

Title: Utilizing Artificial Intelligence (AI) to Monitor the Quality of Infection Therapy: Integrating CaseMix and Clinical Data to Enhance Care Quality

Introduction

CaseMix data is widely employed to develop specific quality indicators for monitoring healthcare quality. In Australia, the Hospital-acquired Complications (HAC) system is established, while Germany utilizes the Inpatient Quality Indicator (IQI) classification, with similar systems implemented in nearly every country that employs CaseMix for activity-based funding.

Despite these methodologies, certain questions necessitate additional clinical data. A critical area is Antimicrobial Stewardship (AMS), given that microbial resistance poses a global threat and the rational use of antibiotics is essential. Infectious disease (ID) specialists remain scarce in hospitals, and current AMS programs typically rely on cumulative analyses of antibiotic prescriptions, complemented by ward rounds. However, cumulative analyses do not provide insights into the specific infections for which drugs were prescribed, and ward rounds are time-consuming and lack broader applicability across wards, departments, or hospitals.

Our current research focuses on integrating CaseMix data, clinical information, and medication data using AI to enhance prescription quality. We have initiated a pilot project with a hospital in Germany.

Methods

We utilize CaseMix data to extract information on infections and bacteria, as well as resistance patterns, through the Infection Grouper (IMR). After grouping patients by IMR, each patient is associated with one or more infection episodes. Next, we link laboratory and antibiotic prescription data to these infection episodes. Using AI (ChatGPT), we convert local therapy guidelines into machine-readable formats.

Subsequently, we conduct an algorithmic analysis of all prescriptions to assess whether treatments are guideline-compliant and appropriate. Typical quality indicators include:

- Timely initiation of therapy (within 1-8 hours after admission)
- Guideline-adherent initial therapy (correct substance, dosage, and application)
- Consideration of microbiology results
- Appropriate duration of therapy

Results

This approach enables us to analyze specific infections, such as Community-Acquired Pneumonia (CAP), using an extensive dataset. We gain insights into length of stay, patient outcomes, and other economic results relative to the quality of antibiotic prescriptions. Furthermore, we can evaluate whether the antibiotic treatments align with guidelines.

The picture shows an overview:

| Type of infection | Cases | Therapy completely correct | Initial Therapy not correct | No combination | Begin too late (> 8 hours from adm) |
|------------------------------------|-------|----------------------------|-----------------------------|----------------|-------------------------------------|
| Community acquired Pneumonia (CAP) | 345 | 105 | 240 | 233 | 87 |
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The integration of AI allows for the adaptation of the system to local guidelines.

Discussion/Conclusions

To our knowledge, this is the first tool that combines CaseMix and clinical data for infection analysis. Each hospital has distinct therapy guidelines, often tailored to local resistance patterns. By leveraging AI to process these guidelines and convert them into machine-readable tables, we facilitate the adaptation of analytics to local practices across different hospitals.

Preliminary comparisons with patient records indicate a high validity of the automatically generated assessments. However, validation of AI-generated results on a larger cohort by trained ID specialists is still required.

We created an analysis screen to assess results on a patient level:

Patient-level analysis

The screenshot displays a patient-level analysis interface with several data sections and callouts:

- Fall:** A table with columns: Geschl., Alter, Auf.-Datum, Auf.-Grund, Ent.-Datum, Ent.-Grund, Beat.-h. The patient is a 79-year-old woman admitted on 22.01.2023 at 11:02, discharged on 27.01.2023 at 13:26, with 0 hours of ventilation.
- DRG:** A table with columns: DRG, Text, VWD, uGVD, MVD, oGVD, PCCL, eff. KG, Kat. KG, Eff. Erlös, Kat. Erlös, LK. The DRG is E79C, described as 'Infektionen und Entzündungen der Atmungsorgane ohne komplexe Diagnose, ohne äußerst schwere CC oder ein B...'. Values include 5, 1, 6,6, 14, 0, 0,605, 0,605, 2.420,43€, 2.420,43€ UM.
- Diagnosen:** A table with columns: HD/ND, ICD, Text, Sek.-Code, Text. Diagnoses include J18.1 (Lobärpneumonie, nicht näher bezeichnet), I10.90 (Essentielle Hypertonie, nicht näher bezeichnet: Ohne Angabe ei...), and Z11 (Spezielle Verfahren zur Untersuchung auf infektiöse und parasit...).
- Labor:** A table with columns: LAB7_D, LAB, LAB7. Values include CRP (13,11, 14,60, 10,32, 10,50, 0,40, 2,09, 7,80) and LEUCO (14,60, 10,32, 10,50).
- Antibiose:** A table with columns: Start, Ende, Applikati..., Bezeichnung, Verordnungstext, ATC Code, Medikament, Chemische Gruppe. Medications include AZI-TEVA® 500 mg Filmtabletten (Azithromycin) and Ampicillin/Sulbactam Kabi 2000 mg/... (Ampicillin und Beta-Lactamase-Inhibitoren).

Callouts from the analysis screen:

- "A 79 year old Lady is admitted to hospital for 5 days"
- "The laboratory values strongly suggest a bacterial infection"
- "The PDx is Pneumonia → CAP"
- "She receives guideline adherent therapy"
- "CRP as main infection parameter goes down nicely and we can discharge her 😊"

In conclusion, the use of AI-generated assessments in infection management has the potential to deliver comprehensive results swiftly, thus conserving valuable clinician time.