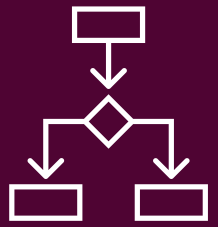

Future of HAI surveillance: Automation and artificial intelligence

13. Symposium zum Internationalen Tag der Händehygiene, Vienna | 5 May 2026

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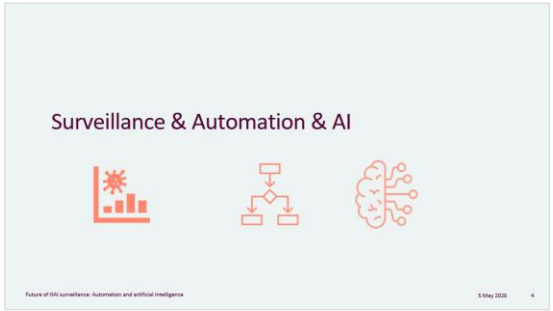
Disclosure

Involved in the company P3S – Patient Safety Surveillance Solutions that works on automated surveillance of adverse events

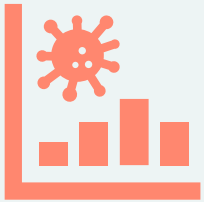
Content

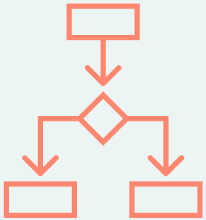

Surveillance & Automation & AI

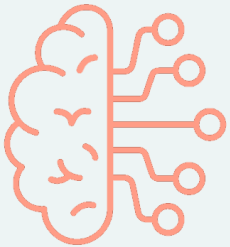

Challenges & considerations


Closing

Surveillance & Automation & AI





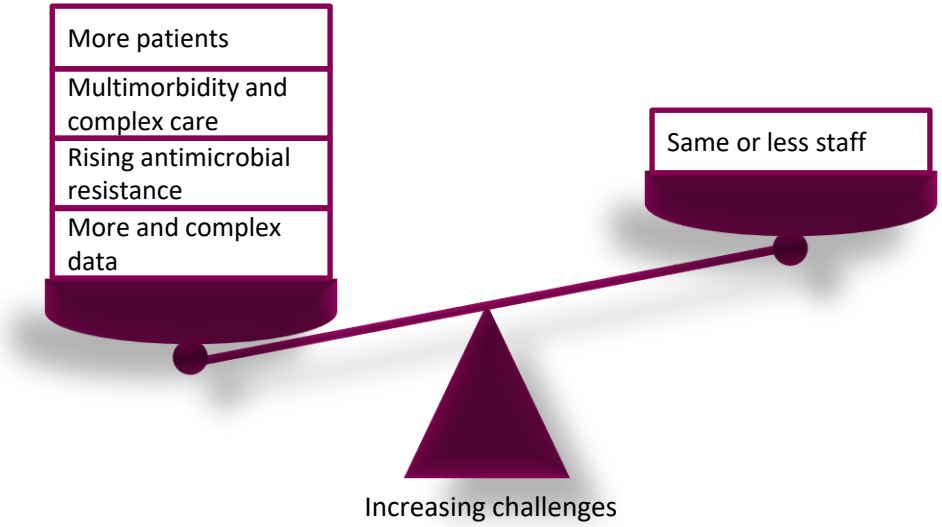


Healthcare-associated infection (HAI) surveillance matters

- HAI are still common, harmful, costly, and under-reported adverse events
  - → In Europe, yearly 8% of patients experience HAI during hospital stay ≈ 4.3 million patients with 4.8 million HAI episodes *(ECDC PPS 2022-23, 2024)*
- Every HAI we prevent saves lives, discomfort, time, and resources
- Surveillance is foundation of prevention & core component in infection prevention and control (IPC) programmes *(WHO, 2016)*
  - → You cannot prevent what you don't know
  - → Surveillance can effectively reduce HAI rates *(Abbas et al. J Hosp Infect 2019; Gastmeier et al. Infect Control Hosp Epidemiol 2009)*
  - → Surveillance is not paperwork → it is patient safety work
- Good surveillance data → better decisions/interventions → safer care

Traditional HAI surveillance

- Traditional HAI surveillance = Manual review of patient records & standardized case definitions = Prone to subjective interpretation, time consuming and resource intensive
  - → Continuous surveillance: 1.5 FTE per 10,000 admissions *(Brossette et al. Am J Clin Path 2006)*
    - E.g., Karolinska University Hospital → ± 73,000 admission/year ≈ 11 FTE
      - → Difficult to scale



Change is needed → automation & artificial intelligence (AI)

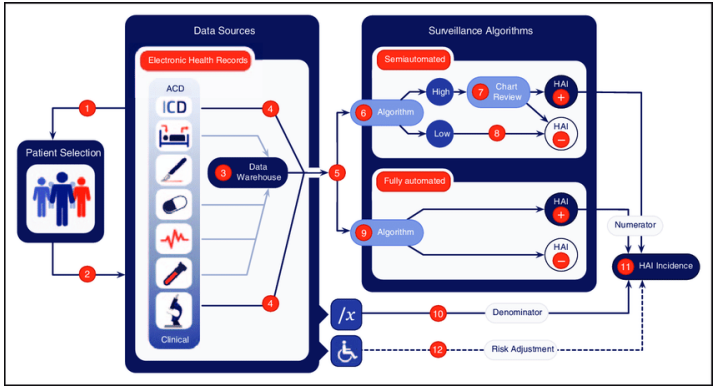
Automation & AI in HAI surveillance

Automation

- Any form of surveillance where (parts of) the manual assessment are replaced by an automated process. This includes **fully automated** and **semi-automated** detection of **healthcare-associated infection (HAI)** and collection, validation and analysis of **denominator data**. AS is based on **routine care data**, usually by applying appropriate **algorithms**. *(van Mourik et al. Clin Microbiol Infect 2021)*

AI

- The application of **advanced algorithms** and **models**, including machine learning, which enables **machines** to **perform tasks** that require **some form of intelligence** *(van der Werff et al. J Intern Med 2025)*
  - → In healthcare and automated surveillance, this means **simulating human intellect** when analysing **complex medical data**



Sips et al. Curr Opin Infect Dis 2017

Algorithm

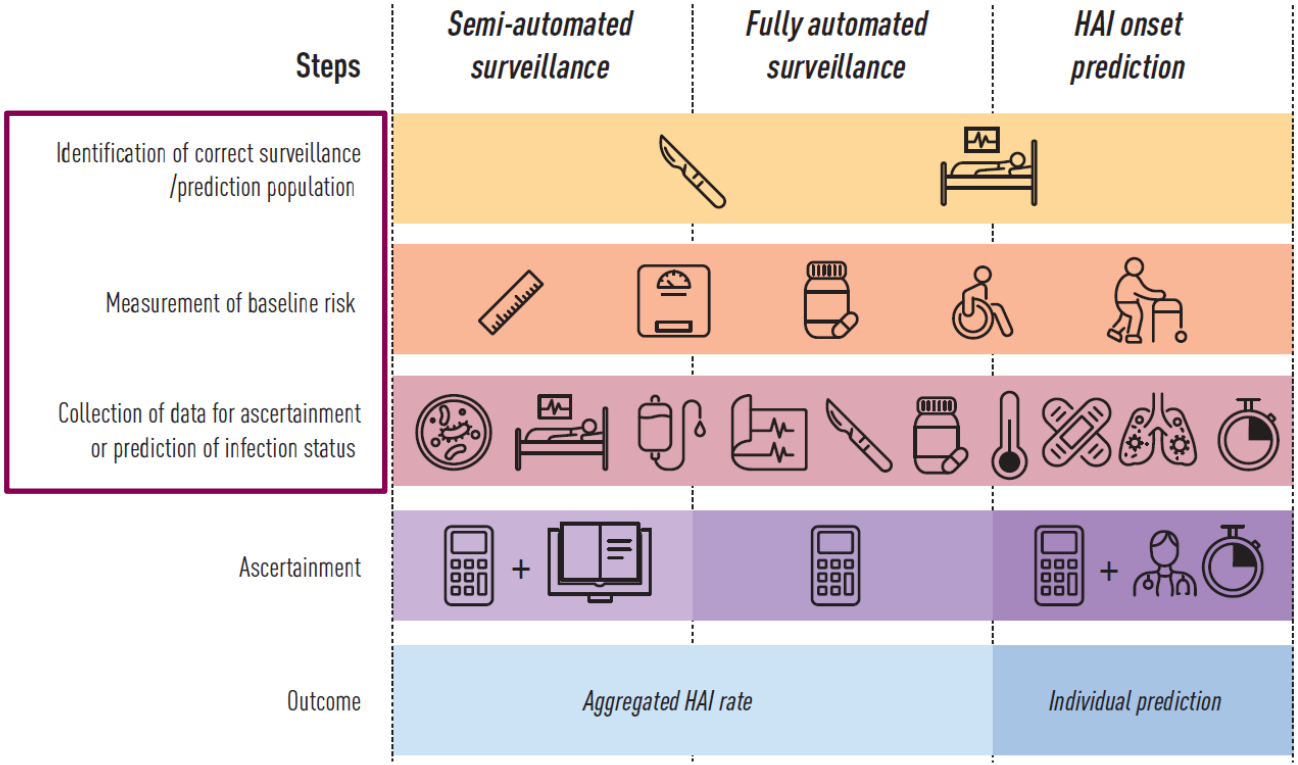
- Step-by-step **set of instructions or rules** designed to perform specific tasks
  - → E.g., learning algorithm for training machine learning models or rule-based system for classification of data

Why automation?

- Data availability in electronic health record (EHR) systems
  - → Reuse routine care data
  - → Improve standardization
  - → More objective and timely HAI rates
  - → Reduce workload
  - → Let computers/machines do what they are good at

- What is doesn’t do
  - → It does not replace clinical/expert judgement
  - → It reduces routine work, not responsibility

Automation for HAI surveillance



van der Werff et al. J Intern Med 2025

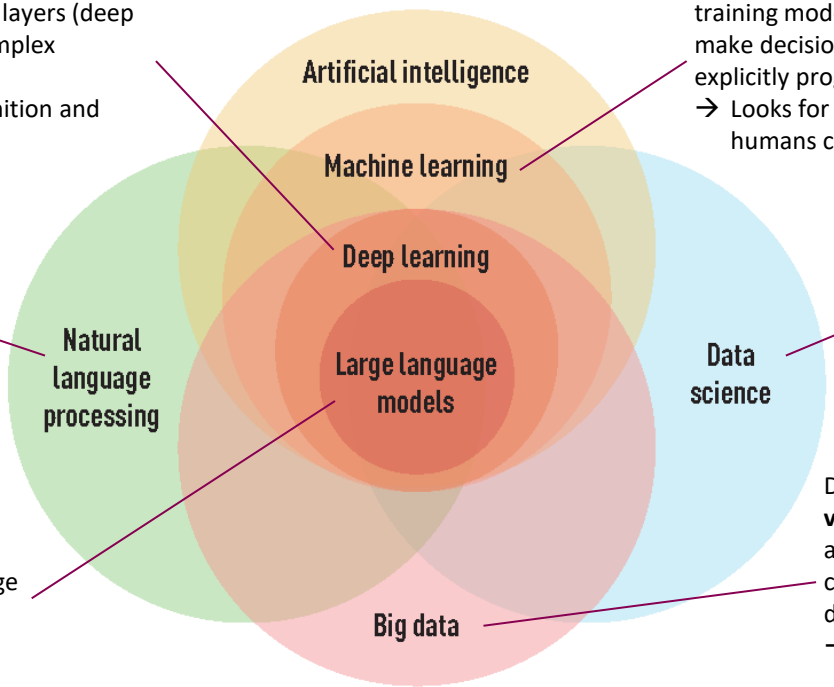
Relevant concepts related to AI

DL: Subset of ML that involves artificial neural networks with multiple layers (deep neural networks) to model complex patterns
→ E.g., tasks like image recognition and natural language processing

ML: Subset of AI that involves using algorithms for training models to learn patterns from data and make decisions or predictions without being explicitly programmed
→ Looks for patterns in large amounts of data that humans cannot easily see

NLP: Application of computational techniques to understand, interpret, translate, and generate human language and speech (linguistics)
→ Converts unstructured text into structured data usable by machines

Multidisciplinary field that uses different scientific methods to extract insights and knowledge from structured and unstructured (big) data
→ AI is new tool



LLM: DL model that has been trained using very large datasets and obtains capabilities for general-purpose language understanding and text generation
→ GPT-4, Med-PaLM, BERT, BioBERT

Data that is characterised by massive **volume**, big **variety** of types and sources, and high **velocity** of generation, and is too complex to be processed by traditional data analysis tools
→ E.g., EHR data

van der Werff et al. J Intern Med 2025

AI vs traditional programming

Traditional programming/rule-based models

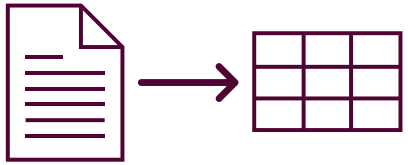
- Rules/models are explicitly programmed by humans
- Input → Programmed logic → Output
- *E.g.: "If temperature >38°C and leukocytes >12,000, then flag as possible infection"*

AI models

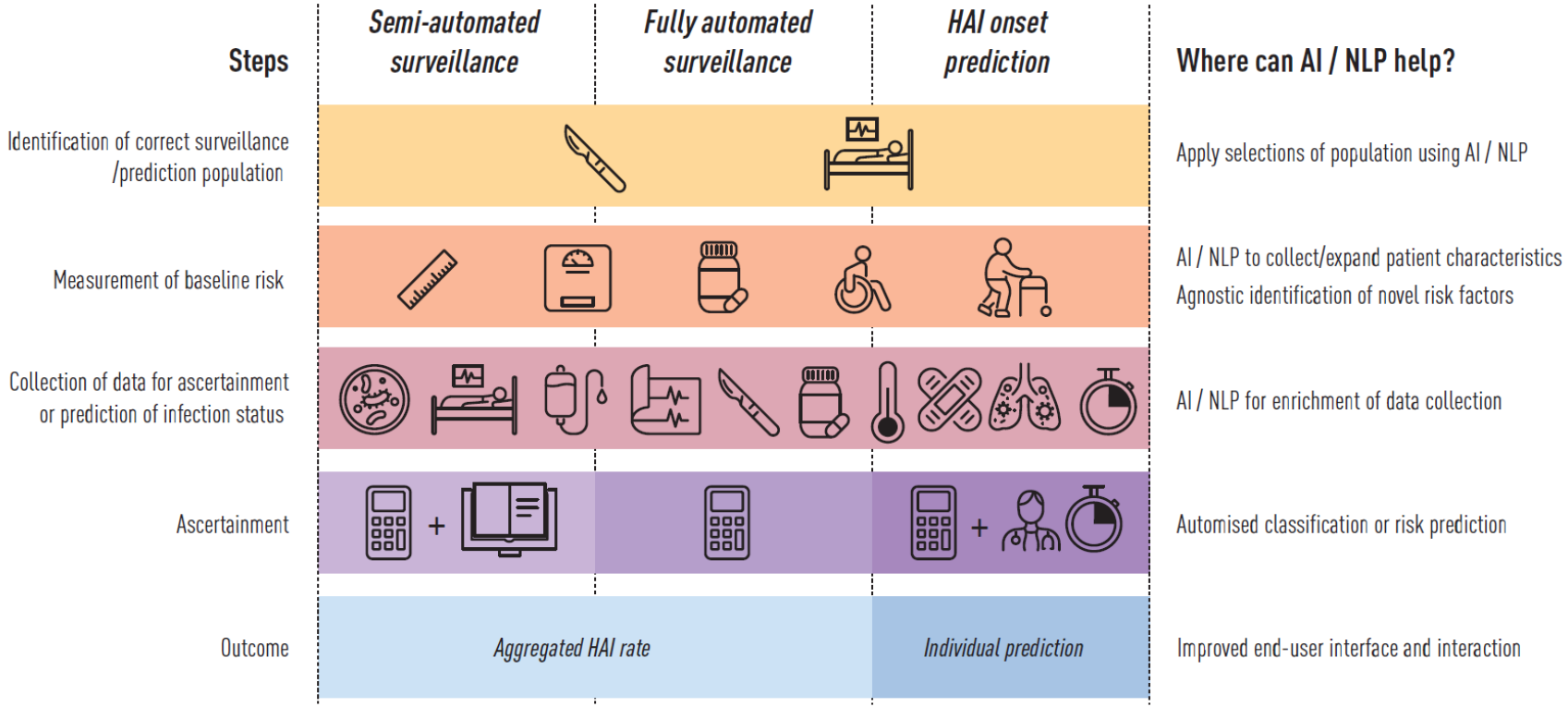
- AI models learns patterns from data
- Input + labels/output data → Learned logic → 'Predict' output
- *E.g.: Thousands of EHRs labelled with "infection/no infection," and the model learns rules of what an infection is by itself*

Potential of AI

- Can handle more data and variables than traditional models
- Deal with more complex data structures
  → Detection new risk factors/predictors or patterns in data
- Unlocking text (& image) data
  → Multimodal models: Combining numerical data with text data (and/or image data)
  → Clinical notes, radiology reports etc.
    - Chills, inflammation, infiltrate, dysuria, pain etc.
- Improved automated surveillance algorithms
  → More comprehensive data for identifying cases & risk factors
  → No modification of surveillance definitions for (fully) automated surveillance (not only using structured source data)



Automation & AI for HAI surveillance



van der Werff et al. J Intern Med 2025

Automation & AI for HAI surveillance

- Automated algorithms/models for most HAI exist *(van der Werff et al. J Intern Med 2025)*
  - → Depending on type of HAI, performance moderate to good
  - → Depending on type of HAI, focus more on fully or semi-automated algorithms
  - → Mostly still rule-based, advanced AI hardly used
    - *AI more used in sepsis prediction and antimicrobial therapy/resistance*
  - → If AI used, mainly NLP applied
    - *AI/NLP not always added value*

Automated surveillance development pipeline

AI ≠ magic

- AI is no magic bullet
  - → Needs (good) data + algorithms + models + resources
  - → Will not improve surveillance/IPC by itself
  - → Much potential but also lot of challenges
- AI is a support tool, not a replacement
  - → Human oversight remains vital
- Always ask: Is AI solution to problem/use case?
- Common requirements data sciences/traditional models also hold for AI

Challenges & considerations

Data requirements

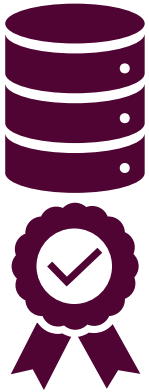
Labelled data

- Algorithms/models need accurately labelled examples to learn patterns
- Labelled data can be difficult to get (time-consuming, may require expert review)

Data quantity

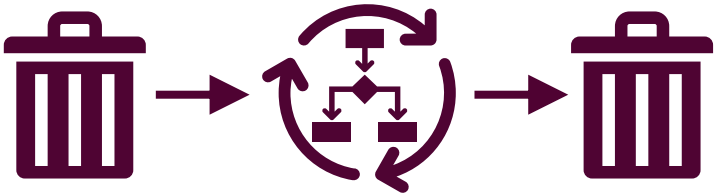
- Especially AI needs many examples to learn well, especially for rare outcomes like HAI
  → Train, test and validation data
- More data often beats better algorithms—but only if it's high quality

Data requirements



Data quality

- Incomplete, inconsistent or outdated data leads to poor model performance → inaccurate & misleading outcomes
  - → Missing timestamps
  - → Poorly documented symptoms
  - → Inconsistent microbiology labels
  - → Mislabelled infections



Data requirements

Data bias

- If training/development data isn’t representative, model may not generalise
- AI also learns bias if present in data
  - → Can worsen health disparities if not addressed
- Examples of types of bias
  - → Sampling bias: Over-representation of certain wards, age groups, or hospitals
  - → Label bias: Different infection definitions across data sources
  - → Historical bias: Systemic differences in care access or diagnosis over time
- Implications
  - → Under-detect infections in under-documented populations
  - → Could over-prioritize resources to high-data areas (e.g., ICUs) and neglect others

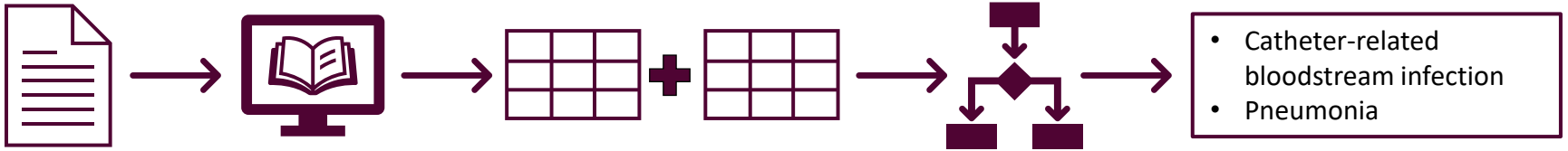
Use of LLM

- Prompt to determine presence HAI events

  → “Which HAI are present?”

- Annotate criteria data & application of traditional rule-based algorithm

  → “Assess presence of catheters and respiratory infection symptoms”



Medical language

- Medical language is messy and full of abbreviations, typos, and context-dependent meanings

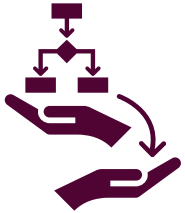
→ NLP/LLM needs clinical fine-tuning (generic NLP models/LLM often insufficient)

- Abbreviations/typos: microorganism, micro-organism, microorganims, microrganism, MO, M-O
- Meaning: e.g. in Swedish ‘var’ can mean ‘where’, ‘was’ or ‘pus’ depending on use in sentence

→ LLM needs training on HAI definitions

- Temporal aspect challenging
- Lower performance in non-English/uncommon languages
- Hallucination/confabulation: generating an answer rather than admitting uncertainty

Transferability & resources



- Transferability to other settings (hospitals, countries) and languages often not guaranteed
  - → Models also learn underlying healthcare patterns
  - → Retraining AI models probably necessary

- Can require substantial resources/computational power (esp. LLM)
  - → Possible and/or worth the effort?

Explainability & trust

- Explainability matters
  - → Stakeholders/users need to understand and trust why model made assessment/prediction
  - → Black-box AI can undermine adoption and accountability
  - → Reproducible results necessary (esp. problem with LLM)

- Potential approaches
  - → Simpler models where possible
  - → Explainable AI (XAI)
    - Feature importance: e.g., “fever” and “indwelling catheter” drove risk prediction

Validation & regulation

- Validation matters
  - → Algorithms/models must be tested on independent datasets (ideally multi-site) to confirm reliability
- Regulatory landscape
  - → In Europe: Medical Device Regulation (MDR)
  - → CE marking can be required for clinical deployment
- Re-evaluation & revalidation
  - → Models degrade over time/performance drift (e.g., new pathogens, coding changes, new lab test etc.)

Closing

Role/task of IPC/medical professionals

- Develop AI literacy
  - → AI is here to stay
  - → *“Once a new technology rolls over you, if you’re not part of the steamroller, you’re part of the road.”* – Stewart Brand
- Collaborate on model development, validation & implementation in multidisciplinary team
  - → IT experts (+ AI experts) + domain knowledge experts
- Help shape relevant, safe, ethical and responsible use of automation and AI in HAI surveillance

Summary

- Surveillance is essential for patient safety
  - → Automation and AI can strengthen continuous surveillance

- AI
  - → AI ≠ magic: it's good data + algorithms + models + resources
  - → AI is a new supportive tool, not a replacement → human oversight essential

- Automation & AI model development
  - → Importance of data (labelling, quality, quantity, bias)
  - → Unlock unstructured data
  - → Adjusting to medical data
  - → Explainability/trust, validation, and regulation is important
  - → Retraining, re-evaluation & revalidation necessary

- The future of HAI surveillance is not about machines. It is about better tools for better care!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