

What-You-See-Is-What-You-Get Computer-Interpretable Guidelines: The Case of NoviGuide Neonatal

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Abstract. Complex clinical decision support (CDS) that goes beyond representing simple clinical flowcharts to supporting the totality of a care encounter may help improve care quality and consistency. However, integrating a large volume of clinical guidelines applicable to a care encounter poses unique design and safety considerations. We present the visual and technical methods employed in developing NoviGuide, a platform for complex CDS. Assuring safe functioning required transparency of all outputs, which we achieved using a JSON formalism for capturing logic. Unlike raw computer code, logic-as-data can be presented clearly in context to non-informatician reviewers. Two different styles for visualizing CDS logic, random-access and narrative, support different review contexts. We assess the fitness of these solutions for encoding hundreds of neonatal-care guidelines into integrated multi-topic CDS.

Keywords. Clinical decision support, knowledge bases, practice guidelines

1. Introduction

Public health and clinical safety advocates have long hoped that clinical decision support (CDS) could increase clinicians' adoption of and adherence to clinical guidelines [1]. Single-topic CDS that queries electronic medical records and generates alerts is common in high-resource settings, but CDS that models and supports the complex Task-Network Model of a complete care encounter, integrating diverse guidelines [2], is limited.

The World Health Organization (WHO) advocates a five-layer model for capturing clinical knowledge [3]. Passing in stages from narrative clinical guidelines to "dynamic algorithms," clinical knowledge is to be represented by numerous artifacts as it moves from medical experts to informaticians to code. The safety of this strategy rests on an assumption that CDS software is only a change in form from expert-verified source material. The prospect that CDS software may be a novel integration whose clinical content extends beyond narrative guidelines, is not confronted.

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Herein we describe our effort to transform a large volume of content, typical not of a set of narrative guidelines but of a pocket guide, into a tablet-based CDS application for newborn care that can integrate into clinical workflows in low-resource settings. We describe the complexity of that task and how it led us away from a paradigm that required multiple sequential artifacts. We highlight the need to develop visual conventions and computational models that prioritized transparency to ensure safety and predictability. We then analyze the adequacy of our approach using a neonatal CDS deployment in sub-Saharan Africa as a real-world test case.

2. Methods

2.1. Application parameters

NoviGuide Neonatal offers clinicians a choice of several broad assessment types (first assessment of a newborn, rounding, discharge, etc.) modeled on a typical encounter TNM. A series of screens prompts observation and data input, each screen a node in a directed acyclic graph (DAG). Indications of danger may lead to a warning “popup” (Figure 1), a diversion into a longer line of questioning, or both. When indicated by guidelines and desired by the user, NoviGuide also calculates drug dosages and feed quantities. Adaptation to resource availability and protocol variation was a requirement. At the end of each assessment, a summary is presented and dosages may be reviewed.

2.2. Visual methods

We developed two key modalities for visualizing the medical knowledge in NoviGuide. The Algorithm Architect allows free-ranging review and testing of the end-user application, and with sufficient privileges, modifications to it (Figure 2). The assessment DAG is presented in one pane, with colors distinguishing different topics. To its right is the fully usable end-user experience. Entered data is displayed in another pane at extreme right. Changes to configuration options, at left, have instant effect on the DAG and the end-user experience. Popups prompted by concerning findings appear in response to input, but can also be revealed via gridded buttons on each row.

```

{
  "id": "5210.bp-low-very-preterm",
  "logRank": 3,
  "pickCriteria": [
    {
      "sufficientToPick": [
        {
          "dataKey": "blood-glucose-band",
          "operator": "=",
          "referenceValue": "blood-glucose-band.LOW"
        },
        {
          "dataKey": "gestation",
          "operator": ">=",
          "referenceValue": "gestation.PRETERM"
        },
        {
          "dataKey": "HELPERS.NEONATAL_adjustedGestationalAge",
          "operator": "<=",
          "referenceValue": 34
        }
      ]
    },
    {
      "payLoad": {
        "resource": "card",
        "indicator": "warning",
        "summary": "You indicated a low glucose in a baby less than 34 weeks"
      }
    }
  ]
}

```

1 Please check the baby's glucose now.

Reveal Logic

5210.bp-low-very-preterm IF blood-glucose-band = LOW & gestation = PRETERM & HELPERS.NEONATAL.adjustedGestationalAge < 34

You indicated a low glucose in a baby less than 34 weeks old. It is unlikely that the baby will feed sufficiently to raise the glucose. We will now calculate the dose of IV dextrose to help treat this baby's sugar.

Hide HELPERS.NEONATAL_adjustedGestationalAge

```

function calculate(calcData) {
  var weeks = calcData.gestational-age;
  var postBirthWeeks = Math.round((calcData[day-of-life] / 7);
  return weeks + postBirthWeeks;
}

```

Observe Knowledge Base

Figure 1. Warning “popups,” in essence CDS Hooks cards, are the “payload” of encoded conditions or “pickCriteria.” The JSON formalism (left) is formatted for review in the Algorithm Architect (right). A referenced Javascript function (“helper”) is coerced to a string and presented in-context to the reviewer.

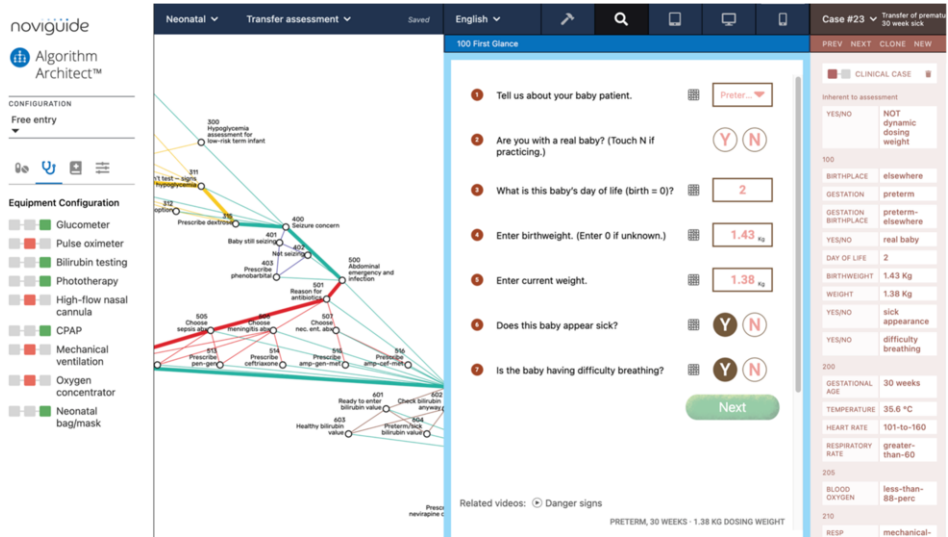


Figure 2. NoviGuide in Algorithm Architect mode. Each node in the assessment DAG is a screen composed of questions for the clinician. Traversal logic is indicated below the screen preview. Other logic is revealed using the gridded button shown only in this mode. Configuration options at left have immediate effect.

The second key visualization is Alignment mode (Figure 3), in which medical knowledge across all assessments in a library is presented in a guided “wizard” format, which also gives access to geography-level configuration options such as lab value thresholds, dosing schemes, and emergency contact names.

2.3. Technical methods

We captured almost all CDS logic not as computer code, but as data using a formalism we open-sourced as PickLogic [4]. In this way NoviGuide presents not descriptions of desired logic, but renderings of it — “What You See Is What You Get.” The dosing scheme in Figure 3 is a direct representation of the JSON-encoded logic used to calculate dosages. At a high level, we followed the CDS Hooks standard as part of a service-oriented architecture, and where practical, used the HL7 FHIR standard.

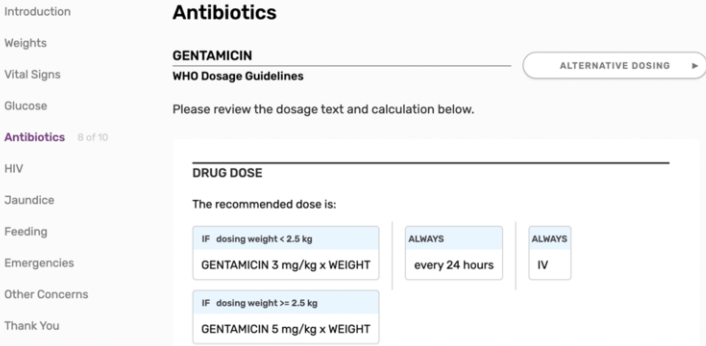


Figure 3. NoviGuide in Alignment mode. Key assessment content is organized topically and configuration options are shown. JSON-encoded logic used to calculate dosages is rendered for non-informaticians.

In rare cases we needed logic that went beyond the capabilities of our formalism, which it could incorporate by reference. Since the Javascript language treats functions as first-class objects, we could programmatically coerce these “helper” functions to strings and present them in context within the Algorithm Architect (Figure 1).

John Fox and others have advocated for encoding argumentation logic for increased explainability [5]. While our formalism for capturing logic would lend itself to composing automatic “because” statements, for now we have preferred to write our own text explaining to the user why she/he has been sent down a particular pathway.

3. Results

3.1. *Quantifying CDS for complex care encounters*

The creation of NoviGuide Neonatal revealed the dimensions of data needed to digitize complex medical assessments. Seven assessment types range in size from 3 to 56 nodes, with a total of 163 unique nodes and 322 edges. The nodes elicit 126 unique datapoints, inputs for 82 of which may surface one of 306 cards (usually “popups”). Dosing is available for 22 medications or neonatal feeding protocols, with alternate dosing schemes for 4 medications. There are 49 possible summary components.

3.2. *Adequacy of visualizations*

The Algorithm Architect (Figure 2) was a critical tool for developing, vetting, refining, and sharing the neonatal assessments. The experience of addressing such a large volume of content highlighted the inadequacy of narrative guidelines to encompass the clinical content needed for dynamic assessments. Specific areas poorly captured in narrative guidelines included antibiotic decision making, the feeding of preterm infants, and anomalous findings (e.g. a newborn with an unlikely gestational age/weight combination). We shared the Algorithm Architect in well over 50 meetings. For gatherings of medical experts in Uganda, Alignment mode (Figure 3) was the preferred method for reviewing and configuring the medical logic in the assessments. Experts requested only two minor changes to the algorithms [6].

3.3. *Adequacy of CDS Hooks*

All NoviGuide CDS services provide a JSON payload when linked conditions are met. Some services required custom response objects, but where appropriate, we employed CDS Hooks cards, extending the specification as follows:

- Added a “rejected” indicator (13.7% of cards), used in cases of contradictory or unacceptable user input, when the inciting datapoint should not be recorded.
- Added a “silent” indicator and “effects” attribute (another 13.7% of cards), used to update one or more datapoints without showing a card — e.g., to decompose a single clinician response into two datapoints, a “silent” card with “effects” is used.
- Provided services with access to equipment availability and configuration data.

3.4. Adequacy of knowledge model

We successfully encoded the majority of the neonatal clinical knowledge in scope with only our simple JSON formalism. Across all CDS functionality, 628 payloads are triggered using 1,654 total expressions encoded as data. Only 138 of these expressions (8.3%) require helper functions to be evaluated. 38 helper functions totaling about 500 lines of Javascript code cover these complex evaluations as well as text literalization.

4. Discussion

Our experience modeling and integrating CDS into the entire TNM of a care encounter required extending and synthesizing content found in narrative guidelines. Managing this complexity safely led us to pursue a strategy that emphasized comprehensive transparency of outputs and minimized the use of logic-as-code, since programming language syntax is opaque to medical reviewers. To address these design challenges, we adopted a solution from the early days of word processing: “What You See Is What You Get” (WYSIWYG) — the idea that content be reviewed and edited in a form that resembles the finished product. WYSIWYG authoring of complex, configurable CDS assessments removes intermediary artifacts and translation steps, closing the gap between human logic and machine logic. Additionally, it prioritizes safety by allowing guideline authors to see recommendations in their ultimate point-of-care manifestation.

5. Conclusions

The NoviGuide platform, shaped by the imperative to digitize the hundreds of best practices that shape a comprehensive neonatal assessment, highlights key CDS design and safety considerations. The lessons learned structuring guidance into interactive assessments that mimic care delivery, allow for configurability, and offer in-context transparency for reviewers likely apply to areas outside of neonatal care.

References

- [1] Bates DW, Kuperman GJ, Wang S, Gandhi T, Kittler A, Volk L, Spurr C, Khorasani R, Tanasijevic M, Middleton B. Ten commandments for effective clinical decision support: making the practice of evidence-based medicine a reality. *J Am Med Inform Assoc.* 2003 Nov;10(6):523-30, doi: 10.1197/jamia.M1370.
- [2] Peleg M, González-Ferrer A. Guidelines and workflow models. In: Greenes RA 2nd, editors. *Clinical Decision Support: the road to broad adoption.* Amsterdam: Academic Press; 2014. p. 435-64, doi: 10.1016/B978-0-12-398476-0.00016-6.
- [3] Mehl G, Tunçalp Ö, Ratanaprayul N, Tamrat T, Barreix M, Lowrance D, Bartolomeos K, Say L, Kostanjsek N, Jakob R, Grove J. WHO SMART guidelines: optimising country-level use of guideline recommendations in the digital age. *Lancet Digit Health.* 2021 Apr;3(4):e213-6, doi: 10.1016/S2589-7500(21)00038-8.
- [4] See <https://github.com/GlobalStrategies/picklogic>
- [5] Fox J, Glasspool D, Grecu D, Modgil S, South M, Patkar V. Argumentation-based inference and decision making—A medical perspective. *IEEE Intell Syst.* 2007 Dec;22(6):34-41, doi: 10.1109/MIS.2007.102.
- [6] Muhindo M, Bress J, Kalanda R, Armas J, Danziger E, Kanya MR, Butler LM, Ruel T. Implementation of a newborn clinical decision support software (NoviGuide) in a rural district hospital in Eastern Uganda: feasibility and acceptability study. *JMIR Mhealth Uhealth.* 2021 Feb;9(2):e23737, doi: 10.2196/23737.