From Data Quality to Clinical Quality – Episodes as Enablers for Next Generation Dashboarding

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Background

The Australian National Cancer Data Framework calls for the maturation of a harmonised national performance reporting system. This work builds on existing frameworks such as the National Cancer Control Indicators[1] and the Australian Health Performance Framework[2]. Although many of the quality indicators listed in these frameworks are population based and thus more well-suited to traditional cancer case-registration functions (such as population screening, long-term linked outcomes), there remains a significant number that can be drawn directly from clinical systems. The advantages of moving from the longer reporting cycles of the clinical quality registry to near real-time availability are significant. Most notably, although aggregate downstream reporting may be informative in helping to guide practice at a bulk level, it is only with timely, contextualised data that can be linked back to patients currently under care that clinicians may accurately delineate variation that is truly unwarranted (Figure 1).

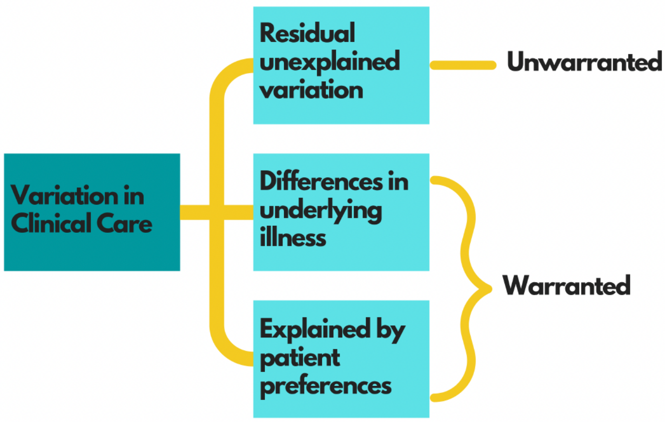

Figure 1: Unwarranted Variation Definition

Methods

We have developed a clinical quality indicator visualisation framework that leverages the OMOP Common Data Model to support configuration-only deployment of clinical quality indicators, and which is generalisable across all cancer domains. This work builds upon an established infrastructure framework to deploy near real-time dashboards, adaptable to target use-cases at the system, craft-group and individual clinician level. By supporting bulk reporting against benchmarks, visualisations of practice change over time, as well as the ability to drill-down to patient level details, this platform closes the feedback loop between multidisciplinary teams and individual patients at a timescale that is able to affect real practice change.

In its first iteration, we have mapped clinical quality indicators from the LUCAP (Lung Cancer Clinical Quality Data Platform) programme[2] to the OMOP CDM, successfully demonstrating the grounding of these concepts through combinatorial logic and complex mapper objects. These dashboards have been refined through a series of clinician-led co-design activities to improve their ability to accurately represent clinically meaningful care quality. The next phase of the project (currently underway) is to extend these definitions into other cancer areas – namely head and neck cancer and colorectal cancer. These cancers were selected as exemplars for this effort due to their maturity of data driven reflection and praxis (lung), complexity of care pathways including supportive care and highly heterogenous population (head and neck), and large population size and potential capacity to demonstrate measurable impact on patient outcomes (colorectal).

Results

The architecture of the solution is built from loosely coupled modules, using best in breed open-source frameworks for hosting, data handling, serialisation and visualisation. We have built a series of complex mapping objects based on the OMOP Alchemy library[4] to define reusable modular combinations of concepts and tables (Figure), which are often linked through disease and treatment episodes, and form the basis of this work.

```python
class DemographyConcepts(ConceptEnum):
    cob = 4155450
    language_spoken = 4052785
    postcode = 4083591


person_postcode = (
    sa.select(
        Observation.person_id,
        Observation.value_as_number.label('post_code')
    )
    .filter(Observation.observation_concept_id==DemographyConcepts.postcode.value)
    .subquery()
)

person_cob = (
    sa.select(
        Observation.person_id,
        Concept.concept_name.label('country_of_birth')
    )
    .join(Concept, Concept.concept_id==Observation.value_as_concept_id)
    .filter(Observation.observation_concept_id==DemographyConcepts.cob.value)
    .subquery()
)

person_lang = (
    sa.select(
        Observation.person_id,
        Concept.concept_name.label('language_spoken')
    )
    .join(Concept, Concept.concept_id==Observation.value_as_concept_id)
    .filter(Observation.observation_concept_id==DemographyConcepts.language_spoken.value)
    .subquery()
)
```

```python
demographics_join = (
    sa.select(
        Person.person_id,
        Person.year_of_birth,
        Death.death_datetime,
        Person.person_source_value.label('mrn'),
        Concept.concept_name.label('gender'),
        person_lang.c.language_spoken,
        person_cob.c.country_of_birth,
        person_postcode.c.post_code
    )
    .join(Concept, Concept.concept_id==Person.gender_concept_id)
    .join(Death, Death.person_id==Person.person_id, isouter=True)
    .join(person_lang, person_lang.c.person_id==Person.person_id)
    .join(person_cob, person_cob.c.person_id==Person.person_id)
    .join(person_postcode, person_postcode.c.person_id==Person.person_id)
).subquery()

class Person_Demography(Base):
    __table__ = demographics_join
    person_id = demographics_join.c.person_id
    mrn = demographics_join.c.mrn
    year_of_birth = demographics_join.c.year_of_birth
    death_datetime = demographics_join.c.death_datetime
    language_spoken = demographics_join.c.language_spoken
    country_of_birth = demographics_join.c.country_of_birth
    person_postcode = demographics_join.c.post_code
```

Figure 2: Example complex mapper objects underpinning data serialisation API

Importantly, to produce actionable clinical indicators, it is necessary to be able to support handling of relative event temporality as well as their combination, as opposed to simply their existence or counts. The episode model is a fit for purpose solution to this requirement, allowing local business processes to inform the extract-transform-load (ETL) pipeline in such a way that downstream relationships can be trusted and accurate inferences made at scale.

Measures are supported according to disease, treatment, observation, procedure, measurement and demography-based definitions (Figure 3, 5). The underlying queries are either met or not met according to definitions of hierarchy, exact matches or substring labels. Delivery in the cancer setting means that the ability to link modifiers and condition records (e.g. cancer stage, morphology) is integral to the ability to fully map informative clinical subgroupings, further underscoring the importance of a fully implemented episode model in the target CDM database for successful deployment (Figure 4, 6).

We have thus produced a framework for arbitrarily-complex measure definitions that can be aligned with distinct cohorts and benchmarks, and thereby configured into custom, modular reports.

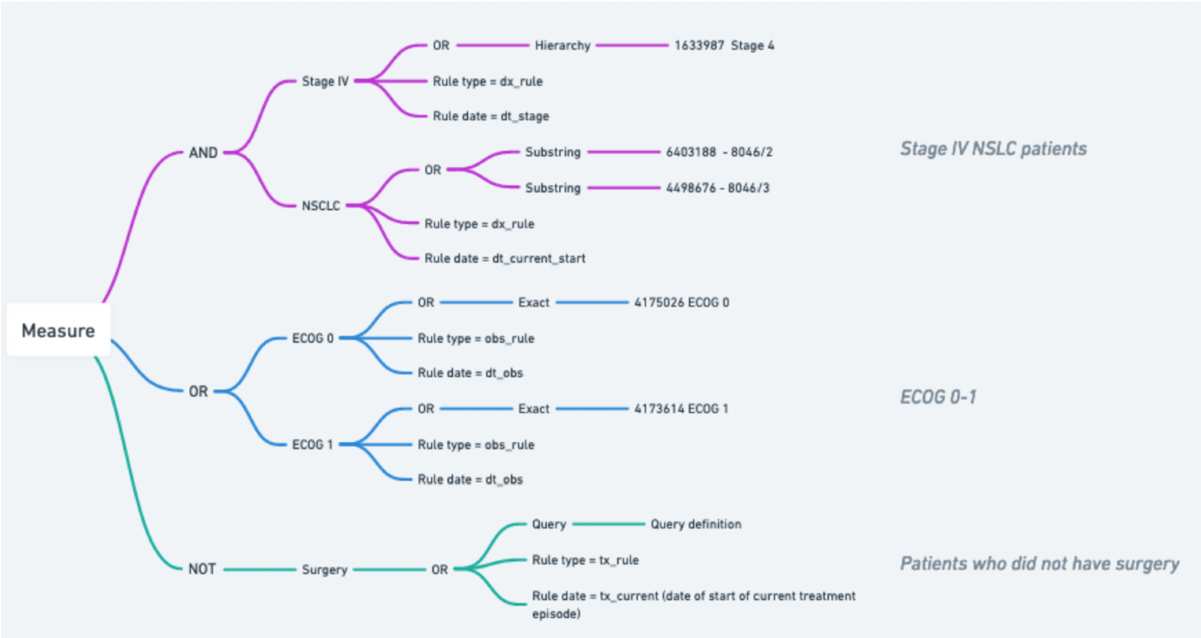

Figure 3: Example measure definition showing hierarchical boolean logic structure

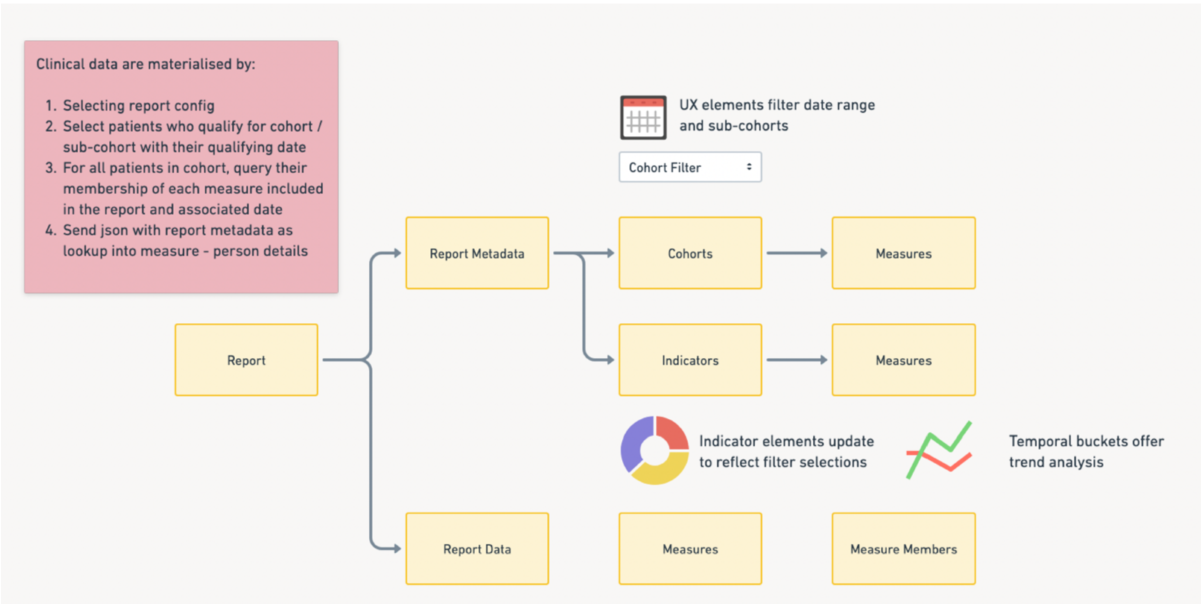

Figure 4: Workflow schematic

Conclusion

To move towards a true learning health system, clinical quality reporting measures must be able to respond to new information, provide timely and actionable feedback, and fit within the existing care processes. By leveraging the OMOP harmonised common data model, this work is generalisable and deployable into diverse clinical settings.

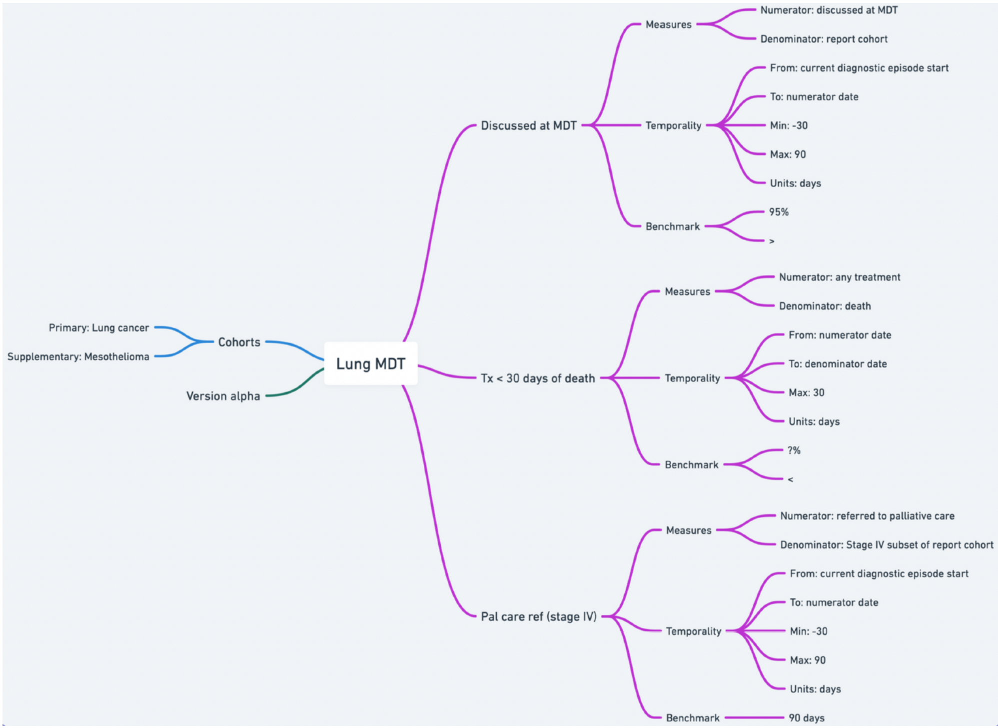

Figure 5: Combination of measures into indicators (numerator, denominator, benchmark) / report (cohort, indicators)

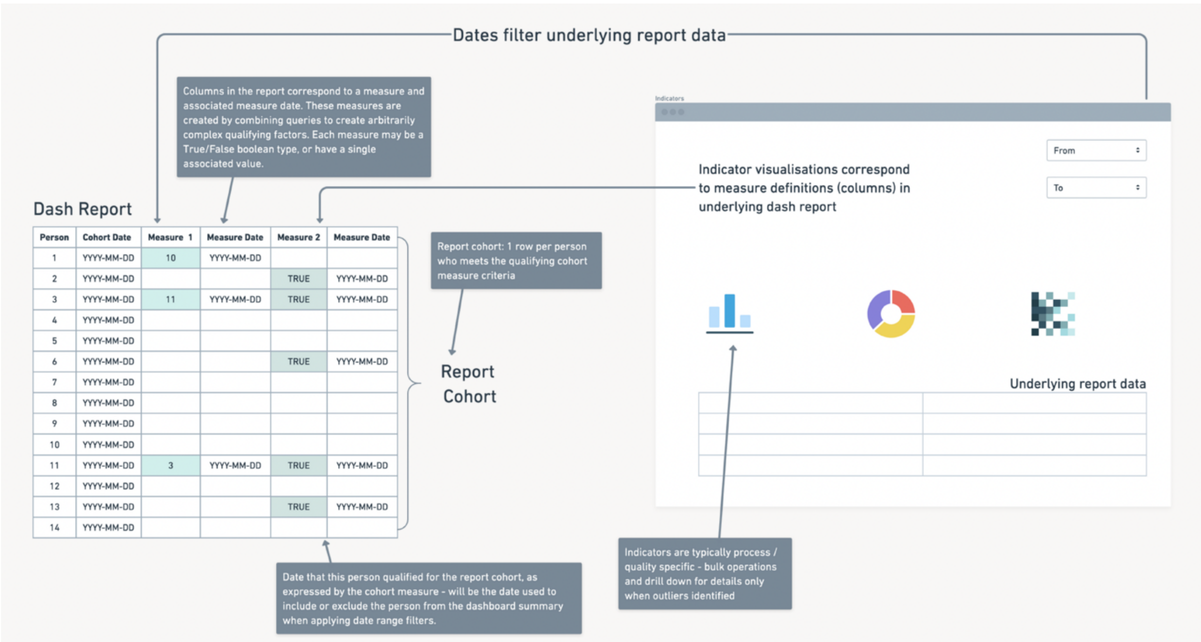

Figure 6: Overall solution structure for report data serialisation

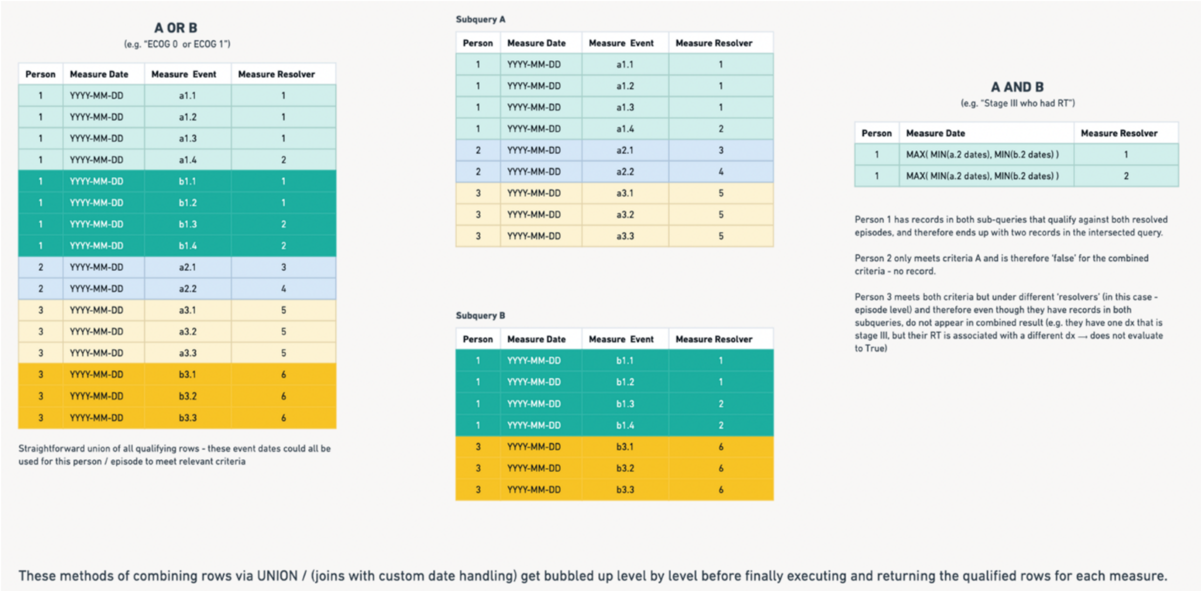

Figure 7: Extended logic resolution for accurate date attributions

Figure 8: Functional dashboard prototype showing trend analysis for existing LUCAP CQI

References

1. https://ncci.canceraustralia.gov.au/
2. https://www.aihw.gov.au/reports-data/ahpf/australias-health-performance-framework
3. Nash J, Stone E, Vinod S, Leong T, Dawkins P, Stirling RG, Harden S, Bolton A, McWilliams A, O'Byrne K, Wright GM, Brunelli VN, Guan T, Philpot S, Navani N, Brims F, Lung cancer (internet-based) Delphi (LUCiD): A modified eDelphi consensus process to establish Australasian clinical quality indicators for thoracic cancer, Respirology, 2024;29:1085–1094
4. https://github.com/AustralianCancerDataNetwork/OMOP_Alchemy