Computer-Based Generation of Drug Regimens

What is the optimal design and functionality of a treatment data model and algorithm that can efficiently process patient data, diagnosis information, and a collection of treatment options to dynamically generate personalized treatment regimens and provide administration advice?

Introduction

Clinical Decision Support Systems (CDSS) that aid clinicians through the medical management process have been identified as a potential solution to mitigate medication errors and address the discrepancy in standards of care between low and high income countries by addressing the knowledge and financial gap (Hak, Guimarães, & Santos, 2022, p7). There is however a lack of electronic decision support algorithms and treatment model designs that can be applicable to a wide range of use-cases. Developing a algorithm that is not bound to a clinical guidline and that encapsulates the processes of selection and dosing of medication would allow for a CDSS to be deployed more rapidly without the need for changes to an existing code base.

Methods

1. Review currently existing decision support algorithms, and clinical decision support systems built for medication selection and dosing.

2. 1. Design a treament data model that can abstractly represent a multitude use-cases and treaments.
   2. Design a treatment decision algorthm to handle the selection and dosing of treatments and medication

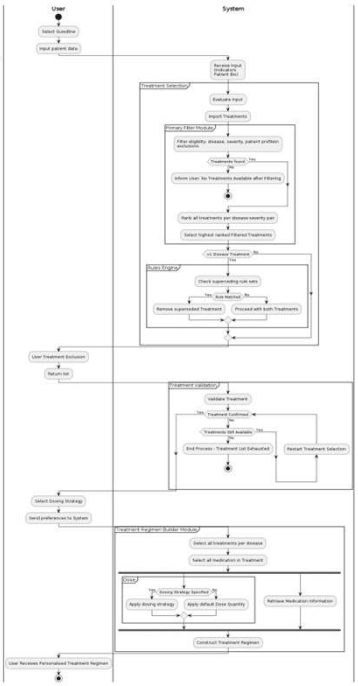
3. 1. Itiratively develop a Proof-Of-Concept that can demonstrate the functionality of the algorithm and the corresponding data model

Results

Design of Treatment Data Model

```
{
  "treatment_id":"<string: unique identifier for the treatment>",
  "disease":"<string: name of the disease>",
  "description":"<string: detailed summary of treatment>",
  "eligibility":[
    {
      "strategy":"<string: treatment strategy>",
      "severity":{
        "<Measure of Severity (e.g., Seriousness, CURB-65)>":"<string: Level of severity>"
      },
      "exclusion":[
        "<string: list of exclusions or contraindications>"
      ],
      "patient_profile":{
        "age_range_unit":"<string: unit of time, e.g., 'years', 'months'>",
        "age_range":{
          "min":"<int: minimum age>",
          "max":"<int: maximum age>"
        },
        "min_weight":"<int: minimum weight in kg>",
        "max_weight":"<int: maximum weight in kg - optional>"
      }
    }
  ],
  "rank":[
    {
      "<string: Guideline Name>":"<int: rank of the treatment for given profile>"
    }
  ],
  "medication":[
    {
      "drug":"<string: name of the medication>",
      "form":{
        "type":"<string: form of medication, e.g., 'tablet', 'liquid', etc>",
        "divisible":"<boolean: indicates if the medication can be divided>"
      },
      "site":"<string: site of administration, e.g., 'arm', 'mouth'>",
      "route":"<string: route of administration, e.g., 'oral', 'IV'>",
      "method":"<string: method of administration, e.g., 'swallow'>",
      "dose_strategy":[
        {
          "strategy":"<string: Type of dosing strategy, e.g. 'maintenance'>",
          "calculation":"<string: dose calculation e.g. 'mg/kg' >",
          "sequence":"<int: order of medication>",
          "instruction":"<string: detailed dosing instructions>",
          "patientInstruction":"<string: instructions - optional>",
          "therapeuticDose":"<string: dose description - optional>",
          "ratio":{
            "<string: Drug A name>":"<int: ratio Drug A - optional>",
            "<string: Drug B name>":"<int: ratio Drug B - optional>"
          },
          "rate":{
            "repeat":{
              "frequency":"<int: number of times to administer per period>",
              "period":"<int: length of the period>",
              "periodUnit":"<string: unit of time for the period>"
            }
          },
          "doseQuantity":{
            "value":"<int: amount of medication per dose>",
            "unit":"<string: unit of measure, e.g., 'mg'>"
          },
          "maxDosePerPeriod":{
            "numerator":{
              "value":"<int: maximum dose per period>",
              "unit":"<string: unit of measure>"
            },
            "denominator":{
              "value":"<int: period for the maximum dose>",
              "unit":"<string: unit of time for the period>"
            }
          }
        }
      ]
    }
  ]
}
```

Decision Support Algorithm Design



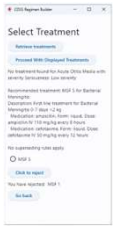
Proof of Concept

1.Select guidelines

2: Patient Input

3: Indicator Input

4: Treatment Selection



Rejection/ Selection

5. Dosing Strategy Selection

Personalized Regimen

User Input data:

{'weight': '2', 'height': '40', 'dob': '10/04/2024', 'cpg': 'MSF_CPG_3', 'diseases': [{'disease': 'Acute Otitis Media', 'severity': 'Seriousness: Low severity'}, {'disease': 'Bacterial Meningitis', 'severity': 'Seriousness: Moderate severity'}], 'medications': [], 'exclusions': []}

Output:
Regimen for MSF 5 - Bacterial Meningitis:
Medication: ampicillin
Dose per administration: 200.00 mg
Volume for administration: 16.67 units
Daily dose: 660.00 mg (limited to 600 mg/day)
Strategy: loading dose
Sequence: 1
Instruction: ampicillin IV 110 mg/kg every 8 hours
Patient Instruction: none
Therapeutic Dose: 110mg/kg every 8 hours
...

Discussion

The initial review of existing algorithms and CDSSs highlighted the lack of openly available resources for developing a medication selection and dosing application. While there are plentiful dosing applications finding an algorithm that dealt specifically with the medication and selection processes was difficult. Another challenge was finding a available algorithms that were not centred on a specific guideline. The reasoning was for requiring a algorithm to not be guideline specific was allow it to be as adaptable as possible to varying LMICs. The design of the algorithm was therefore based on the clinical process of selection and dosing of medication. Using an abstract process that multiple treatment guidelines use, would allow the algorithm to be made separate from the treatments.

The POC was able to demonstrate that the algorithm does function and is able to handle treatments from various guidelines, independent of each other. The treatment model has enough parameters to encapsulate all the treatment data without being too specific. Ratios, dosing strategies, calculations, eligibility criteria, rates, and medication quantities are all abstract concepts that can be utilized to encompass a wide range of treatments. The rate of medication changing after a time period could also be handled through the creation of dosing strategies. By containing all the treatment data inside the model, there is no need to change the algorithm for each deployment to a new health system or country. The treatments themselves will have to be fit into the new standard model, however once made, they can be used by other member countries. If one country wants to use guidelines from another country or organisation, one way they could adapt the guidelines would be to change the ranking of treatment. If one antibiotic is not used for first line treatment in one country due to anti-microbial resistance, it could be given a lower ranking or prioritisation, but the treatment content itself could remain the same. The iterative development process enabled the design of the model to evolve and implement feedback from the multi-disciplinary team.

Conclusion

The review revealed the challenges in sourcing freely available algorithms for a medication selection and dosing application, particularly those not bound by specific guidelines, underscoring a critical need for adaptability across diverse healthcare settings, especially in low- and middle-income countries (LMICs). It was also challenging to find algorithms that dealt with comorbidities, and multiple exclusion criteria. The algorithm is designed around a generic clinical process for selecting and dosing medication, which enables separation from any specific treatments or guidelines. This abstract approach ensures flexibility but necessitates a treatment data model capable of encapsulating necessary data without being overly prescriptive. The algorithm can also handle superseding logic and enables the treaments to be assigned ranking in order to prioritize treatments.

The finalized treatment data model is versatile enough to address diverse medical standards and practices, yet specific enough to manage precise disease-severity pairs and patient profiles. Its design facilitates easy adaptation and sharing of treatments if needed, potentially filling gaps in local healthcare practices with internationally sourced guidelines. This of course is hypothetical however demonstrates that using a standardized model for all treaments would ensure interoperability. The model contains eligiblity strategy which can be used by an interpreter to identify the treatment for a given patient profile and disease-severity pair. Despite its broad applicability, the model allows for straightforward integration into existing health systems without needing significant modifications to the algorithm, simplifying implementation. It should be noted that more treatments and testing are required to undertand ist applicability outside the test scenarios.

Hak, F., Guimarães, T., & Santos, M. F. (2022). Towards effective clinical decision support systems: A systematic review. *PLOS ONE*, *17*(8), e0272846. https://doi.org/10.1371/journal.pone.0272846,

http://hl7.org/fhir. (2014). *CarePlan - FHIR V4.0.1*. https://fhir-ru.github.io/careplan.html