Understanding privacy risk in electronic health records: a case study on Discharge Summaries

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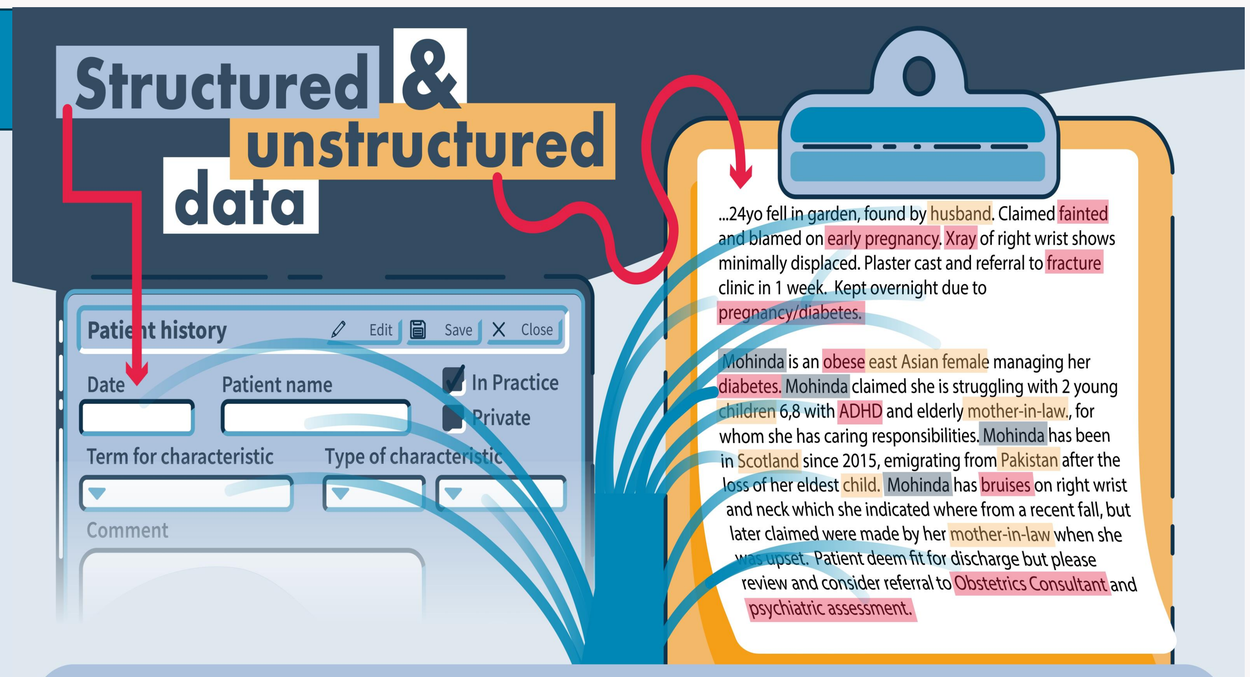
DARE UK
Phase 1 Driver Project

Privacy risk assessment is key when releasing health data to ensure released data does not contain identifiable patient information

CHALLENGE: Risk assessments for data release are often manual, time consuming and can prohibit data release, ultimately limiting new health and social care innovation. Most health research is conducted using structured data. Although unstructured data makes up 70-80% of health data, due to both its unstructured format as well as privacy risks for patients its use is limited. Risk assessment frameworks are not well defined for unstructured data and more work is needed to understand privacy risks, the risk of revealing patient identity, from this type of data to enable its release.

AIM: We apply Natural Language Processing (NLP) techniques to explore a year's worth of hospital Discharge Summaries looking at privacy risks and how these accumulate across reports, building a privacy risk map.

Using the privacy risk map, we are building a dashboard that helps gain a better insight into privacy risks and enables assessment ahead of data release.



70-80% of health data is unstructured but its use in research is limited due to privacy risk concerns. We define privacy risks as direct or indirect.

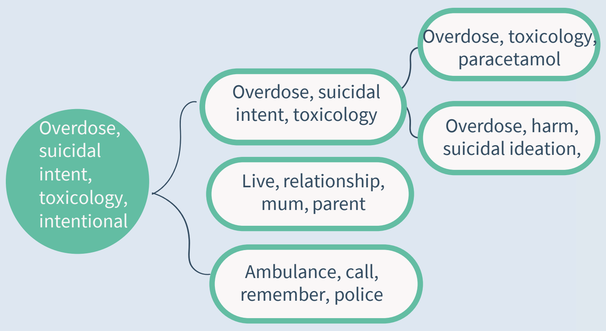
Finding Indirect Privacy Risks

~89,000 hospital discharge summaries

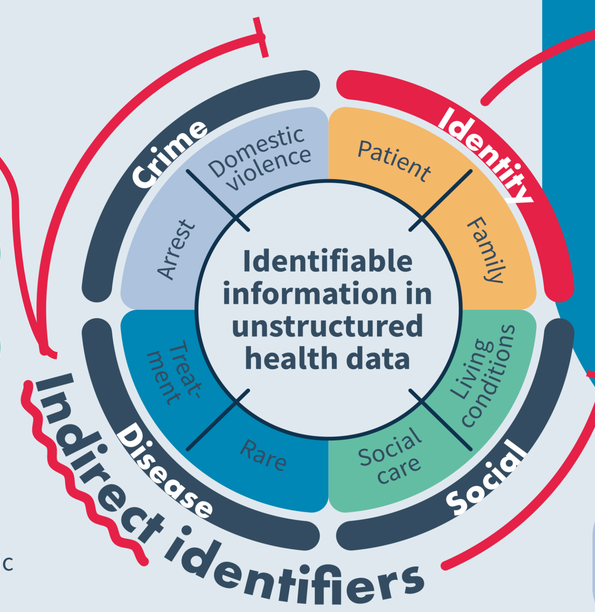
Remove irrelevant parts of report using clinical templates (drug lists, headers etc.)

Apply text mining approaches to explore the data: phrase & word freq. BERTopic modelling

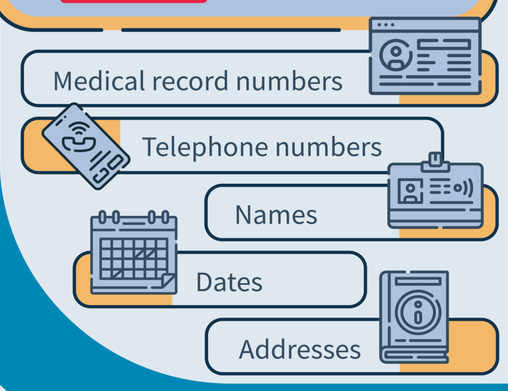
Use cluster labels to focus report reading with qualitative approach to build privacy risk map



Example: Sentence-based clusters with BERTopic, topic representation generated using class-based TF-IDF

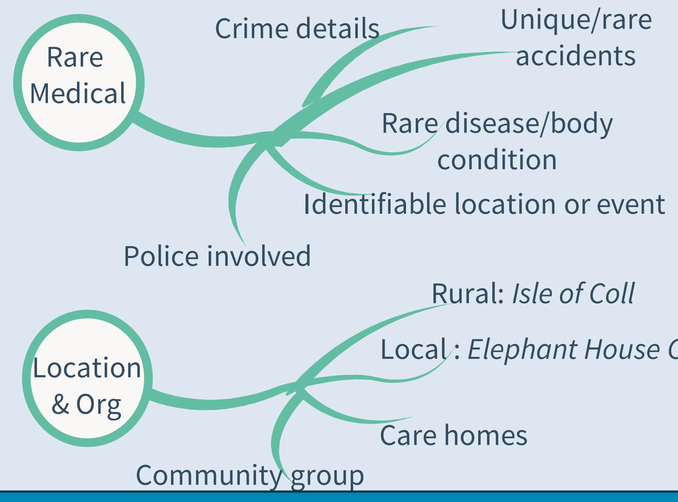


Direct identifiers



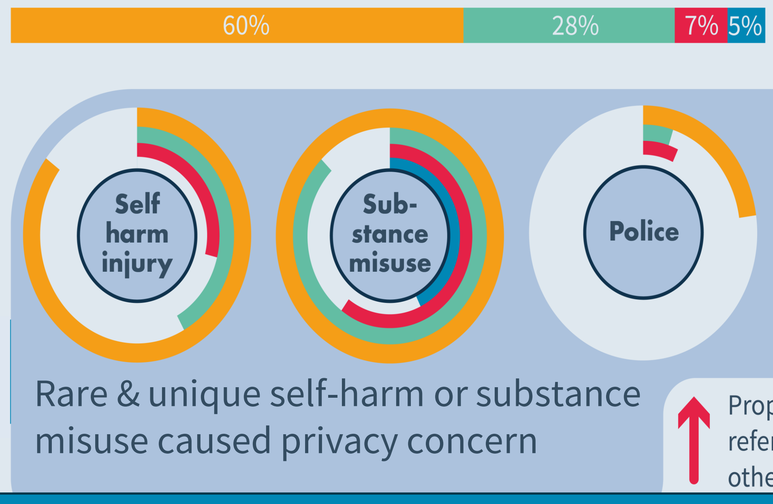
Indirect identifiers are rare and hard to find, and not well defined.

Most prevalent indirect privacy risks. Rare and unique events give most concerns particularly in younger ages as does cumulative information of frequent patients.



Examples of Rare accidents
'fell concrete pit at work'
'wood-chipper accident'
'died in kiteboard accident'
'jump from window in burning apartment'
'loss of hand/foot or a specific digit'

Discharge summaries for patients who have attempted suicide



Key
Years of age
18-30
31-50
51-70
71+

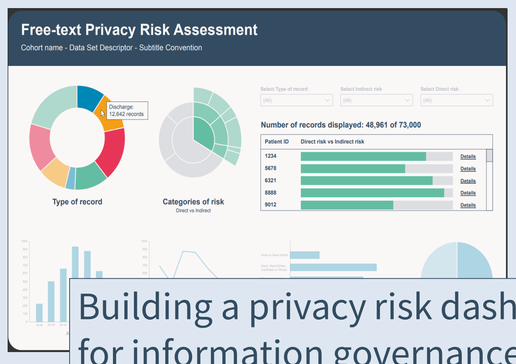
Public Involvement & Engagement Work

PPIE: explored public opinion of identifiers and how semi-automation can be used to address risks.

The public are broadly supportive of the use of semi-automation to address privacy risks but believe:

- Some data should be coded to ensure valuable details for research are not lost while preserving confidentiality. The process should involve discussion with specialists.
- Audit trails and human assessment are necessary to ensure processes run correctly

Next Steps



Building a privacy risk dashboard for information governance to assess a cohort's privacy risk, based on known direct and our map of indirect identifiers

Evaluating and developing tools for semi-automation of finding identifiers in collaboration with the Scottish Safe Haven Network and partners

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Image panels 2,4,6 on this poster were designed by Dr Lana Woolford at Cloud Chamber Studios (lana@cloud-chamber-studios.com)