Revista Brasileira de Computação Aplicada, April, 2026

DOI: 10.5335/rbca.v18i1.16937
Vol. 18, Nº 1, pp. 33–42
Homepage: seer.upf.br/index.php/rbca/index

ORIGINAL PAPER

A computational cognitive modeling framework for care pathways representation and its operational use in primary health care

Anderson Aires Eduardo [1], Lídia Maria Lourençön Rodrigues Agia [2], Renata Panseri Rodrigues[2], Antonia Michele Almeida[1], Thilara Najara Dos Santos Araújo[2], Adriana Morelli Martins[2], Ligia Paolinelli Bambirra[2], Erica Marvila Garcia[1], Natalia Tatiani Goncalves Brito[1], Demian de Oliveira e Alves Brito[1], Eduardo Segalla de Mello[1], Roberto Alves de Sousa Junior[2], André Pires dos Santos[2]

[1]Digital Platform, Hospital Israelita Albert Einstein, São Paulo, Brazil., [2]Primary Health Care Department, Hospital Israelita Albert Einstein, São Paulo, Brazil.

*anderson.eduardo@einstein.br; lidia.agia@einstein.br; renatapanseri@einstein.br; antonia.almeida@einstein.br; thilara.araujo@einstein.br; adriana.morelli@einstein.br; ligia.bambirra@einstein.br; erica.marvila@einstein.br; natalia.brito@einstein.br; demian.alves@einstein.br; eduardo.mello@einstein.br; roberto.alves@einstein.br; andre.dsantos@einstein.br

Received: 2025-04-08. **Revised:** 2025-04-08. **Accepted:** 2025-04-08.

Abstract

This paper proposes a lean computational cognitive modeling framework for representing care pathways in primary health care and its operational use. The framework is based on logical decision trees that can model any feed-forward boolean decision process using widely accessible technologies. A user interface and API allow users to define pathways as trees by specifying nodes, rules, and outputs. The framework was experimentally implemented for care pathways from the Brazilian Ministry of Health and from a major Brazilian hospital. Load testing showed responses below 40ms for 1000 simulated users. Integration with an electronic health record displayed pathway recommendations to users in real-time. Analysis of time spent on consultations before and after deployment found a statistically significant 2-minute reduction, suggesting improved efficiency. The proposed framework provides a simple yet effective approach to automating care pathways using only open-source tools, with potential to support primary care delivery and decision-making at scale.

Keywords: Population health; decision support systems; artificial intelligence; health informatics.

Resumo

Este artigo propõe um framework enxuto de modelagem cognitiva computacional para representar digitalmente Linhas de Cuidado (LC) na Atenção Primária à Saúde (APS) e seu uso operacional. O framework baseia-se em árvores de decisão lógicas que podem modelar qualquer processo de decisão booleana com fluxo unidirecional e para frente ("feed-forward"), usando tecnologias amplamente acessíveis. Uma interface de usuário e uma API permitem que os usuários definam LCs como árvores de decisão, especificando nós de decisão, regras e saídas. O framework foi implementado experimentalmente para LCs do Ministério da Saúde do Brasil e de um hospital brasileiro de grande porte. Testes de carga mostraram respostas abaixo de 40 ms para 1000 usuários simulados. A integração com um prontuário eletrônico operacional exibiu recomendações de LCs para os usuários em tempo real. A análise do tempo gasto em atendimentos antes e depois da implantação encontrou uma redução estatisticamente significativa de cerca de 2 minutos/atendimento, sugerindo maior eficiência. O framework proposto oferece uma abordagem simples, porém eficaz, para automatizar LCs usando apenas ferramentas de código aberto, com potencial para apoiar atendimentos no contexto da APS e a assertividade da tomada de decisão de profissionais de saúde em larga escala.

Palavras-Chave: Saúde populacional; sistemas de supote à decisão; inteligência artificial; informática em saúde.

1 Introduction

The health status of populations and subpopulations, as well as the inquiry of emergent patterns and disparities among groups of individuals, have progressively structured the core of relevant discussions in Health over the past two decades (Kindig and Stoddart, 2003; Merchant et al., 2016; Babbar et al., 2022). Together with the design of tailored collective interventions envisioning the equitative promotion of healthcare, such concerns circumscribe the concept of Population Health (PH) (Bambra et al., 2020). As the Population Health perspective becomes clearer and more tangible (*e.g.*, Bambra et al. (2020)), issues related to the development of health care strategies and population-level interventions continue challenging researchers and decision makers in building a unified and accessible praxis. Notably, populational interventions are based on a complex decision-making process, typically involving allocation of financial and human resources, guided by the expectancy of simultaneously reducing health care costs and the effects of diseases on individuals, given a focal population (Ardito et al., 2020).

In this context, Primary Health Care (PHC) stands out as a reference for offering essential primary care, based on appropriate technologies and scientific evidence. Essentially, PHC is configured as a gateway to a network of health services, designed to attend the population demands ranging from basic needs to higher complexity healthcare issues (de Almeida et al., 2018). Moreover, PHC is evolving rapidly not only in terms of health policies, but also in terms of technological developments, with many digital health innovations already available.

Naturally, the extent of the practical benefits yielded by the current technological status varies across geographical and socio-economic contexts (Shachak et al., 2013; Pagliari, 2021; Filho et al., 2021). More specifically, this is the very case of Care Pathways (CP) in health care provisioning (Schrijvers et al., 2012; Aspland et al., 2021). Despite having been widely discussed and well established as an effective and efficient tool for quality of care (Schrijvers et al., 2012; Aspland et al., 2021), it stills surprisingly challenging to widespread the technologies which digitalize and automatize CPs in larger healthcare systems, even considering the natural propensity of CPs in being tackled by IT processes and methodology (Aspland et al., 2021). Both the literature and our practical experience show that, on a routine basis, PHC professionals with increased difficulties in accessing CPs tend to treat patients based on isolated episodes of care, becoming less compliant with the PHC precepts, which are inherently focused on integral and continued patient care.

In the present study, we focus on proposing a lean framework able to represent any feed-forward boolean decision process, built upon accessible technologies, omnipresent even in a modest IT infrastructure of healthcare providers. Moreover, we use the Brazilian health system as an application case, providing experimental implementations either for the CP defined by the National Health Ministry (Ministério da Saúde do Brasil, 2020) and the CP of a large private health care provider, the Hospital Israelita Albert Einstein (HIAE).

2 Methodology

2.1 Computational cognitive modeling concepts

Cognitive modeling refers to a formal approach to capture some human cognitive process and represent it as a conceptual, mathematical or computational model. It has an extensive research history, crossing disparate areas such as psychology, management science, applied mathematics, computer science and artificial intelligence. Here we focus on a logic-based (or boolean, or rule-based) computational cognitive modeling approach (*LCCM*), specifically. An extensive exploration of its formal basis is beyond the scope of this paper, so, please refer to the excellent text of Bringsjord (2001) for a comprehensive theoretical and conceptual review. Essentially, the *LCCM* approach proposes a top-down strategy for modeling cognitive processes (as opposed to bottom-up strategies, such as artificial neural networks). In doing so, declarative (or propositional) statements are the core concept in the modeling process. Declarative statements are truth-valuated affirmative sentences (or parts of a sentence), presenting a formidable formalism for representation of healthcare protocols and guidelines. Thus, a declarative statement P is atomic enough to be evaluated as *true* or *false*, and a number of declarative statements, $P_1, P_2, ..., P_n$, can be combined using logical connectors, being specially relevant the conjunctions (*e.g.*, $P_i \wedge P_j$), disjunctions (*e.g.*, $P_i \vee P_j$) and negation (*e.g.*, $\neg P_i$).

Declarative statements also can be arranged in a tree-like logical structure, or logical decision tree (*LDT*). The *LDT*s are conveniently tackled computationally and have been the subject of computer scientists and applied computational scientists for years. For decision making in health sciences, in particular, it has a long history in building expert systems. To do this, researchers and developers define a main problem, *MP* (or an expert cognitive process regarding a specific knowledge topic), which can be decomposed into a number of minor interrelated subproblems, $SP_1, SP_2, ..., SP_m$, involving quantitative or qualitative variables and parameters, $x_1, x_2, ..., x_p$. Such subproblems are called basic problems and they are defined as declarative statements (*i.e.*, $SP_i := P_j$) that could be evaluated given some instantiation for the variables and parameters involved in the main problem. Being the subproblems $SP_1, SP_2, ..., SP_m$, related to each other in a graph-like fashion, the *MP* is then represented as a unidirectional acyclic graph, G, composed of m vertices, each one corresponding to the subproblems $SP_1, SP_2, ..., SP_m$, and u edges, corresponding to the links connecting logically the nodes SP_i and SP_{i+k} – this last one being assessed (or not) following the evaluation of the node SP_i, for the cases SP_i is evaluated as *true* or *false*, respectively.

We believe that the *LCCP* approach, through *LDT*s, by having, at the same time, a good fit for scalable computational implementations, an intuitive and translucid knowledge representation and reasoning

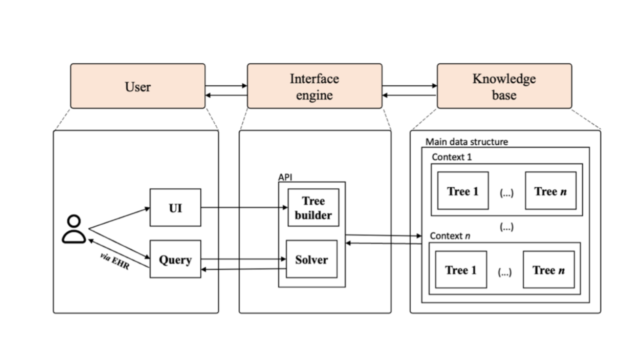

Figure 1: The framework proposed in the present study. On the top, the coloured blocks represent the general design for knowledge-based systems (see Sutton et al. (2020)). Our concept is detailed right below it, being directly related with each block of the general design.

concepts, and a consistent theoretical ground, stills representing a suitable strategy to a knowledge-based system implementation, such as the very case of *CP*. In the following sections, we describe our framework for an easy-to-use computational system able to represent *CP*s as *LDT*s, allowing user queries, integration with other technologies (specially, electronic health records – EHR) and capable of supporting large-scale operational routines of organizations providing health services.

2.2 Framework conceptualization and definitions

Conceptually, an ideal framework for *CP*s should be easily implementable (considering the existing IT technologies currently available as a baseline), easily maintainable (considering stakeholders engagement), and easily integrable (minimizing IT resources). On the one hand, it is challenging (possibly impossible) to make such an ideal system tangible. But on the other hand, the closer we get, the more valuable it is to health providing organizations (private and governmental). This is exactly the reason making them a valuable reference system. Thus, we propose a lean framework completely focusing on open source and omnipresent technologies in organizations.

The framework follows the conventional general design for knowledge-based systems, in the context of clinical decision support systems (Sutton et al., 2020). So, it comprises an (i) interface engine, (ii) a knowledge base and (iii) the data. Here, the data is specifically the *CP* contents. The interface engine is centered a usual web site form, and the knowledge base is a computational data structure tailored for our purposes here (*i.e.*, our computational implementation of LDTs). Fig. 1 depicts the proposed framework.

The user interface (UI) centers the user resources for *LDT* parametrization, creation and update. It follows a simple template, with two mandatory form fields named "Decision tree name" and "Context name". On the "Decision tree name", the user should provide an unique string as a name for the tree being created; on the "Context name" should be imputed a unique string and an arbitrary number of LDTs can be related to it, meaning a same organizational scope (*e.g.*, telemedicine department, *etc.*). Following, the user should push the button "Add" to create the decision nodes for the respective decision tree. Each decision tree node must have (i) a node name, (ii) the definition of the variable being to be evaluated on the current decision node, (iii) the data type of the such variable, (iv) the operation to be performed on the current decision tree node, regarding the defined variable, (v) the definition of what the decision tree should do in cases where the defined rule is valuated as true and (vi) the definition of what the decision tree should do in cases where the defined rule is valuated as false. Once all the decision tree nodes are imputed, user should press the button "Create decision tree". On the back-end side, all the user inputs are properly parsed and sent to the API. For the UI implementation, the python library streamlit (version 1.40.0) was used.

The declaration of node rules and its outputs, in the back-end side, are heavily based on python boolean expressions. In fact, basically it is an explicit declaration of a pythonic boolean expressions with some specific and intuitive additions. Such additions are related to the declaration of (i) variables and (ii) outputs. Table 1 shows the API (*i.e.*, back-end side) specification for implementing any LDT structure supported by our framework, with examples.

Also, bundles of parameter values can be declared using a common spreadsheet, containing a sheet named as "BUNDLES", allowing a visually clean node rules declaration (*e.g.*, all ICD-10 codes for, lets say, migraine could be grouped in a unique bundle; see Table 1). An template file, containing an example, is provided along the source code on the GitHub repository (please, see next section).

The back-end side is performed by an Application Programming Interface (API), including the ingestion of the user-defined LDT parametrization, as well as the public route exposition for querying requests. The API also provides other functional resources, such as listing the LDTs available in the system, listing the node rules, deleting LDTs or nodes, *etc*. Table 2 lists all the API resources implemented for our purposes here.

2.3 Experimental computational implementation

In the present work, we conducted an experimental implementation of the proposed framework. We focused on the CP for obesity as defined and made publicly available by the National Health Ministry (Ministério da Saúde do Brasil, 2020) (link: `https://linhasdecuidado.saude.gov.br/portal/obesidade-no-adulto/unidade-de-atencao-primaria/`). All our implementation was conducted using *python* programming language (version 3.11.4), employing conventional packages for data science and API development (*e.g.*, *pandas*, *numpy*, *flask*) as well as python built-in modules, such as *os*, *pickle* and *datetime*.

To evaluate the functioning of our implementation, we designed and executed a load test. A virtual population of 1000 users were simulated using the python package locust (version 2.16.1). The population begins with 1 user, being added to 1 new user per second (up to 1000 users).

Table 1: Specification of programming terms for node rules and output implementation. The term structure for instantiation is shown on the Pattern column and its rationale is summarily exposed on the Meaning column. Practical examples are provided in the Examples column.

Pattern	Meaning	Examples
variable:[variable name]	Variables should be explicitly declared in LDT node rules specification. The reserved term variable: performs as a tag, allowing such declaration.	*variable:IMC* *variable:ICD-10*
output:[output contents]	The output to be returned to the user should be explicitly declared in the LDT node output specification. The reserved term output: performs as a tag, allowing such declaration.	*output:Assessment for indication of surgery* *output:Therapeutic planning*
bundle:[bundle name]	A list of values can be declared as a bundle.	*variable:ICD-10 in bundle:obesity-ICD-10*
>, <, >=, <=	Logical comparisons are interpreted by the system normally.	*variable:IMC >=35* *variable:time-under-clinical-protocols >= 2*
==, !=	Logical comparisons are interpreted by the system normally.	*variable:comorbidities == "true"* *variable:ICD-10 == "E66"*
in, not in	Logically check if a variable value can be found (or not) in a sequence of values. The reserved terms in and not in can be used, as usual in Python programming.	*variable:ICD-10 in "E66, E66.8, E66.9, R63.5"*
"true", "false"	Logical True and False statements can be properly employed as strings.	*variable:comorbidities == "false"*
1, 2, 3,...	Integers can be employed as usual.	*variable:time-under-clinical-protocols == 0*
1.0, ..., 2.0,...	Float numbers also can be employed as usual.	*variable:IMC <= 49.9*
"[string]"	Strings can be employed as usual (with simple or double quotes).	*variable:ICD-10 not in "E66, E66.8, E66.9, R63.5"*

Each virtual user executes a new query to the implemented system (running in localhost) within an interval of 2 (minimum) up to 15 (maximum) seconds. The parameters for each query were set to be randomly chosen values. The load test was run over 20 minutes and all the results were recorded in a CSV file, which was statistically analyzed. The parameters considered were the number of requests per second (RPS), the 50th and the 90th percentiles of the API response time (in milliseconds) for each user query, and the population size (in terms of the number of users interacting with the system).

Also, all the computation experiments were performed using a standard DELL notebook, using a licensed Windows operating system, with an Intel®Core™ $i5-10210U$ processor, 1.60GHz 2.11GHz CPU and 16GB RAM. The source code (including the load test parametrization file and the CSV with the raw results) is available on the *GitHub* repository `https://github.com/AndersonEduardo/framework-dss.git`.

2.4 Assessment in a real-world operational scenario

We adapted our experimental implementation in order to make possible the deployment and integration of our system with a real-world operational EHR. Thus, we focused on the Cockpit™, which is the proprietary HIAE's cloud-based platform for EHR. Since 2018, this system has been used by the whole division of PHC of HIAE, comprising a population of 300 health professionals.

Our system received information security and containerization layers (using the Docker technology) for its proper working as a microservice. It was then connected to the Cockpit™ back-end and our system's outputs were captured and displayed as recommendations in the EHR's front-end, to the user. A custom integration was carried out by the Cockpit™ developers' team in such a way that a query to our system is automatically triggered when all the parameters for the implemented LDTs are filled by the user through the EHR. Although this implementation relied on the Cockpit™ infrastructure, the same integration approach could be implemented using widely adopted health interoperability standards (e.g., HL7 FHIR, openEHR, or CDS Hooks), which were not explored in the present work.

We modeled and provided LDTs for nine HIAE institutional CPs: (i) childcare, (ii) child & adolescent health, (iii) women's health or trans men, (iv) health of trans men or women, (v) hypertension, (vi) diabetes, (vii) obesity, (viii) prenatal, (ix) mental health. The institutional CPs accommodate the National Health Ministry and enrich it with more detailed suggestions and recommendations (*e.g.*, medication prescription, referral to specialists, *etc.*).

We deployed our system and monitored the IT infrastructure of Cockpit™ from June 2023 to December 2023, actively observing its behavior facing the volume of user requests and searching for system failures. Finally, we employed the time spent (in minutes) by users in filling the Cockpit™ form before (from June 2022 to

Table 2: Resources implemented for the API in our experimental implementation. The API routes are illustrated in this table as it should be consumed in a local machine (*i.e.*, local host). The HTTP method and the rationale of each API resource are also provided. The parameters needed in order to successfully use an API resource is listed in the Parameters column.

API route	HTTP method	Resource	Parameters
localhost:5000/query	POST	User query, given the implemented LDTs.	Variables specified at LDT implementation.
localhost:5000/tree-builder		Module for LTD creation and update (via UI).	Not applicable.
localhost:5000/list-trees	GET	Lists all the LDT available in the system.	*context*
localhost:5000/list-tree-rules	GET	Lists all nodes and its respective rules, given a LDT.	*context*; *decision-tree-name*
localhost:5000/delete-tree	DELETE	Delete a specific LDT.	*context*; *decision-tree-name*
localhost:5000/update-tree-node	POST	Overwrites the rule of a specific LDT node.	*context*; *decision-tree-name*; *focal-node-name*; *rule*; *if-true*; *if-false*
localhost:5000/list-tree-bundles	GET	Lists all the bundles available in the system.	No parameters.
localhost:5000/delete-bundle	DELETE	Delete a specific bundle.	*bundle-name*; *context*

December 2022) and after the system deployment, using retrospective administrative data (*i.e.*, aggregate time length measures and countings for user interactions with Cockpit^{TM}, without any access or contact with sensitive data and in accordance with the guidelines established by the Brazilian General Data Protection Law – Brasil (2018)). As our system outputs suggestions based on institutional *CP*s, we hypothesized that some decrease in the time spent for filling the EHR could be detected for the population of Cockpit^{TM} users. So, we statistically compared the data for time lengths before and after the system deployment using the non-parametric Mann-Whitney *U* test (assuming a $\alpha = 0.05$).

3 Results

The experimental implementation for the CP defined by the Brazilian National Health Ministry showed that the proposed framework works properly in tangible use cases. We modeled the CP for obesity, which is depicted on Fig. 2. The user interface form was used and worked as expected (see Fig. 3). We provide a spreadsheet template in order to document the LTDs implemented here. It is available along the source code, on the *GitHub* repository (please, refer to *Methodology*). Table 3 shows a summary of its contents.

Both the LDT implementation and querying have been shown to work according to the preconized framework concept. A sample of the queries used for testing the implemented system is provided on Fig. 4.

The load test results showed that, for the user population simulated, no failures happened in the experiment. The response time was below 40 milliseconds for the whole experiment (*i.e.*, $< 0.04 seconds$). We observed an alteration on stability pattern starting at 200 requests per second (600 users, under the load test specifications). Above this threshold, the worst response time was observed to exceed the stable limit of 10 milliseconds and smoothly increases as new users are added to the population. After the maximum population size is reached, we observe that the response time also stabilizes (Fig. 5).

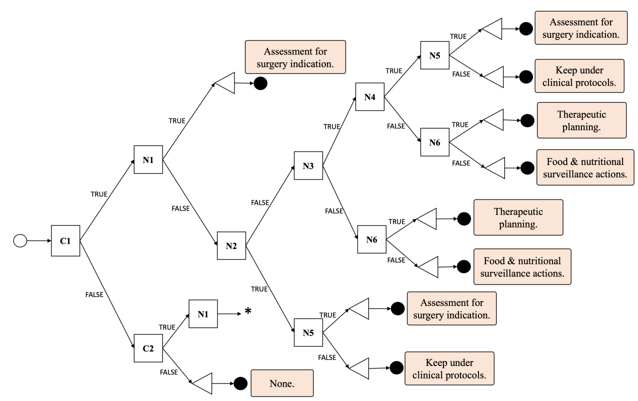

Figure 2: Logical Decision Tree model for the obesity CP, as provided by the Brazilian National Health Ministry. The circles mean the start (white) and the end (black) for the tree navigation fluxes. The squares represent decision nodes (filled with their respective names) and the triangles represent end nodes. The output of each end node is depicted by the colored boxes. This conceptual model was computationally implemented using the framework proposed in the present study.

Our implementation for the assessment of the proposed framework in a real-world operational context also showed positive results. The integration with Cockpit^{TM}, the HIAE proprietary EHR, was efficiently implemented and the LDTs querying and output processes properly worked. No instabilities or abnormalities were observed in the IT infrastructure after the deployment. Fig. 6 shows some instances of the recommendations displayed

Table 3: Parametrization used in our experimental implementation of the obesity CP, by the Brazilian National Health Ministry.

Parameter	Valued	If *false*	If *true*
Context	*CP-BRA*	-	-
Decision tree name	*obesity-LTD*	-	-
Bundles definition	CIAP: *T82*; *T07*; *T83* ICD-10: *E55*; *E66.8*; *E66.9*; *R63.5*	- -	- -
Node *C1*	*variable:ciap in bundle:obesity-CIAP*	*N1*	*C2*
Node *C2*	*variable:icd-10 in bundle:obesity-ICD-10*	*N1*	*output:None*
Node *N1*	*variable:IMC >= 50*	*output:Assessment for indication of surgery*	*N2*
Node *N2*	*variable:IMC >= 40*	*N5*	*N3*
Node *N3*	*variable:IMC >= 35*	*N4*	*N6*
Node *N4*	*variable:comorbidities == True*	*N5*	*N6*
Node *N5*	*variable:time-under-clinical-protocols >= 2*	*output:Assessment for indication of surgery*	*output:keep-under-clinical-protocols*
Node *N6*	*variable:IMC >= 25*	*output:Therapeutic planning*	*output:Food and nutritional surveillance actions*

in Cockpit™ by our system.

The analysis of the time spent by users in filling the Cockpit™ form showed a decreasing pattern, with the EHR filling taking 2 minutes less time after the implementation, considering the timeframe of our analysis (Fig. 7). Such difference is statistically significant (Mann-Whitney $U = 4135606.5$, $p < 0.01$).

4 Discussion

The present study explores a lean cognitive modeling framework for the computational representation of CPs, its application and use in PHC operational context. We have focused on a simple-to-use system, with light and translucent algorithms, and on widely accessible technologies for its implementation and maintenance, as well. Our results suggest that the framework proposed and investigated in the present study is able to reasonably cover these points.

Along with the proper logical consistency in delivering the main goals of a system that it intends to be (*i.e.*, to correctly represent CPs as LDTs, allowing user queries), we observed no exceptional issues for its implementation, its application to real-world CP instances, its integration with an EHR, and its use by developers and PHC professionals. The implemented system offered sufficient flexibility to implement LDT node-rules, and we were able to conveniently model ten CPs (one from the Brazilian National Health Ministry, and nine from the HIAE institutional CPs). Both the load test and the assessment in a real PHC operational context did not reveal any critical functioning limitation or instability in the carried-out evaluations. Here, it is interesting to point out that our load test parameterization (1000 users, with simultaneous queries in a few seconds of interval) covers an user population far larger than the actual existing one on the HIAE's PHC department (300 users, with queries intervaled by minutes). As the HIAE is one of the largest health care providers in Brazil, our findings suggest that our system should be able to support the operation of PHC departments of a relevant fraction of the currently existing Brazilian health care providers, even speaking in conservative terms.

Other researchers also addressed the issue of CP automatization and its application in a real-world operational context. Such efforts range from simple hypertext representation of CPs (*e.g.*, the CPs from Brazilian National Health Ministry) to complex ontology-based modeling frameworks (*e.g.*, Fudholi and Mutawalli (2018); Alahmar et al. (2020); Ta et al. (2023)), passing through a number of other strategies of modeling and implementation (*e.g.*, Katzan et al. (2015); Smulowitz et al. (2018); Hoelscher and McBride (2020)). On the one hand, when compared to simplistic systems (*e.g.*, HTML representation of CPs), our framework has the advantage of being easier to implement and update and also is fully integrable with EHR. On the other hand, compared to ontology-driven frameworks, our framework is conceptually simpler to understand and use, for both IT developers and PHC professionals – despite being less sophisticated, indeed. Regarding the literature on non ontology-based frameworks and systems, we were not able to find anyone similar to the framework we propose here. Moreover, authors commonly report difficulties related to the modeling process and the generalization of its application in health organizations (see Alahmar and Alkhatib (2022)), issues which are well handled by our system. Furthermore, we empirically observed a reduction in the time spent by PHC professionals in filling the EHR form (small, but statistically significant), a pragmatic result rarely explored by other researchers. Together, the literature we reviewed indicate that our findings complement the knowledge available on computationally modeling CPs, its automatization, and its application in real-world contexts.

Also, we agree with other authors arguing that the standardization of terms related to CPs is of paramount relevance for health information systems and technologies, in general (Alahmar et al., 2020; Alahmar

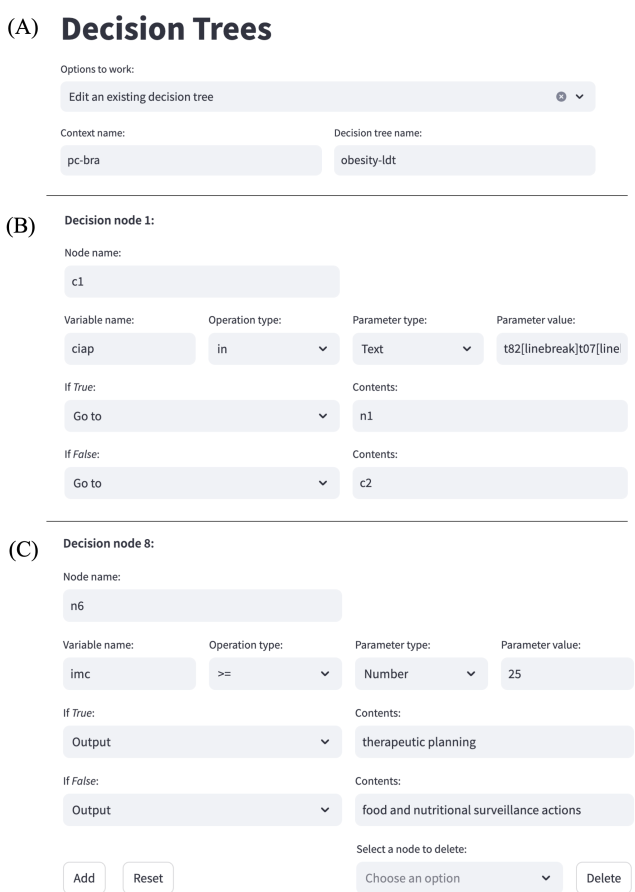

Figure 3: Implementation of the LDT (for the obesity CP) using the framework here proposed. (A) first part of the user interface, where the decision tree name and context are imputed by the user; (B) the implementation of the first (of 8) decision rules for the LDT; (C) the 8th decision rule (the last one) for the LDT, showing the buttons "Add", "Reset" and "Delete" (see main text for detailed descriptions).

Figure 4: Examples of queries and its respective responses using the implemented in the present study for the obesity CP, as provided and made available by the Brazilian National Health Ministry.

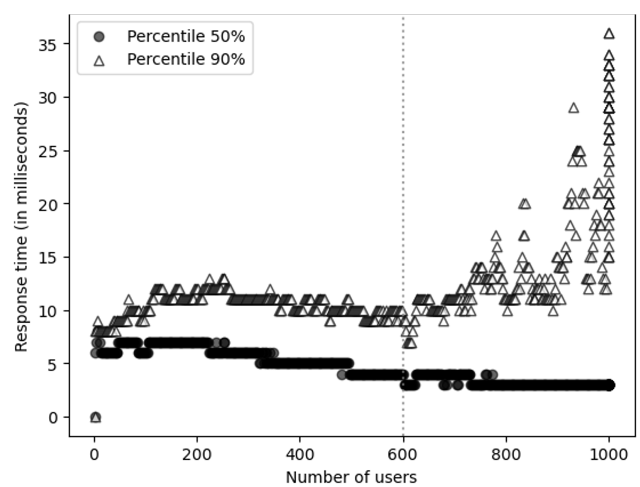

Figure 5: Results of the load test, in which a population of 1000 users was simulated, as a spawn rate of 1 new user per second and in which users can request a new query to the system in an interval of at least 2 and at the most 15 seconds. The response time (in milliseconds) is shown as a response to the requests per second (*x* and *y* axes, respectively). The dotted vertical line informs a threshold where the response time (for the worst cases) starts to increase smoothly (200 requests per second, 600 users).

and Alkhatib, 2022; Schulz et al., 2023). In our case, the LDTs implemented were modeled keeping in mind a specific operational context (*i.e.*, for the HIAE). So, we must recognize that the transfer of LDTs implemented using our framework must be carefully conducted, as the terminology assumed for a given CP could change among institutions, negatively impacting the querying algorithm by losing the information attached to unrecognized parameters. Despite being a major issue, we think it could be circumvented by extending our framework to accommodate an "ontology layer", interfacing the query algorithm and the actual user queries. More work should be conducted on this topic.

Future work should cover at least three topics in order to advance our findings in the present study. Firstly, in our experimental implementation, the information employed in the modeling process of the LDTs are restricted to those available as the user fills the EHR form. Thus, no additional information is being considered, at this point. But information from other contexts, such as historical patient information (*e.g.*, previous surgeries, previous acute health issues, cases of genetic disease in the patient family, *etc.*) or pertinent epidemiological information (*e.g.*, eventual rise in incidence of some infectious disease in particular), should expand the ability of our system in comprehending LDTs for a wide range of application cases. This could be implemented as modular functions, specific

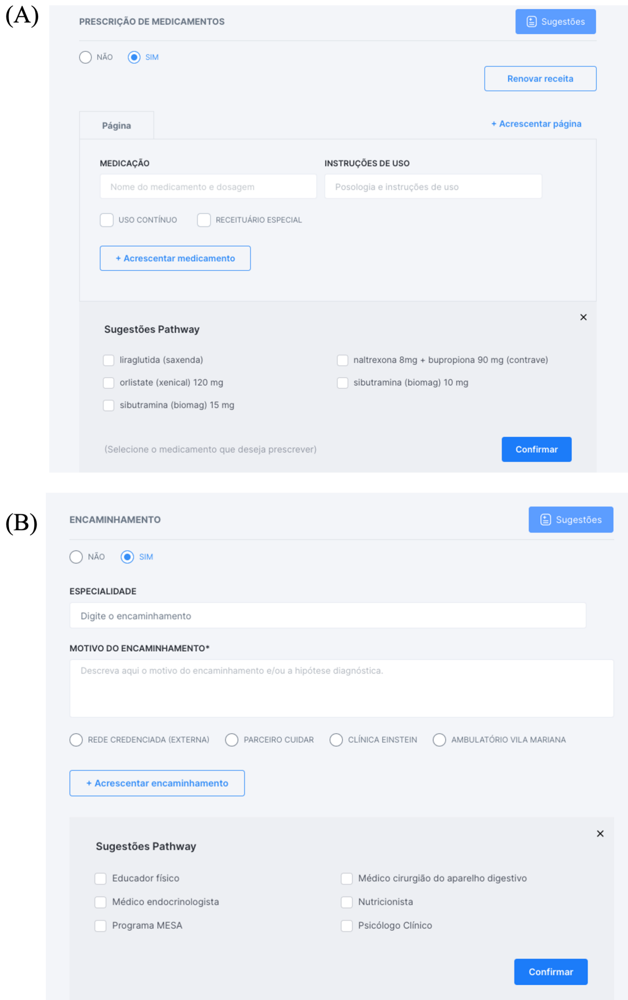

Figure 6: Examples of the recommendations that PHC professionals receive from our system along the EHR filling. The suggestions from the implemented LDT (for the obesity CP) were implemented to be conveniently displayed on the box "Sugestões Pathway" (Portuguese language, as the system works on the real-world operational context of HIAE). In panel (A): CP suggestions displayed for medication prescription on respective EHR section; panel (B): CP suggestions displayed for referral on the respective EHR section. The suggestions are automatically displayed as the user fills the previous EHR fields (see Methodology section).

for each situation, to be employed in the modeling step for node-rules formulation and LDT implementation. Ideally, such modular functions should be designed and consumed as any other function or class in python programming language, promptly advancing the framework proposed in the present study.

Secondly, as we centered the interface engine on an as simple as possible web site form, the strategy for LDT parametrization and instantiation could be expanded and diversified, exploring possibilities beyond our purposes here. For example, a set of new API resources could be

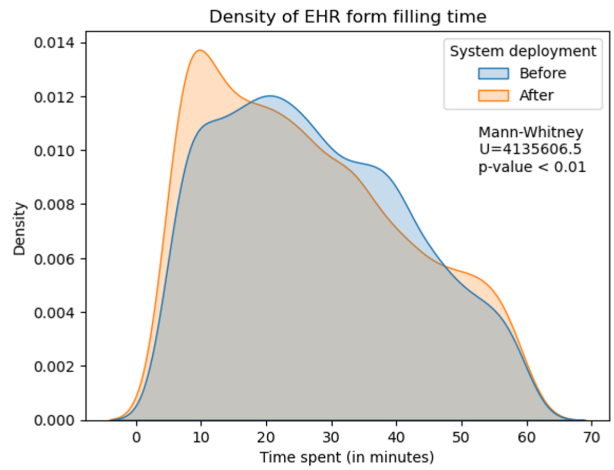

Figure 7: Distribution of the length of time spent in filling the EHR (CockpitCockpit^{TM}) in consultancies performed on HIAE operational routine by the PHC professionals. The "Before" curve, in the figure, refers to the period from June 2022 to December 2022. The "After" refers to the period from June 2023 to December 2023.

developed to make it possible to allow the user build a new LDT by clicking, selecting and typing through a more sophisticated web interfaces, specifically designed considering the user experience in proceeding with CPs automatization. In this sense, the flexibility of our framework, in terms of user interface possibilities, is open to be largely experimented.

Thirdly, for the present study, our implementation returns a very simple data structure. The development of new modules, able to parse the outputs in specific ways, could improve our framework towards more comprehensive output possibilities. This is relevant for overcoming potential complexities and specificities eventually demanded by data interoperability protocols (Marco-Ruiz et al., 2016; Strasberg et al., 2021).

Finally, although this study was conducted in a specific institutional setting, the modular architecture of the proposed framework suggests that it could be implemented in electronic health record systems used in public health networks without substantial loss of efficiency.

We hope that our findings help to promote the automation of CPs in primary health care by offering a system amenable to developers, managers and health professionals. We believe this has the potential to positively impact the quality of health services provided to the population, facilitating PHC professionals in focusing integral and continued patient care.

Acknowledgments

Authors thank the HIAE for supporting this research. Also, we thank the Cockpit^{TM} developers' team for the valuable collaboration with the integrations.

References

Alahmar, A. and Alkhatib, O. (2022). Computerization of clinical pathways: A literature review and directions for future research. http://arxiv.org/abs/2203.00815.

Alahmar, A., Crupi, M. E. and Benlamri, R. (2020). Ontological framework for standardizing and digitizing clinical pathways in healthcare information systems, *Computer Methods and Programs in Biomedicine* **196**: 105559. https://linkinghub.elsevier.com/retrieve/pii/S0169260719324356.

Ardito, C., Caivano, D., Colizzi, L., Dimauro, G. and Verardi, L. (2020). Design and execution of integrated clinical pathway: A simplified meta-model and associated methodology, *Information* **11**: 362. https://www.mdpi.com/2078-2489/11/7/362.

Aspland, E., Gartner, D. and Harper, P. (2021). Clinical pathway modelling: a literature review, *Health Systems* **10**: 1–23. https://www.tandfonline.com/doi/full/10.1080/20476965.2019.1652547.

Babbar, K., Martin, J., Ruiz, J., Parray, A. A. and Sommer, M. (2022). Menstrual health is a public health and human rights issue, *The Lancet Public Health* **7**: e10–e11. https://linkinghub.elsevier.com/retrieve/pii/S2468266721002127.

Bambra, C., Riordan, R., Ford, J. and Matthews, F. (2020). The covid-19 pandemic and health inequalities, *Journal of Epidemiology and Community Health* **74**: 964–968. https://jech.bmj.com/lookup/doi/10.1136/jech-2020-214401.

Brasil (2018). Lei nº 13.709, de 14 de agosto de 2018. lei geral de proteção de dados pessoais, Diário Oficial da União, Brasília, DF, 15 ago. 2018. Available at: https://www.planalto.gov.br/ccivil_03/_ato2015-2018/2018/lei/l13709.htm.

Bringsjord, S. (2001). *Declarative/Logic-Based Cognitive Modeling*, Cambridge University Press, pp. 127–169. https://www.cambridge.org/core/product/identifier/9780511816772%23c85741-ch5/type/book_part.

de Almeida, E. R., de Sousa, A. N. A., Brandão, C. C., de Carvalho, F. F. B., Tavares, G. and Silva, K. C. (2018). Política nacional de atenção básica no brasil: uma análise do processo de revisão (2015–2017), *Revista Panamericana de Salud Pública* **42**. http://iris.paho.org/xmlui/handle/123456789/49559.

Filho, R. V. C., de Souza, J. N., de Andrade, L. O. M., de Oliveira, A. M. B., Denis, J.-L., Ribeiro, L. L. S., Ribeiro, K. G., de Andrade, D. B. and Pereira, S. S. L. (2021). Lariisa: soluções digitais inteligentes para apoio à tomada de decisão na gestão da estratégia de saúde da família, *Ciência & Saúde Coletiva* **26**: 1701–1712. http://www.scielo.br/scielo.php?script=sci_arttext&pid=S1413-81232021000501701&tlng=pt.

Fudholi, D. H. and Mutawalli, L. (2018). An ontology model for clinical pathway audit, *2018 4th International Conference on Science and Technology (ICST)*, IEEE, pp. 1–6. https://ieeexplore.ieee.org/document/8528615/.

Hoelscher, S. H. and McBride, S. (2020). Digitizing infectious disease clinical guidelines for improved clinician satisfaction, *CIN: Computers, Informatics, Nursing* **38**: 303–311. https://journals.lww.com/10.1097/CIN.0000000000000612.

Katzan, I. L., Fan, Y., Speck, M., Morton, J., Fromwiller, L., Urchek, J., Uchino, K., Griffith, S. D. and Modic, M. (2015). Electronic stroke carepath, *Circulation: Cardiovascular Quality and Outcomes* **8**: S179–S189. https://www.ahajournals.org/doi/10.1161/CIRCOUTCOMES.115.001808.

Kindig, D. and Stoddart, G. (2003). What is population health?, *American Journal of Public Health* **93**: 380–383. https://ajph.aphapublications.org/doi/full/10.2105/AJPH.93.3.380.

Marco-Ruiz, L., Pedrinaci, C., Maldonado, J., Panziera, L., Chen, R. and Bellika, J. G. (2016). Publication, discovery and interoperability of clinical decision support systems: A linked data approach, *Journal of Biomedical Informatics* **62**: 243–264. https://linkinghub.elsevier.com/retrieve/pii/S153204641630065X.

Merchant, R. K., Inamdar, R. and Quade, R. C. (2016). Effectiveness of population health management using the propeller health asthma platform: A randomized clinical trial, *The Journal of Allergy and Clinical Immunology: In Practice* **4**: 455–463. https://linkinghub.elsevier.com/retrieve/pii/S2213219815006650.

Ministério da Saúde do Brasil (2020). Estratégia de saúde digital para o brasil 2020–2028, *Technical report*, Ministério da Saúde, Brasília. https://bvsms.saude.gov.br/bvs/publicacoes/estrategia_saude_digital_Brasil.pdf.

Pagliari, C. (2021). Digital health and primary care: Past, pandemic and prospects, *Journal of Global Health* **11**: 01005. http://jogh.org/documents/2021/jogh-11-01005.pdf.

Schrijvers, G., van Hoorn, A. and Huiskes, N. (2012). The care pathway concept: concepts and theories: an introduction, *International Journal of Integrated Care* **12**. http://www.ijic.org/article/10.5334/ijic.812/.

Schulz, S., Case, J. T., Hendler, P., Karlsson, D., Lawley, M., Cornet, R., Hausam, R., Solbrig, H., Nashar, K., Martínez-Costa, C. and Gao, Y. (2023). Snomed ct and basic formal ontology – convergence or contradiction between standards? the case of "clinical finding", *Applied Ontology* **18**: 207–237. https://journals.sagepub.com/doi/full/10.3233/AO-230018.

Shachak, A., Montgomery, C., Dow, R., Barnsley, J., Tu, K., Jadad, A. R. and Lemieux-Charles, L. (2013). End-user support for primary care electronic medical records: a qualitative case study of users' needs, expectations, and realities, *Health Systems* **2**: 198–212. https://www.tandfonline.com/doi/full/10.1057/hs.2013.6.

Smulowitz, P. B., Dizitzer, Y., Tadiri, S., Thibodeau, L., Jagminas, L. and Novack, V. (2018). Impact of implementation of the heart pathway using an electronic clinical decision support tool in a community hospital setting, *The American Journal of Emergency Medicine* **36**: 408–413. https://linkinghub.elsevier.com/retrieve/pii/S0735675717306964.

Strasberg, H. R., Rhodes, B., Fiol, G. D., Jenders, R. A., Haug, P. J. and Kawamoto, K. (2021). Contemporary clinical decision support standards using health level seven international fast healthcare interoperability resources, *Journal of the American Medical Informatics Association* **28**: 1796–1806. https://academic.oup.com/jamia/article/28/8/1796/6294980.

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N. and Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success, *npj Digital Medicine* **3**: 17. https://www.nature.com/articles/s41746-020-0221-y.

Ta, P., Gupta, B., Jain, A., C, S. S., Sarkar, A., Ram, K. and Sivaprakasam, M. (2023). Automated knowledge modeling for cancer clinical practice guidelines, *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, IEEE, pp. 1–4. https://ieeexplore.ieee.org/document/10341037/.