisability across staining protocols and institutions Need for high-quality annotated data for training Explainability concerns in clinical adoption Integration hurdles with existing pathology workflows Ethical considerations around post-mortem data use
Application examples	Used in NHSX Skunkworks project with University of Oxford and University of Manchester Supports research into Parkinson's progression and treatment efficacy Potential for adaptation to Alzheimer's and other neurodegenerative diseases
Sources	NHS AI Knowledge Repository Case Study: https://digital.nhs.uk/services/ai-knowledge-repository/case-studies/identifying-andquantifyingparkinsons-disease-using-ai-on-brain-slices Code: https://github.com/nhsx/skunkworks-parkinsons-detection A full technical report including background, model selection, performance metrics and known limitations, and detailing the data pipeline/processes emplo yed: https://github.com/nhsx/skunkworks-parkinsonsdetection/blob/main/docs/skunkworks-phase-2-technical-report.pdf
Additional information	a. The original slide, containing the α-syn proteins stained in a brownish colour. b. A processed version of the original slide, filtered for the brownish colour. c. The synthetically stained image after the algorithm has been applied to it. The α-syn proteins are now highlighted in a greenish colour.

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3.4.4 AI-Driven Preparation of Medical Imaging Data for Machine Learning

Module: Foundations of AI in Healthcare

Unit: Overview of Healthcare Data and AI Integration

Use case name	AI-Driven Preparation of Medical Imaging Data for Machine Learning
Use case description	This use case explores how artificial intelligence (AI) is integrated into the healthcare data pipeline, specifically in preparing medical imaging data for machine learning (ML) applications. It addresses the challenges of data availability, structure, and labelling, and outlines the steps required to transform raw imaging data into usable formats for AI model development. The goal is to enhance diagnostic accuracy, streamline workflows, and enable scalable AI solutions in clinical radiology. (Willemink et al., 2020)
Stakeholders	Radiologists AI developers and data scientists Hospital IT departments Ethics committees and regulatory bodies Patients Medical imaging vendors Clinical researchers
Inputs	Raw medical images: computed tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), X-ray DICOM metadata (Digital Imaging and Communications in Medicine (DICOM) is a technical standard for the digital storage and transmission of medical images and related information) Radiology reports (structured and unstructured) Biopsy results, lab data (for ground truth) Patient demographics and clinical outcomes
Process	Ethical Approval: Institutional review board clearance for data use. Data Access & Querying: Extracting images and metadata from PACS and EMRs. Picture archiving and communication system (PACS) is a medical imaging technology which provides economical storage and convenient access to images from multiple modalities. Electronic Medical Records (EMR) are digital versions of patients' healthcare charts used within healthcare practices. De-identification: Removing protected health information per HIPAA/GDPR. Quality Control: Ensuring image clarity and relevance. Structuring Data: Converting to machine-readable formats (e.g., DICOM, NIFTI). The NIfTI format (Neuroimaging Informatics Technology Initiative) is a file format used primarily for storing neuroimaging data, particularly from functional Magnetic Resonance Imaging (fMRI) and other medical imaging techniques. Labelling: Annotating images with expert input or Natural Language Processing (NLP) from reports. Storage: Secure local or cloud-based storage. Linking to Ground Truth: Connecting images to clinical outcomes or pathology.
Results/Output	Curated, labelled, and structured imaging datasets Ground truth annotations for supervised learning Segmentation maps and diagnostic labels Ready-to-use datasets for training, validation, and testing AI models

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Benefits	Enables development of clinically relevant AI algorithms Improves diagnostic accuracy and workflow efficiency Facilitates multi-institutional collaboration Supports regulatory approval through robust testing datasets Promotes ethical and secure data handling
Limitations and challenges	Limited access to large, diverse datasets High cost and time for expert labelling Data silos and interoperability issues Privacy risks in data sharing Bias due to single-source data Computational demands for high-resolution image processing
Application examples	DeepLesion is a large-scale, publicly available dataset developed by the NIH Clinical Center. It contains over 32,000 annotated lesions from CT images across various body parts and disease types. The dataset is designed to support research in universal lesion detection, helping AI models learn to identify abnormalities without being limited to a single organ or condition. https://nihcc.app.box.com/v/DeepLesion
Sources	Willemink, M. J., Koszek, W. A., Hardell, C., Wu, J., Fleischmann, D., Harvey, H., Folio, L. R., Summers, R. M., Rubin, D. L., & Lungren, M. P. (2020). Preparing Medical Imaging Data for Machine Learning. Radiology, 295(1), 4–15. https://doi.org/10.1148/radiol.2020192224
Additional information	[] Diagram shows process of medical image data handling.

3.4.5 Enhancing Empathy in Doctor–Patient Relationships through AI-Assisted Clinical Support

Module: Foundations of AI in Healthcare

Unit: Potential impact of AI on patient care, provider roles, and healthcare systems

Use case name	Enhancing Empathy in Doctor–Patient Relationships through AI-Assisted Clinical Support
Use case description	This use case explores how AI tools can be deployed in healthcare settings to support, rather than replace, human clinicians—specifically to enhance empathetic and compassionate doctor–patient relationships. By automating routine tasks and providing decision support, AI can free up time for clinicians to engage more meaningfully with patients, fostering trust, shared decision-making, and person-centred care (Sauerbrei et al., 2023).
Stakeholders	Physicians and clinicians Patients Hospital administrators Medical educators AI developers and vendors Policy makers

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Inputs	Electronic health records (EHRs) Diagnostic imaging Patient-reported outcomes AI-generated treatment recommendations Real-time monitoring data from wearables
Process	AI systems analyze patient data to: Identify patterns and generate diagnostic suggestions Rank treatment options based on clinical evidence Monitor patient health metrics continuously
Results/Output	AI-generated diagnostic and treatment suggestions Time savings for clinicians Enhanced patient autonomy through shared decision-making tools Improved communication and trust between doctors and patients
Benefits	Empathy and Compassion: More time for clinicians to engage empathetically with patients Trust: Transparent AI systems can foster trust in clinical decisions Efficiency: Reduced administrative burden and faster data analysis Patient Autonomy: Support for shared decision-making through explainable AI Education: Better preparation of future clinicians for AI-integrated care environments
Limitations and challenges	Explainability: Black-box AI systems may hinder trust and accountability Value Purity: AI must account for diverse patient preferences to avoid paternalism Ethical Concerns: Risk of dehumanizing care if AI replaces relational aspects Systemic Constraints: Time saved may be used for higher patient throughput rather than empathetic care Educational Gaps: Need for curricula that balance technical and relational skills
Application examples	IBM Watson's role is to rank treatment options based on outcome statistics presented in terms of 'disease-free survival' and to show a synthesis of the published evidence relevant to the clinical situation (McDougall, 2019).
Sources	McDougall, R. J. (2019). Computer knows best? The need for value-flexibility in medical AI. Journal of Medical Ethics, 45(3), 156–160. https://doi.org/10.1136/medethics-2018-105118 Sauerbrei, A., Kerasidou, A., Lucivero, F., & Hallowell, N. (2023). The impact of artificial intelligence on the person-centred, doctor-patient relationship: some problems and solutions. BMC Medical Informatics and Decision Making, 23(1), 73. https://doi.org/10.1186/s12911-023-02162-y
Additional information	

3.4.6 Principles of medical ethics

Module: Foundations of AI in Healthcare

Unit: Principles of medical ethics

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Use case name	Two Ethics frameworks (the Responsible Design Process and the Spheres of Technology Experience) and an example ethical analysis in the context of AI-Augmented Online Therapy for Depression and Anxiety (Peters et al., 2020)
Use case description	This use case involves the development and deployment of a text-based online therapy platform for individuals experiencing depression and anxiety. The platform uses AI to support therapists by analysing patient messages, suggesting therapeutic responses, and tracking patient progress. The goal is to increase access to mental health care, improve therapeutic outcomes, and reduce the burden on healthcare systems, while ensuring ethical integrity through responsible design. The use case is structured using two ethics frameworks: the Responsible Design Process (research, insights, ideation, prototyping, evaluation) and the Spheres of Technology Experience (adoption, interface, task, behaviour, life, society). Empirical tools like Consequence Scanning and Self-Determination Theory are recommended for ethical evaluation. Participatory design with patients and therapists is emphasised to ensure inclusivity and justice.
Stakeholders	Patients with depression or anxiety Therapists and counsellors Clinical psychologists AI developers and data scientists Healthcare administrators Data privacy officers Regulatory bodies
Inputs	Patient text messages and therapy session transcripts Therapist responses and annotations Patient demographic and health history data AI training datasets Feedback from patients and therapists
Process	Data Collection: Patient-therapist interactions are securely recorded. AI Analysis: Natural Language Processing (NLP) models analyse text for sentiment, risk indicators (e.g., suicidal ideation), and therapy progress. Therapist Support: AI suggests responses or therapeutic strategies based on best practices. Feedback Loop: Therapists review and adjust AI suggestions; patient outcomes are monitored. Ethical Oversight: Continuous evaluation using the Responsible Design Process and Spheres of Technology Experience frameworks.
Results/Output	AI-generated therapy suggestions Progress reports for therapists and patients Alerts for high-risk situations Anonymised data for research and model improvement
Benefits	Increased access to therapy, especially in underserved areas Reduced therapist workload Early detection of worsening symptoms Personalised, data-driven care Transparent and explainable AI decisions
Limitations and challenges	Risk of over-reliance on AI by therapists Potential bias in training data Privacy concerns with sensitive mental health data Difficulty in maintaining

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	relational authenticity Need for continuous ethical evaluation post-deployment
Application examples	IESO Digital Health: A real-world example where online therapy is delivered via text and supported by AI tools.
Sources	Peters, D., Vold, K., Robinson, D., & Calvo, R. A. (2020). Responsible AI—Two Frameworks for Ethical Design Practice. IEEE Transactions on Technology and Society, 1(1), 34–47. https://doi.org/10.1109/TTS.2020.2974991
Additional information	[] Connections among six fields centrally involved in the ethical design and development of AI and data-enabled systems (based on Sloan foundation's hexagonal mapping of "connections among the cognitive sciences" 1978, reproduced in Gardner 1985, p. 37) key: unbroken lines = strong interdisciplinary ties, broken lines = weak interdisciplinary ties.

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3.5 MOOC 5: AI in Healthcare for VET

This MOOC contains 13 use-case scenarios covering various aspects of ai in healthcare for vet.

3.5.1 AI-Assisted Early Detection and Management of Heart Failure Decompensation

Module: Basic digital and AI literacy

Unit: AI-Assisted Healthcare Systems

Use case name	AI-Assisted Early Detection and Management of Heart Failure Decompensation
Use case description	This use case describes how AI supports clinicians in detecting early signs of worsening heart failure and guiding timely interventions. The AI system combines diagnostic imaging analysis, clinical decision support in the electronic health record (EHR), and continuous remote monitoring via wearable devices. By identifying subtle patterns in imaging, medication risks, and changes in patient vitals, AI provides early alerts that help clinicians intervene before a patient's condition deteriorates. This reduces hospitalizations, improves outcomes, and ensures safer, more personalized care.
Stakeholders	• Cardiologists • Emergency physicians • Nurses and heart failure care teams • Radiologists • Patients with chronic heart failure • Hospital/clinic administrators • Digital health monitoring service providers
Inputs	• Chest X-ray or echocardiography images • Patient EHR data (medications, laboratory results, comorbidities) • Vital signs and biometrics from wearable devices (heart rate, weight, activity, oxygen saturation) • Patient-reported symptoms collected via a mobile app or chatbot
Process	1. Diagnostic Imaging Analysis • AI algorithms analyse chest X-rays or echocardiograms to detect early signs of congestion (e.g., pulmonary edema, fluid buildup). 2. Clinical Decision Support • The EHR-integrated AI system checks for unsafe medication combinations (e.g., interactions with diuretics or ACE inhibitors) and flags dosing inconsistencies.

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	3. Continuous Remote Monitoring • Wearable devices send patient vitals to an AI model trained to detect early deterioration patterns (e.g., sudden weight gain, increased resting heart rate). 4. Alert Generation • When abnormalities are detected, AI sends real-time alerts to the clinical team via the hospital system or mobile app. 5. Clinical Action • Nurses or doctors review the AI alert, validate findings, and adjust treatment (e.g., modifying diuretic dose, scheduling a check-up).
Results/Output	• Early identification of worsening heart failure symptoms • Automated alerts for medication risks or missed treatment steps • Real-time notifications about concerning changes in patient vitals • A summarized clinical report supporting timely decision-making
Benefits	• Earlier intervention, reducing risk of hospitalization or emergency deterioration • Increased diagnostic accuracy through AI-augmented imaging • Improved medication safety by identifying contraindications or risky combinations • Continuous patient support, even after discharge • Reduced workload for care teams, as AI handles data-heavy monitoring • Better long-term patient outcomes due to proactive management
Limitations and challenges	• Need for high-quality imaging and reliable wearable device data • Risk of false alerts, leading to potential alert fatigue among clinicians • Integration difficulties with existing hospital EHR systems • Variability in patient adherence to remote monitoring devices • Privacy and data security concerns related to home monitoring • Requirement for staff training and trust-building to ensure adoption
Application examples	• Hospitals using AI to analyse echocardiography for early signs of fluid overload • Clinics employing AI-driven medication safety checks in EHR systems • Remote heart failure programmes using wearables paired with AI to reduce readmissions • Cardiology units using automated alerts to prioritize high-risk patients • Home-based care teams monitoring vulnerable patients post-discharge
Sources	• "Early-Warning Algorithm Targeting Sepsis Deployed at Johns Hopkins" — Hopkins Medicine news article.

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	• "Prospective, multi-site study of patient outcomes after…" (Nature Medicine) — shows the clinical evaluation of TREWS. • Malone Center project page: description of TREWS from Johns Hopkins. • "Study: AI Surveillance Tool Successfully Helps to Predict Sepsis, Saves Lives" — UCSD press release. • "The Role of Artificial Intelligence in Echocardiography" (MDPI review) — covers imaging. • "Leveraging AI-enabled remote cardiac monitoring…" (diCardiology article) — remote monitoring.
Additional information	/

3.5.2 Recognising retinal diseases with AI at Moorfields Eye Hospital

Module: Basic digital and AI literacy

Unit: Introduction to Digital Tools in Healthcare

Use case name	Recognising retinal diseases with AI at Moorfields Eye Hospital
Use case description	In 2018, Moorfields Eye Hospital in London, in collaboration with DeepMind (Google), introduced an AI system that analyses OCT scans (optical tomography of the eye) to detect retinal diseases such as diabetic retinopathy and AMD. The AI identifies over 50 types of pathologies with an accuracy comparable to that of experienced ophthalmologists. This increases the detection rate and shortens the diagnosis time while reducing the burden on specialists.
Stakeholders	Ophthalmologists Patients Medical professionals Hospital administration AI team / DeepMind Health authorities (e.g. NHS, MHRA)
Inputs	OCT scan of the patient's eye The patient's medical history Reference data from specialists
Process	The OCT scan is scanned automatically. The AI model analyses the retinal structure and the segmentation of the tissue. The AI recognises anomalies and flags suspicious areas. The result of the analysis is recorded by an ophthalmologist in a follow-up questionnaire.
Results/Output	Labelled retinal images with problem warnings Diagnostic report for the doctor Probability rankings for various diseases
Benefits	Disease detection increases by ~94% with the competitive accuracy of experienced physicians Early diagnosis – faster start of treatment Reduced

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	workload for doctors – they can focus on complex cases Transparency – the AI system enables interpretation of results by specialists
Limitations and challenges	Requires large OCT dataset and clinical validation The need for explainability Legal and ethical issues associated with the use of medical data Limited availability of technology in poorly equipped facilities
Application examples	Initial diagnosis of diabetic retinopathy in outpatients Monitoring the progression of retinal diseases Decision support in ophthalmological committees
Sources	https://www.moorfields.nhs.uk/research/google-deepmind https://www.moorfields.nhs.uk/research/google-deepmind/google-deepmind-updates
Additional information	https://www.youtube.com/watch?v=MCI0xEGvHx8 https://www.youtube.com/watch?v=d58_mb95oVY https://blog.google/technology/health/deepmind-health-joins-google-health/ https://deepmind.google

3.5.3 Data Breach at Banner Health

Module: Basic digital and AI literacy

Unit: Managing Patient Data and Privacy

Use case name	Data Breach at Banner Health
Use case description	In August 2016, Banner Health, a major non-profit healthcare provider in the U.S., experienced a massive data breach exposing the personal and medical information of approximately 3.7 million patients. The breach highlighted the dangers of insufficient cybersecurity practices in AI-integrated healthcare environments. AI systems, which require vast amounts of data, can be vulnerable if organisations do not comply with basic data protection laws like HIPAA. This scenario demonstrates how organisational negligence – not just advanced cyberattacks – can lead to severe violations of patient privacy.
Stakeholders	Patients IT security teams Hospital administrators Healthcare compliance officers Government regulators (e.g. HHS, OCR) AI system developers and vendors

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Inputs	Electronic protected health information (ePHI) Payment processing data (credit card details) Patient demographic data (names, addresses, social security numbers) Appointment and physician data AI activity logs and user authentication data
Process	A healthcare system managed sensitive patient and financial data across multiple locations. Due to systemic noncompliance with HIPAA standards, cybercriminals gained unauthorised access to one of the payment processing servers. The breach went unnoticed until staff identified unusual system activity in the logs.
Results/Output	Exposure of 3.7 million individuals' data Investigation and enforcement action by the Office for Civil Rights (OCR) $1.25 million settlement and mandated corrective action Development of a new risk management plan and data protection policies
Benefits	Increased awareness of the real-world consequences of weak data governance Better understanding of how AI and healthcare data systems can be exploited Reinforcement of the need for compliance, monitoring, and continuous system testing Development of future-ready, secure AI workflows in healthcare settings
Limitations and challenges	Long-term failure to comply with HIPAA Security Rule Lack of regular system audits or employee training Poor authentication and access control mechanisms No AI-specific safeguards to prevent improper access to ePHI Lack of transparency about attack vectors used
Application examples	Hospitals adopting AI-based diagnostics must integrate proper security policies and enforce access controls Data breach response plans should include AI system vulnerabilities Regular audits of AI tools and data environments using HIPAA and GDPR frameworks
Sources	https://www.twingate.com/blog/tips/banner-health-data-breach https://www.hhs.gov/hipaa/for-professionals/compliance-enforcement/agreements/banner-health/index.html https://www.hhs.gov/hipaa/for-professionals/complianceenforcement/agreements/banner-health-ra-cap/index.html
Additional information	Teaching aid: Use this case as a basis for a classroom discussion or simulation on breach response and recovery

3.5.4 AI-based detection of retinal diseases using DeepMind

Module: Collaboration with AI systems

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Unit: AI in medical diagnostics

Use case name	AI-based detection of retinal diseases using DeepMind
Use case description	This AI system analyzes retinal images such as OCT scans and fundus photographs to identify signs of eye diseases at early stages. It supports clinicians by detecting patterns linked to conditions like diabetic retinopathy, age-related macular degeneration, and glaucoma. The system improves diagnostic accuracy, speeds up screening processes, and helps prioritize urgent cases, especially in healthcare systems with limited specialist availability.
Stakeholders	Ophthalmologists General practitioners Optometrists Patients Medical imaging technicians Hospital and clinic administrators Healthcare system planners
Inputs	Retinal images (OCT scans, fundus photographs) Patient metadata (age, risk factors, medical history where applicable) Clinical imaging records
Process	The AI system uses deep learning models trained on large datasets of labeled retinal images. It performs image analysis and pattern recognition to identify abnormalities, classify disease types, and assess severity. The model highlights suspicious regions and generates probability scores for different conditions.
Results/Output	Disease detection and classification Risk scoring and urgency assessment Visual heatmaps highlighting affected retinal areas Clinical decision support reports
Benefits	Early detection of eye diseases Improved diagnostic consistency Reduced workload for specialists Faster screening processes Better access to eye care in underserved regions Scalable population-level screening
Limitations and challenges	Need for large, high-quality training datasets Limited explainability of deep learning models Risk of bias in training data Integration challenges with hospital IT systems Regulatory and ethical approval requirements Dependence on image quality
Application examples	Screening diabetic patients for early signs of diabetic retinopathy in primary care clinics Triage systems in ophthalmology departments to prioritize urgent referrals Remote screening programs in rural or underserved areas Support tools for optometrists during routine eye exams
Sources	De Fauw, J., Ledsam, J. R., Romera-Paredes, B., Nikolov, S., Tomasev, N., Blackwell, S., … & Suleyman, M. (2018). Clinically applicable deep learning

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	for diagnosis and referral in retinal disease. Nature Medicine, 24(9), 1342–1350. https://doi.org/10.1038/s41591-018-0107-6 Ting, D. S. W., Cheung, C. Y., Lim, G., Tan, G. S. W., Quang, N. D., Gan, A., … & Wong, T. Y. (2019). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA, 318(22), 2211–2223. https://doi.org/10.1001/jama.2017.18152 Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., … & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402–2410. https://doi.org/10.1001/jama.2016.17216 Brown, J. M., Gardner, T. W., Shahzad, M., & Abràmoff, M. D. (2020). Automated diabetic retinopathy screening and monitoring using retinal fundus image analysis. Journal of Diabetes Science and Technology, 14(2), 238–247. https://doi.org/10.1177/1932296819886909 Schlegl, T., Waldstein, S. M., Bogunović, H., Endstraßer, F., Sadeghipour, A., Philip, A.-M., … & Schmidt-Erfurth, U. (2018). Fully automated detection and quantification of macular fluid in OCT using deep learning. Ophthalmology, 125(4), 549–558. https://doi.org/10.1016/j.ophtha.2017.10.031
Additional information	Scientific studies show that DeepMind's models can achieve performance comparable to expert clinicians in detecting certain retinal conditions. This use case is often cited as a leading example of explainable medical imaging AI because it can highlight regions of interest in scans, helping clinicians interpret results.

3.5.5 AI-Generated Clinical Summaries for Care Coordination

Module: Collaboration with AI systems

Unit: AI-powered clinical workflows

Use case name	AI-Generated Clinical Summaries for Care Coordination
Use case description	A US health system partnered with Pieces and Concord Health Partners to implement a generative AI tool that produces "Working Summaries" from clinical documentation. These summaries integrate fragmented patient data into a single, coherent report, supporting clinicians in decision-making and care coordination.
Stakeholders	Physicians and nurses (primary users) Care coordinators and case managers Hospital IT and data teams Patients (indirectly, through improved care)

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Inputs	Electronic Health Records (EHR) data Clinical notes and discharge summaries Lab results and imaging reports Patient demographic and visit history
Process	1. AI system ingests structured and unstructured patient data from EHR. 2. Generative AI creates a concise, coherent "Working Summary" for each patient. 3. Clinicians review, edit, and validate the summary before it is shared with the care team.
Results/Output	Automatically generated patient summaries Unified and structured clinical information for teams Reduction in manual data retrieval and note-writing
Benefits	Saves clinicians' time by reducing documentation workload Improves accuracy and consistency of patient information Enhances care coordination across departments Frees up more time for direct patient interaction
Limitations and challenges	AI-generated text may still contain inaccuracies and requires human review Risk of over-reliance on AI without critical validation Integration with existing hospital IT systems can be complex Data privacy and compliance concerns with generative AI
Application examples	Used in inpatient wards to prepare discharge summaries faster Supporting emergency departments by creating quick summaries for admitted patients Helpful in chronic disease management where multiple visits and data points must be consolidated
Sources	
Additional information	https://www.aha.org/system/files/media/file/2024/04/pieces-empowering-clinicians-casestudy-2024.pdf https://www.piecestech.com/

3.5.6 AI-Driven Early Detection of Sepsis (SepsisLab)

Module: Collaboration with AI systems

Unit: AI-powered clinical workflows

Use case name	AI-Driven Early Detection of Sepsis (SepsisLab)
Use case description	Sepsis is a life-threatening condition where quick diagnosis is essential. The SepsisLab system was developed to support clinicians by analysing patient data and predicting sepsis risk earlier than traditional methods. Unlike many

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	"black box" AI tools, SepsisLab was designed for human–AI collaboration: it provides risk scores, visual explanations, and suggests additional tests. This allows clinicians to remain in control while using AI insights to act faster.
Stakeholders	Emergency department doctors and nurses Intensive care unit (ICU) teams Hospital administrators (patient outcomes, resource use) Patients and families (direct beneficiaries)
Inputs	Vital signs (heart rate, blood pressure, temperature, oxygen levels) Lab results (blood tests, infection markers) Patient demographics and medical history
Process	1. The AI system continuously monitors incoming patient data. 2. It applies machine learning models to identify patterns linked to early sepsis. 3. The system provides a risk score, visual explanation (e.g. trend graphs), and recommended next steps (such as ordering a specific lab test). 4. Clinicians review AI insights and decide on interventions.
Results/Output	Real-time sepsis risk alerts for clinicians Visual dashboards explaining risk predictions Recommendations for additional diagnostic steps
Benefits	Earlier detection of sepsis → quicker treatment → higher survival rates Supports staff in high-pressure emergency or ICU settings Provides transparency by showing why the AI flagged a patient Helps allocate resources effectively (ICU beds, antibiotics)
Limitations and challenges	Requires high-quality, continuous data streams from hospital systems Risk of false alarms leading to "alert fatigue" Clinicians must still interpret AI results; over-reliance could be dangerous Integration with existing hospital EHRs can be technically complex
Application examples	Pilot studies in US hospitals where SepsisLab detected sepsis several hours earlier than staff alone Used in ICUs to continuously monitor hundreds of patients simultaneously Example scenario: an AI alert for subtle lab value changes prompted immediate action, reducing mortality risk
Sources	
Additional information	https://arxiv.org/pdf/2309.12368 https://pmc.ncbi.nlm.nih.gov/articles/PMC11470769/ https://www.the-microbiologist.com/news/a-human-centered-ai-tool-to-improve-sepsis-management/3953.article

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	https://www.insideprecisionmedicine.com/topics/patient-care/researchers-from-the-ohio-state-university-develop-human-centered-ai-tool-to-improve-sepsis-management/

3.5.7 Watson for Oncology (WFO) in Cervical Cancer Treatment Recommendation

Module: Collaboration with AI systems

Unit: AI-powered clinical workflows

Use case name	Watson for Oncology (WFO) in Cervical Cancer Treatment Recommendation
Use case description	This retrospective study compared the treatment recommendations given by IBM Watson for Oncology with real clinical decisions made by multidisciplinary teams (MDTs) in a large hospital in China for patients with cervical cancer. The goal was to assess how often Watson's suggestions aligned with real-world clinical practice — i.e. their concordance.
Stakeholders	Oncologists and MDTs in hospitals Patients with cervical cancer Hospital administration (quality, standardization) Developers/AI teams maintaining the Watson system Regulators and ethics committees
Inputs	Patient clinico-pathologic data: age, cancer stage, tumor features, metastasis, pathology, prior treatments Past medical records and treatment history Watson's internal knowledge base (clinical guidelines, literature, evidence)
Process	1. Clinical teams collected the patient's detailed data and input key variables into WFO (Watson for Oncology). 2. WFO processed the data and generated treatment options, categorized as "Recommended", "For Consideration", or "Not Recommended." 3. The actual treatments used by clinicians (MDT decisions) were compared to what WFO recommended. 4. Cases where WFO did not provide recommendations (unsupported cases) were also noted. 5. Discordant cases (where clinical decision and WFO differed) were reviewed by oncologists to understand reasons.
Results/Output	Out of 300 initial cases, 246 were included (others excluded for unsupported data) Watson did not support about 18% of cases (i.e. could not give recommendation) Among supported cases, concordance (i.e. Watson's recommendation matched or was considered acceptable by clinical team) was ~65.8% Discordance in ~34.2% of supported cases, and reasons included local treatment practices, unavailable drugs, patient comorbidities, and regional differences in guidelines

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Benefits	Watson can provide evidence-backed suggestions quickly, drawing from vast medical literature. It may help standardize treatment decisions in regions with fewer resources. It can support less experienced clinicians by offering reference to guidelines and evidence. In cases where Watson's suggestion aligns with clinical practice, it reinforces trust and supports decision-making.
Limitations and challenges	Watson did not support a portion of cases (i.e. "unsupported cases"), limiting its applicability. Discordance was non-trivial; human clinicians often deviated due to local practice, patient-specific factors, drug availability, or comorbidities. Watson's recommendations are based on literature and guidelines, which might not capture individual patient context (e.g. other illnesses, patient preference). Lack of transparency: clinicians may not always know how Watson arrived at its suggestions. Integration into local health systems and regulatory, ethical constraints.
Application examples	Used in over 80 hospitals in China for oncology decision support (breast, lung, cervical cancer) Particularly in rural or underserved settings, where access to cancer experts is limited — Watson helps fill knowledge gaps. In clinical studies for lung cancer and other tumour types comparing WFO vs MDT decisions.
Sources	
Additional information	https://www.researchgate.net/publication/316202671_IBM%27s_Watson_Analytics_for_Health_Care https://www.henricodolfing.com/2024/12/case-study-ibm-watson-for-oncology-failure.html?utm_source=chatgpt.com https://pmc.ncbi.nlm.nih.gov/articles/PMC6231834/ https://pmc.ncbi.nlm.nih.gov/articles/PMC3680569/ https://pmc.ncbi.nlm.nih.gov/articles/PMC7105853/

3.5.8 Collaborative AI Decision Support for Treatment Planning in Oncology

Module: Integrated ethical and adaptive competences

Unit: Human-AI Collaboration and Decision-Making

Use case name	Collaborative AI Decision Support for Treatment Planning in Oncology
Use case description	This use case demonstrates how an AI-based clinical decision support system collaborates with oncologists during cancer treatment planning. The AI analyzes patient data and clinical guidelines to suggest evidence-based treatment options, while clinicians remain fully responsible for final decisions. Explanations are provided to support understanding and discussion, enabling a human–AI partnership where AI augments clinical

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	expertise rather than replacing it. The system is designed to support multidisciplinary decision-making and improve consistency, transparency, and confidence in complex treatment choices.
Stakeholders	• Medical oncologists • Multidisciplinary tumor board members • Oncology nurses • Clinical data scientists and AI developers • Patients and caregivers • Hospital administrators
Inputs	• Patient clinical data (age, cancer stage, biomarkers) • Histopathology and imaging reports • Genomic or molecular test results (where available) • Clinical guidelines and treatment protocols • Model-generated risk scores and treatment suggestions
Process	1. The AI system analyzes patient-specific data and relevant clinical guidelines. 2. It generates ranked treatment options with estimated outcome probabilities. 3. Post-hoc explainability methods (e.g. SHAP) clarify which patient factors influenced recommendations. 4. Clinicians review AI suggestions during tumor board meetings. 5. Human experts accept, modify, or reject recommendations based on clinical judgment. 6. The final treatment decision is documented with human and AI inputs clearly distinguished.
Results/Output	• Ranked list of treatment options • Predicted outcomes (e.g. survival probability, recurrence risk) • Transparent explanations of contributing factors • Clinician-selected final treatment plan • Audit trail of human–AI interaction
Benefits	• Supports informed, evidence-based clinical decisions • Enhances transparency and clinician trust in AI systems • Encourages multidisciplinary discussion and consensus • Reduces cognitive load in complex decision-making

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	• Preserves clinician autonomy and accountability • Improves patient understanding of treatment options
Limitations and challenges	• Risk of automation bias if clinicians over-trust AI outputs • AI recommendations may not capture patient preferences • Integration into existing workflows can be time-consuming • Requires training to interpret explanations correctly • Ethical responsibility remains with human decision-makers
Application examples	• Tumor boards using AI to support therapy selection • Oncology departments standardizing treatment planning • Shared decision-making discussions with patients • Clinical training environments demonstrating AI-assisted care
Sources	• Rajkomar et al., 2019 – Machine Learning in Medicine • Lundberg & Lee, 2017 – SHAP • Holzinger et al., 2019 – Explainability and causability in medical AI • WHO – Ethics and governance of AI for health
Additional information	/

3.5.9 Regulatory Compliance Assessment for an AI-Based Clinical Decision Support System

Module: Integrated ethical and adaptive competences

Unit: Regulatory and Policy Frameworks

Use case name	Regulatory Compliance Assessment for an AI-Based Clinical Decision Support System
Use case description	This use case focuses on evaluating and preparing an AI-based clinical decision support system for regulatory approval and compliant clinical use. The system assists clinicians by providing risk assessments and treatment recommendations, but before deployment it must meet regulatory, ethical, and legal requirements. The use case illustrates how developers and healthcare institutions align an AI system with medical device regulations, data protection laws, transparency requirements, and clinical governance frameworks to ensure safe, lawful, and trustworthy use in healthcare settings.

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Stakeholders	• Regulatory and compliance officers • Hospital administrators • AI developers and product managers • Clinicians using AI-supported tools • Ethics committees • National and international regulators
Inputs	• AI system documentation (intended use, risk classification) • Model performance and validation reports • Explainability and transparency documentation • Data governance and privacy policies • Clinical workflow descriptions • Post-market monitoring plans
Process	1. The AI system is classified according to applicable medical device regulations (e.g. risk level and intended use). 2. Compliance requirements are identified (safety, transparency, human oversight, data protection). 3. Clinical validation evidence and performance metrics are reviewed. 4. Explainability mechanisms are assessed to ensure meaningful human oversight. 5. Data handling practices are evaluated for privacy and security compliance. 6. Risk management and post-deployment monitoring plans are established. 7. Documentation is prepared for regulatory review and internal governance approval.
Results/Output	• Regulatory compliance assessment report • Risk classification and conformity documentation • Evidence of clinical validation and safety • Transparency and explainability statements • Approved governance and oversight procedures • Readiness decision for clinical deployment
Benefits	• Enables lawful and ethical deployment of medical AI • Reduces regulatory and legal risks • Builds institutional and public trust in AI systems • Clarifies accountability and responsibility

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	• Supports long-term sustainability and scalability of AI solutions
Limitations and challenges	• Regulatory requirements differ across jurisdictions • Evolving AI regulations may require system updates • Compliance processes can be time-consuming and resource-intensive • Translating legal requirements into technical design is complex • Over-regulation may slow innovation if not managed carefully
Application examples	• Hospitals preparing AI tools for clinical rollout • Medical AI vendors seeking regulatory approval • Ethics boards reviewing AI-supported decision systems • Policymakers evaluating real-world AI deployments in healthcare
Sources	• World Health Organization – Ethics and Governance of Artificial Intelligence for Health (2021) • European Commission – EU Artificial Intelligence Act • European Commission – Medical Device Regulation (MDR 2017/745) • OECD – AI Principles and Policy Observatory • Council of Europe – Guidelines on AI and Human Rights
Additional information	/

3.5.10 Creating a medical AI prototype

Module: Practical technical skills in AI contexts

Unit: Creating a medical AI prototype

Use case name	Prototype AI System for Predicting 30-Day Hospital Readmission Risk
Use case description	This use case focuses on developing a medical AI prototype that predicts whether a patient is at risk of being readmitted to the hospital within 30 days of discharge. The prototype is designed as a proof-of-concept rather than a production-ready system and demonstrates the full AI development pipeline: data selection, preprocessing, model training, evaluation, and basic explainability. The goal is to help learners understand how medical AI systems are built, tested, and iteratively improved before clinical deployment.
Stakeholders	• Healthcare data scientists and AI developers • Clinicians involved in discharge planning

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	• Hospital quality improvement teams • Medical students and AI trainees • Health informatics researchers
Inputs	Electronic Health Record (EHR) data, including: • Patient demographics (age, sex) • Diagnoses and comorbidities • Length of stay • Previous admissions • Lab results and vital signs at discharge • Historical readmission labels (yes/no within 30 days)
Process	1. Relevant patient data are extracted from a historical hospital dataset. 2. Data preprocessing is performed (handling missing values, encoding categorical variables, normalization). 3. A baseline machine learning model (e.g. logistic regression or random forest) is trained to predict readmission risk. 4. The model is evaluated using metrics such as accuracy, recall, and ROC-AUC. 5. Basic post-hoc explainability methods (e.g. feature importance or SHAP) are applied to interpret predictions. 6. Results are reviewed to assess whether the model behaves in a clinically meaningful way.
Results/Output	• A binary prediction: high vs. low readmission risk • A probability score indicating likelihood of readmission • Feature importance or explanation plots showing key drivers (e.g. prior admissions, comorbidities) • Performance metrics summarizing prototype effectiveness
Benefits	• Demonstrates the end-to-end development of a medical AI system • Helps learners understand practical challenges in healthcare data • Provides an interpretable prototype suitable for early validation • Supports hospital efforts to identify high-risk patients • Serves as a foundation for more advanced or specialized AI models
Limitations and challenges	• Prototype performance may be limited by data quality and size • Historical EHR data may contain biases or missing information • Predictions are not causal and should not be used for clinical decisions

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	• Generalizability across hospitals or populations is not guaranteed • Requires clinical expertise to interpret results responsibly
Application examples	• Educational settings where students learn how to build medical AI models • Hospital innovation teams testing early AI concepts before full deployment • Research projects exploring predictors of readmission • Internal benchmarking of different modeling approaches
Sources	• Ribeiro et al., 2016 – LIME • Lundberg & Lee, 2017 – SHAP • WHO – Ethics and governance of AI for health • Rajkomar et al., 2019 – Machine Learning in Medicine
Additional information	/

3.5.11 Medical data and AI training

Module: Practical technical skills in AI contexts

Unit: Medical data and AI training

Use case name	Google Health – Breast Cancer Detection with AI
Use case description	This use case highlights how Google Health developed an AI model to detect breast cancer from mammograms. The project aimed to improve early detection by training an AI system using a large, diverse dataset of de-identified mammogram images. These images were labelled by expert radiologists and linked to biopsy-confirmed outcomes. The project was designed to show how high-quality, well-labelled medical data can lead to safer and more accurate diagnostic AI tools. Google's AI was tested in both the UK and the US, and it demonstrated strong generalisability when compared to human radiologists.
Stakeholders	The project involved several key stakeholders, including clinical AI developers, radiologists, medical data annotators, healthcare institutions conducting screening, and the patients whose images were used (de-identified). Regulatory agencies were also important, as they oversee how such AI tools can eventually be implemented in practice.
Inputs	The model was trained using more than 76,000 anonymised mammogram images collected from different hospitals in the UK and US. Each image was linked to expert-confirmed outcomes — for example, whether a cancer

	diagnosis had been confirmed via biopsy. Detailed metadata such as patient age, screening history, and imaging context supported the training process.
Process	To build the model, Google Health used a supervised learning approach. Expert radiologists labelled the mammograms, identifying areas of concern and linking them to confirmed diagnoses. The AI system was then trained to detect subtle patterns in the images that may indicate cancer. After training, the model was validated using unseen images from different hospital systems to test how well it could generalise. The AI's performance was then compared with that of experienced radiologists, both individually and in double-reading scenarios.
Results/Output	The trained AI system showed strong results, reducing both false positives and false negatives compared to traditional human-only assessments. In some cases, the AI even outperformed individual radiologists in diagnostic accuracy. These results showed how AI could be used to support radiologists by acting as a second reader, helping flag high-risk cases or reduce unnecessary follow-ups.
Benefits	This project demonstrated that high-quality data and strong labelling practices could lead to safer, more effective AI tools in clinical diagnostics. The AI tool had the potential to speed up breast cancer screening, reduce workloads for radiologists, and increase access to quality diagnostic tools in settings with limited staff. It also supported the development of explainable AI techniques and set a benchmark for ethical AI deployment in healthcare.
Limitations and challenges	Despite promising results, the project also revealed limitations. The AI's performance varied across demographic groups, and there were concerns about underrepresentation of certain populations in the training data. Another key challenge was the "black box" nature of the AI system — it could offer highly accurate predictions, but not always with clear explanations. Additionally, the model required large, high-quality datasets, which are not always available in all healthcare contexts. Concerns around data privacy, fairness, and accountability remain relevant for this and similar projects.
Application examples	The model has been used in pilot studies to support radiologists in breast cancer screening. It has served as a strong example of how diagnostic AI tools can be safely developed and tested, especially when supported by robust clinical partnerships. The case has also become a key example in AI ethics discussions, particularly around fairness and explainability in medical decision-making.
Sources	McKinney, S. M., et al. (2020). International evaluation of an AI system for breast cancer screening. Nature. https://www.nature.com/articles/s41586-019-1799-6 Google Health Blog. Breast cancer research. https://health.google/mammography/

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Additional information	e.g. photos, graphs, scientific articles, additional links

3.5.12 Optimised AI System for Sepsis Risk Prediction in Intensive Care Units

Module: Practical technical skills in AI contexts

Unit: Optimising AI for clinical use

Use case name	Optimised AI System for Sepsis Risk Prediction in Intensive Care Units
Use case description	This use case illustrates how an existing AI model for early sepsis detection is optimised for real-world clinical use. While an initial model can identify patients at risk of sepsis, further optimisation is required to ensure reliability, usability, and clinical safety. The optimisation process includes improving model performance, reducing false alerts, calibrating risk thresholds, integrating explainability, and aligning the system with clinical workflows. The final goal is to deliver timely, actionable alerts that clinicians trust and can effectively act upon.
Stakeholders	• Intensive care physicians • Nurses and clinical staff • Hospital quality and patient safety teams • Clinical AI developers and data scientists • Hospital IT and clinical informatics teams
Inputs	• Real-time ICU patient data, including: • Vital signs (heart rate, blood pressure, temperature) • Laboratory results (lactate, white blood cell count) • Medication and treatment records • Demographic and clinical history data • Continuous time-series data streams
Process	1. A baseline AI model predicts sepsis risk based on ICU patient data. 2. Model performance is analysed to identify issues such as high false-positive rates or alert fatigue. 3. Hyperparameters and feature sets are optimised to improve sensitivity and specificity. 4. Risk thresholds are adjusted in collaboration with clinicians to balance early detection and false alarms.

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	5. Post-hoc explainability methods (e.g. SHAP or LIME) are integrated to explain alerts. 6. The system is tested in a simulated or silent deployment before clinical rollout.
Results/Output	• Calibrated sepsis risk scores • Clinically meaningful alerts triggered at optimised thresholds • Explanatory summaries highlighting key contributing factors • Improved performance metrics (e.g. higher precision, reduced false alarms)
Benefits	• Earlier and more reliable detection of sepsis • Reduced alert fatigue for clinical staff • Improved clinician trust through explainability • Better alignment with clinical workflows • Enhanced patient safety and outcomes • Increased likelihood of successful clinical adoption
Limitations and challenges	• Balancing sensitivity and specificity remains context-dependent • Data drift over time may degrade model performance • Integration into hospital systems can be complex • Requires continuous monitoring and periodic retraining • Ethical and regulatory considerations for automated alerts
Application examples	• ICUs implementing AI-assisted early warning systems • Hospitals refining existing AI tools prior to full deployment • Clinical trials evaluating optimised decision support systems • Quality improvement initiatives targeting sepsis outcomes
Sources	• Rajkomar et al., 2019 – Machine Learning in Medicine • Ribeiro et al., 2016 – LIME • Lundberg & Lee, 2017 – SHAP • WHO – Ethics and governance of AI for health
Additional information	/

3.5.13 Pulse Oximeter Oxygen Level Misreading

Module: Practical technical skills in AI contexts

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Unit: Testing AI accuracy in medicine

Use case name	Pulse Oximeter Oxygen Level Misreading
Use case description	Pulse oximeters are medical devices supported by algorithms that estimate blood oxygen saturation (SpO_2) by analysing how light passes through the skin. They are widely used in hospitals, ambulances, and home care, especially for respiratory illnesses. Research has shown that these systems may produce less accurate results for people with darker skin tones, sometimes displaying oxygen levels that appear normal even when they are dangerously low. This example demonstrates how data limitations and device calibration can affect medical AI-supported measurements and lead to unequal healthcare outcomes.
Stakeholders	• Patients • Doctors and nurses • Emergency medical staff • Hospital administrators • Medical device manufacturers • Healthcare regulators and policymakers
Inputs	• Light absorption measurements from the skin (infrared and red light) • Patient physiological data (pulse, blood oxygen signals) • Device calibration data
Process	The pulse oximeter emits light through a fingertip or earlobe and measures how much light is absorbed by the blood. Algorithms then estimate oxygen saturation levels based on these optical signals. If the device or algorithm was calibrated primarily using lighter skin tones, the estimation may be less accurate for darker skin tones because skin pigmentation affects light absorption patterns.
Results/Output	• Displayed oxygen saturation percentage (SpO_2 value) • Pulse rate measurement • Visual or audible alerts if oxygen appears low
Benefits	• Fast, non-invasive oxygen measurement • Immediate clinical decision support • Widely available and easy to use • Useful in emergency and remote care situations
Limitations and challenges	• Reduced accuracy for certain skin tones • Risk of false-normal readings

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	• Overreliance on device outputs without clinical verification • Calibration bias due to non-diverse training and testing data • Ethical and safety concerns related to unequal accuracy
Application examples	Monitoring COVID-19 patients at home Hospital intensive care units Emergency medical services in ambulances Routine health check-ups and chronic disease monitoring
Sources	
Additional information	New England Journal of Medicine – Racial Bias in Pulse Oximetry Measurement https://www.nejm.org/doi/full/10.1056/NEJMc2029240 World Health Organization – Ethics and Governance of AI for Health https://www.who.int/publications/i/item/9789240029200

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4 Conclusion

This deliverable has presented the methodology for developing AI use-case scenarios in medicine and provided a comprehensive collection of 57 practical examples covering the five AI2MED MOOCs. These use-case scenarios represent a valuable educational resource that bridges the gap between theoretical AI knowledge and practical healthcare applications.

The educational value of these use cases lies in their ability to contextualize AI technologies within real healthcare scenarios. By presenting concrete examples of AI applications, including their inputs, processes, outputs, benefits, and limitations, the use cases enable learners to develop a nuanced understanding of how AI functions in medical practice.

The use-case scenarios play a crucial role in bridging theory and practice. Healthcare professionals and students can use these materials to understand not only what AI can do but also how it is implemented, what challenges may arise, and what ethical considerations must be addressed. This holistic perspective is essential for the responsible adoption of AI in healthcare.

The standardized format and comprehensive coverage ensure that these use cases will remain relevant as educational resources, supporting the ongoing development of AI competencies among healthcare professionals across Europe and beyond.

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