An Ontology-Based Coaching Solution For Increasing Self-Awareness of Own Functional Status

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Abstract
Functional Status Information (FSI) describes physical and mental wellness at the whole-person level, and includes information on activity performance, social role participation, and environmental and personal factors that affect well-being and quality of life. Collecting and analyzing this information is critical to addressing the data needs in caring for aging global populations, and providing effective care for individuals with chronic conditions, multi-morbidity, and disability. In this paper, we present a first step towards the design of AI-enabled system increasing the self-awareness of own functional status. In particular, we focus on the underlying semantic layer of the such an AI-enabled system by presenting two modules extending the HeLiS ontology aiming (i) to represent barriers in improving own functional status and (ii) to support the conceptual representation of the arguments leading to the detection of such barriers. Finally, we show through a running example how these modules can be instantiated.

Keywords
Ontology, Functional Status Monitoring, Behavior Change

1. Introduction

There is a growing trend to develop virtual health and well-being assistants to support lifestyle and disease management, partly due to the growing societal needs for managing health and preventing illness. To improve an individual's situation, a change of behavior is typically necessary, which puts focus on how a digital coach can act in collaboration with the individual to support the individual's ambition to improve health through behavior change, e.g. by adhering to medical guidelines or treatment protocols, increasing physical activity, changing nutrition habits, reducing stress or intake of toxic substances, by exploiting functional status information (FSI) of the monitored individual.

A necessary foundation for a medical and health-related system's reasoning, decision making and acting is (i) the medical knowledge that the digital coach utilizes, (ii) the theories and knowledge about how humans form motivation and change behavior as well as manage physical, social, and psychological barriers, and (iii) the FSI (data) about the individual as well as the

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individuals' narrative about their behavior change journey, information that needs to be treated following ethical guidelines and regulations. Moreover, the realization of such systems relies on the integration of effective, efficient and ethical strategies for adapting its behavior in a situation depending on the individual's context, personal preferences, and needs (e.g. display motivational messages that are tailored to each individual's resources and current situation).

In this paper, we present an ingredient that these kind of systems can implement for tackling the challenges above: the underlying ontology. In particular, we provide the description of two modules extending the HeLiS ontology [1] [1]: the "Barriers" module and the "Arguments" module. The adoption of such an ontology as a middle layer for the design of behavior change explainable systems allows (i) to model conceptual information representing individuals' FSI and exploited to drive the generation of explanatory messages; (ii) to support interoperability among different systems which could share for example databases of motivational messages or explainability algorithms; and, (iii) to manage both privacy and ethical issues about user data. Through the conceptualization of each barrier and of arguments, it is possible (i) to acquire personal FSI of users and to properly store them within the ontology; and, (ii) to manage which information can be shared with respect to the target user and, at the same time, to design "transparent by design" systems. Indeed, the use of the ontology enables the linking of information contained in black-box systems with conceptual information for exposing them.

This contribution is organized as follows. Section 2 briefly surveys the literature about the acquisition and exploitation of functional status information. Section 3 presents the two ontology modules we designed for addressing the challenges mentioned above and how such modules have been integrated into an existing virtual coaching system, namely HORUS.AI. Then, in Section 4, we provide a brief running example showing how the modules can be instantiated into a real-world use case. Finally, Section 5 concludes the paper by tracking future directions we aim to explore.

2. Related work

Understanding the functional status of a person is important for developing accurate interventions and providing services for improving their health status as well as maximizing their functional independence, to be able to perform well daily activities and be healthy. Managing health is quite a complex problem and often the health care system is unable to provide adequate support and care especially to persons with chronic and disability conditions [2]. The National Committee on Vital and Health Statistics (NCVHS) [3] states that understanding the functional status of people is key to achieve optimal health and well-being, and this often requires discussions with patients regarding their habits and lives and also collection more formal assessments by physicians and sensors. However, there is a gap between the health goals for people and the data that is available to measure regularly their performances and health status, and this could make difficult achieving a good quality of care [4].

Physicians and researchers for many years studied the correlation between decline in functions and the insurgence of acute illness or an exacerbation of a chronic illness, and identified risk factors to detect elderly most at risk of experiencing decline in functions [5, 6, 7]. Moreover,

[1]The full ontology and its modules are available at https://w3id.org/helis

the early recognition and treatment of an illness is key to a more rapid recovery, to morbidity and mortality in older adults [8, 9, 10]. However, the problem of functional status information is that it is not yet being fully embraced and thus is not used effectively to its full potential [4].

The usefulness and the development of interventions based on functional status measurements is still being studied and is under development and many physicians still do not appreciate the importance of this information [11, 12, 13, 14]. Moreover even if they were informed of patients' health status only a few changed patient management based on the information [15]. The NCVHS defined the problem of collecting patient data, considering not only the issue of the data collection burden and the quality of the data collected but also the issues relating the privacy of the patient that arise when collecting personal and sensitive data [3]. Various studies that are based on the self-report of functional performance and early decline in functions report to successfully predict the actual performance and decline [16, 17]. However, researchers verified that the self-report of functional decline or disability captures only a small portion of the problems [7]. Thus, new ways to detect the patient functional status are needed, especially methodologies that will evaluate patient's functional performance not only in case of problems or healthcare issues, but also in normal function. These new ways should be unobtrusive but accurate and do not always require a face-to-face interaction with a physician or other health care provider. In [18], sensors are used to detect decline in daily activities, especially regarding the physical function and thus define interventions ad hoc. Using sensors system to evaluate functional status seams critical especially given the ever-growing elderly population. Finally, in [18] the authors report that having a system able to detect early changes in the functional status of people, especially elderly people, and intervene with appropriate interventions could help prevent functional deterioration and reduce the decline in functional ability.

Our investigation goes in this direction with the aim of designing an AI-enabled system able to monitor functional status of patients and to avoid functional decline through the usage of a coaching mechanism providing motivational feedback triggering changes people lifestyle.

3. The Barriers and Arguments Modules of HeLiS

The modeling of the two modules followed the same process we used for creating the HeLiS ontology and that is discussed in [1]. Briefly, we applied the METHONTOLOGY [19] ontology engineering methodology by following the described seven stages: Specification, Knowledge Acquisition, Conceptualization, Integration, Implementation, Evaluation, and Documentation. Due to space constraints, we report the first four phases since they are the most important ones.

Specification And Knowledge Acquisition. The *Specification* and *Knowledge Acquisition* stages completely overlapped during the building of the ontology since for both modules the definition of the purposes and the acquisition of the related knowledge have been done jointly with the domain experts during the same timespan. The purpose of the barriers ontology is two-fold. On the one hand, we want to provide a detailed and integrated model of the food and diseases domain. On the other hand, we want to support the definition of the behavior change process by taking into account the barriers that can affect users.

The two ontology modules have been modeled with a *high* granularity level. This knowledge was acquired directly from a set of focus groups run with domain experts. Concerning barriers, we defined which are the main type of barriers that we want to consider for supporting the development of third-party behavior change applications. The conceptualization of barriers and of the different states of change has been created by extracting knowledge from domain-specific unstructured resources [20]. Concerning argumentation, we defined which are the main concepts that can drive the creation of motivational dialogues for acquiring FSI from users or for generating motivational messages allowing users to overcome specific barriers in order to improve their overall quality of life.

Conceptualization. The conceptualization of the two ontology modules was split into two steps. The first one was covered by the knowledge acquisition stage, where most of the terminology is collected and directly modeled into the ontology. While the second step consisted of deciding how to represent, as classes or as individuals, the information we collected from unstructured resources. Then, we modeled the properties used for supporting all the requirements.

During this stage, we relied on several ontology design patterns (ODP) [21]. However, in some cases, we renamed some properties upon the request of domain experts. In particular, we exploit the logical patterns *Tree* and *N-Ary Relation*, the alignment pattern *Class Equivalence*, and the content patterns *Parameter*, *Time Interval*, *Action*, *Classification*.

Integration The integration of the ontology has two objectives: (i) to align them with a foundational ontology, and (ii) to link it with the Linked Open Data (LOD) cloud. The first objective was satisfied by aligning the root concepts of both extensions with ones defined within the DOLCE [22] top-level ontology. While the second objective was satisfied by aligning our ontology with the UMLS Knowledge Base [2] since it has been included within the LOD cloud recently. This way, it may work as a bridge between the latter and the two ontology modules.

3.1. The Barriers Module

The Barriers ontology module is composed of three main branches: (i) the classification of the barriers, (ii) the representation of the different states of changes, and (iii) a new taxonomy for classifying the list of physical activities defined within barriers.

The *Barrier* concept is the root concept of the first branch and it subsumes six macro-categories of barriers. The *EnvironmentBarrier* refers to the impossibility of performing an action due to unfavorable climatic conditions, the cost of the equipment need, the lack of safety, etc.. *HealthBarrier* concerns the presence of some disease-preventing to complete a specific action. This concept enables the possibility of importing external medical knowledge bases (e.g. the UMLS). This way, barriers are connected with medical knowledge that can be exploited at reasoning time. The *PersonalBarrier* concept represents all barriers associated with the real-life situations (e.g. job conditions) that obstruct the performance of specific actions. Then, the *PhysicalBarrier* and *PsychologicalBarrier* concepts are related to hindrances given by physical pains (e.g. knee injury) or emotional status (e.g. fear) that block a person in performing specific actions. Finally, the *SocialBarrier* concept mainly refers to possible lack of support from people close to patients (parents, friends, etc.).

The second branch consists of the abstract representation of the transtheoretical model. Such a model is used in psychology for supporting the behavior change process that a user

[2]https://www.nlm.nih.gov/research/umls/

can perform for changing their lifestyle or habits. Here, we defined the basic concepts which instances can be linked by the *UserStatus* concept already defined in barriers and that is used as a reification of the status in which a *User* is during a specific *Timespan*. The main concepts we defined are *StateOfChange* that is the root concept of this branch, and then the six phases in which a *User* can be: *PreContemplation*, *Contemplation*, *Preparation*, *Action*, *Maintenance*, and *Termination*.

Finally, the third branch provides a new taxonomy of physical activities defined in the core of barriers. The taxonomy defined within the core of barriers classifies physical activities by type. Differently, this extension provides a classification of physical activities from two different perspectives: the energetic system generally used for performing the action (e.g. aerobic or anaerobic), if the activity required flexibility abilities, and the intensity (or effort) level of each activity. The rationale of this classification is given by the necessity of defining the relationships between barriers and physical activities. For instance, in case a user suffers from asthma, such a *HealthBarrier* may obstruct the performance of some *OutdoorActivity*.

3.2. The Arguments Module

The arguments module consists in an ontology aiming at supporting efficient and effective dialogues for motivating behavior change. It has been developed following the model described in [23], and it is structured in a way that helps the formulation of persuasive dialogues aiming at motivate a user/patient toward a healthier lifestyle (or a particular lifestyle goal). The module collects various arguments which are beliefs a person may have concerning healthcare issues. Moreover, each argument has various properties that help define its type, function, topic, context and the healthcare problem or solution it refers to. More in detail, the concepts defined in the arguments module are described below. *Arguments* that represents all the different argumentations. *Concern_category* which represents the healthcare problem or solution an argument refers to, the ontological type that defines the kind of the content of an argument (for example it could be an attitude toward a problem or solution, a benefit from resolving a problem, a risk due to a problem, a side-effect to a solution etc.). *Functional_type* that specifies the role an argument can have in the dialogue (for example, whether the argument is a type of goal a person may have, or some kind of evidence regarding a healthcare problem or an opinion of the user, etc.). *Topic_type* which refers to the specific subject of the argument and the context type that helps to identify a setting of applicability for the argument (for example it could specify the category of people the argument relates to or is indented for). Finally, in order to facilitate the creation of a persuasive dialogue we modeled two properties (i.e. *support* and *attack*) that connect two arguments and specify whether an argument helps to support another of if it could be used to challenge/attack another argument or belief. After having constructed the structure of the argument module we instantiated it with argumentations in the healthcare domain, we collected material from various sources both online (for the physical activity domain [3] and healthy diets [4]) and from domain experts.

[3]https://www.physio-pedia.com/Barriers_to_Physical_Activity
[4]https://www.sanihelp.it/

3.3. The Integration Within HORUS.AI

The two ontology modules described in Section 3 are exploited for monitoring the functional status of a user through their integration into a SPARQL-based reasoner. Such a reasoner is used for detecting undesired situations within users' behaviors. When inconsistencies with respect to the encode guidelines are detected, the knowledge base is populated with individuals of type *UndesiredEvent* that, in turn, can be used by a further component for providing feedback to users. Reasoning can be triggered in two ways. First, each time a new data packages is acquired, or an existing one is modified existing ones, in the knowledge base, the reasoner is invoked for processing the new, or updated, information. Data packages can be manually added by the user or automatically acquired from IoT devices. Second, at the end of specific timespan, such as the end of a day or of a week, with the aim of checking the overall user's behavior in such timespan. In the latter case, the reasoner works on a collection of data labeled with a timestamp valid within the considered timespan. The integrated reasoner relies on the architecture implemented in RDFPro [24]. RDFPro has been chosen for two main reasons. Firstly, the architecture of RDFPro allows the integration of custom methods into reasoning operations (i) for performing mathematical calculations on users' data and (ii) for exploiting real-time information acquired from external sources without materializing them within the knowledge repository. Secondly, as reported in [24], efficient analysis performed on RDFPro demonstrated the suitability of this reasoner with respect to other state-of-the-art reasoners into a real-time scenario. In this work, RDFPro has been adapted and extended in order to better fit with the needs of the proposed solution. The extension consisted in the integration of new methods supporting the real-time stream reasoning from sensors data. This way, we were able to support the real-time processing of users' data in a more efficient manner.

We organize the reasoning in two phases: *offline* and *online*. The *offline* phase consists in an one-time processing of the *static* part of the ontology (i.e. monitoring guidelines, barriers, arguments, activities) when the system starts. This is performed to materialize the ontology deductive closure, based on OWL 2 RL and some additional pre-processing rules that identify the most specific types of each individual defined in the static part of the HeLiS ontology ABox. Furthermore, this kind of information greatly helps in performing the aggregation operations during the online reasoning phase.

Whereas, during the *online* phase, each time the reasoning is triggered by a user event (e.g., a new data package is entered by a user) or by a time event (e.g., a specific timespan ended), the user data is merged with the closed ontology and the deductive closure of the rules is computed. The resulting *UndesiredEvent* individuals and their RDF descriptions are then stored back in the knowledge base. The generation of each *UndesiredEvent* individual is performed in two steps. First, information inferred by aggregating the domain, monitoring, and user knowledge is used for generating the *UndesiredEvent* individuals. Second, accessory information are integrated into the *UndesiredEvent* individuals for supporting the creation of feedback when the explanation concerning the detected undesired event is generated. Accessory information includes, for example, references to other individuals of the ontology enabling the access to the positive and negative aspects associated with the detected behavior, or the number of times that the specific guideline has been violated. This kind of information can be used for deciding the enforcement level of the persuasion contained within the generated feedback.

Figure 1 summarizes the *online* phase of reasoning process which main components and steps are detailed in the following sections.

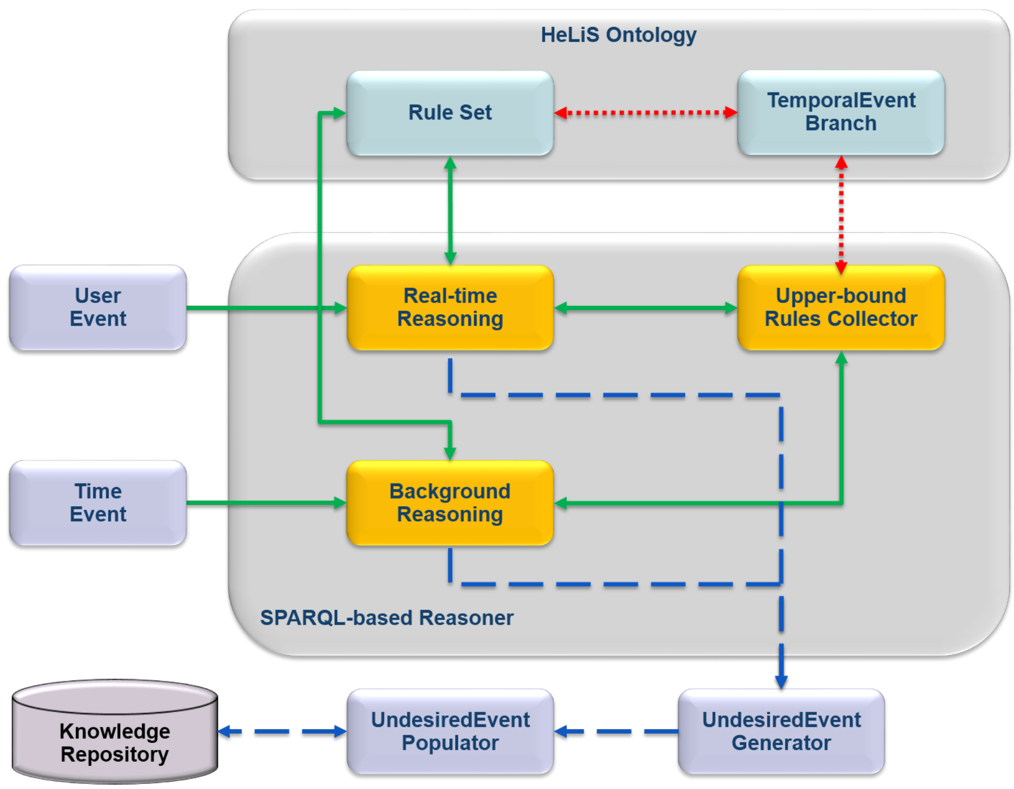

Figure 1: The overall picture of the online reasoning process.

The green path, drawn with a continuous line, executed as first step, is in charge of collecting the rules to validate depending on the trigger received by the reasoner. The red path, drawn with a dotted line, executed as second step, is invoked for collecting rules that can be validated as semantically associated with the ones collected during the green path. The blue path, drawn with a dashed line, executed as third step, generates and populates violations before storing them into the knowledge repository.

4. The Modules in Action

We present in this section a brief scenario showing, in practice, how the two ontology modules can be used into a real context. Let us consider a patient, Michelle, that is affected by hyperglycemia and such a condition compromises her physical functional capacity since she is often very tired. After a colloquium with her physicians, the highlighted problem is that Michele has very stressful job and she uses to unload her stress on food. Moreover, always given her job schedule, she is not able to plan meals consumption properly during the day. Michelle started to be monitored by an AI-enabled application including, among the other, a guideline concerning the total amount of calories contained in each meal that has to be lower than 1000. All these information (i.e. user profile, barriers, and rules) are represented within the AI system in order to make them exploited for reasoning purposes by combining them with the data provided by Michelle [5].

```
1. :Hyperglycemia a :Profile.
2. :Michelle a :User; :hasUserId ”493853”^^xsd:integer; :belongsProfile :Hyperglycemia.
3. :MR1 a :MonitoringRule; :appliesTo :Hyperglycemia; :timing :Meal; :monitoredEntity :Food;
   :command ”hasCalories”; :hasOperator ”lower”; :hasMonitoredValue ”1000”^^xsd:integer;
   :hasRuleId ”1”^^xsd:integer; :hasPriority ”1”^^xsd:integer.
4. :BBPMichelle a :BehaviorBarrierPerformance.
5. :JobCondition a :Barrier.
6. :BBPMichelle :hasUser :Michelle; :refersTo :MR1; :isPreventedBy :JobCondition.
```

Rows 1. and 2. define the profile and assigns it to Michelle. Row 3. describes the guideline that Michelle has to follow. Rows from 4. to 6. define the behavior that the mentioned barrier avoids to perform. For the first two days, Michelle inserted the data about her food intake correctly as shown below (for brevity, we reported only the meals, or snacks, that trigger the detection of an undesired event):

```
:Michelle :consumed :Breakfast-493853-1, :Snack-493853-3, :Dinner-493853-8.
:Breakfast-493853-1 a :Breakfast; :hasTimestamp ”2020-12-14T07:19:00Z”;
    :hasConsumedFood [ :hasFood :AlmondMilk; :amountFood ”250”^^xsd:integer ],
                     [ :hasFood :RiceFlakes; :amountFood ”100”^^xsd:integer ].
:Snack-493853-3 a :Snack; :hasTimestamp ”2020-12-14T11:34:00Z”;
    :hasConsumedFood [ :hasFood :CannedOrangeSoda; :amountFood ”300”^^xsd:integer ],
                     [ :hasFood :Apple; :amountFood ”150”^^xsd:integer ].
:Dinner-493853-8 a :Dinner; :hasTimestamp ”2020-12-15T19:45:00Z”;
    :hasConsumedFood [ :hasFood :CocaCola; :amountFood ”330”^^xsd:integer ],
                     [ :hasFood :Pizza; :amountFood ”450”^^xsd:integer ].
```

Based on the provided data, combined with the knowledge contained within the HeLiS ontology, the reasoner determines that the amount of kilo-calories consumed during each meal, except for *Dinner-493853-8*, satisfies the rule *MR1*. This event triggers into the knowledge base the assertion of the following *UndesiredEvent* individual:

```
:undesiredevent-493853-8-20161215 a :UndesiredEvent;
    :hasUndesiredEventRule :MR1; :hasUndesiredEventUser :Michelle;
    :hasUndesiredEventMeal :Dinner-493853-8; :hasUndesiredEventQuantity 1356;
    :hasUndesiredEventExpectedQuantity 1000;
    :hasUndesiredEventLevel 2; :hasTimestamp ”2016-12-15T19:45:00Z”; :hasPriority 1; ...
```

[5]For brevity, we avoid to discuss the different ways with which the information expressed in natural language way can be formalize as shown in this section. This aspect is out of scope of this paper.

The generated individual completes the amount of knowledge that can be exploited by the system for starting an interaction with the user. Indeed, the knowledge linked with the *UndesiredEvent* individual can be used for generating the feedback sent to Michelle. In this particular case, Michelle is advised that consumed too much calories during a specific dinner together with further information describing how this kind of behaviors can affected their health. At the same time, the results of the monitoring activity can be sent to the physician as well that can use such information for better understanding the reasons led Michelle to perform undesired behaviors.

5. Conclusion And Future directions

In this work, we presented two modules extending the HeLiS ontology providing a conceptualization of "Barriers" and "Arguments". These modules aim to enhance the AI capabilities of coaching systems designed for supporting the monitoring of users' functional status. Beside the description of the two modules, we shown how such modules have been integrated into a working AI coaching system, namely, HORUS.AI, and we provide a brief but useful running example showing how the main concepts of these two modules can be instantiated.

As mentioned in Section 1, this work represents a first step toward the long-term achievement of having a full-fledged AI coaching system. Future efforts will be focused on three main directions. First, to expand the knowledge base since ontologies are inevitably subject to constant changes. This will involve domain experts and the exploration of techniques that leverage some form of data mining able to detect hidden information from large textual data. Second, to integrate the ontology with natural language understanding (NLU) and natural language generation (NLG) components. This way, we will be able to investigate strategies about how to automatically transform natural language texts into their equivalent semantic argument-based representation, as well as, to exploit the output of the reasoning process for generating effective contextual feedback. Third, to evaluate the system into a real-world coaching scenario. In this work, we did not provide a living lab evaluation since the ontology itself cannot be evaluated without addressing the point above (i.e. integration with both NLU and NLG). We will focus on doing such an integration in order to deploy the end-to-end system into real-world scenarios and to observe the effectiveness of the two ontology modules presented.

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References

[1] M. Dragoni, T. Bailoni, R. Maimone, C. Eccher, Helis: An ontology for supporting healthy lifestyles, in: International Semantic Web Conference (2), volume 11137 of *Lecture Notes in Computer Science*, Springer, 2018, pp. 53–69.

[2] A. Baker, Crossing the quality chasm: a new health system for the 21st century, volume 323, British Medical Journal Publishing Group, 2001.

[3] N. C. on Vital, H. Statistics, Classifying and reporting functional status, 2001. URL: http://www.ncvhs.hhs.gov/.
[4] I. LI, G. MS, Capturing and classifying functional status information in administrative databases, Health Care Financ Rev 3 (2003) 61–76. URL: https://pubmed.ncbi.nlm.nih.gov/12894635/.
[5] L. P. Fried, K. Bandeen-Roche, P. Chaves, B. A. Johnson, et al., Preclinical mobility disability predicts incident mobility disability in older women, Journals of Gerontology-Biological Sciences and Medical Sciences 55 (2000) M43.
[6] G. Onder, B. W. Penninx, L. Ferrucci, L. P. Fried, J. M. Guralnik, M. Pahor, Measures of physical performance and risk for progressive and catastrophic disability: results from the women's health and aging study, The Journals of Gerontology Series A: Biological Sciences and Medical Sciences 60 (2005) 74–79.
[7] F. D. Wolinsky, D. K. Miller, E. M. Andresen, T. K. Malmstrom, J. P. Miller, Further evidence for the importance of subclinical functional limitation and subclinical disability assessment in gerontology and geriatrics, The Journals of Gerontology Series B: Psychological Sciences and Social Sciences 60 (2005) S146–S151.
[8] K. S. Boockvar, M. S. Lachs, Predictive value of nonspecific symptoms for acute illness in nursing home residents, Journal of the American Geriatrics Society 51 (2003) 1111–1115.
[9] J. Hogan, Why don't nurses monitor the respiratory rates of patients?, British Journal of nursing 15 (2006) 489–492.
[10] S. Ridley, The recognition and early management of critical illness., Annals of the Royal College of Surgeons of England 87 (2005) 315.
[11] E. Nelson, B. Conger, R. Douglass, D. Gephart, J. Kirk, R. Page, A. Clark, K. Johnson, K. Stone, J. Wasson, et al., Functional health status levels of primary care patients, Jama 249 (1983) 3331–3338.
[12] D. R. Calkins, L. V. Rubenstein, P. D. Cleary, A. R. Davies, A. M. Jette, A. Fink, J. Kosecoff, R. T. Young, R. H. Brook, T. L. Delbanco, Failure of physicians to recognize functional disability in ambulatory patients, Annals of internal medicine 114 (1991) 451–454.
[13] D. R. Calkins, L. V. Rubenstein, P. D. Cleary, A. R. Davies, A. M. Jette, A. Fink, J. Kosecoff, R. T. Young, R. H. Brook, T. L. Delbanco, Functional disability screening of ambulatory patients, Journal of General Internal Medicine 9 (1994) 590–592.
[14] E. J. Cassell, Doctoring: The nature of primary care medicine, Oxford University Press, USA, 2002.
[15] M. Espallargues, J. M. Valderas, J. Alonso, Provision of feedback on perceived health status to health care professionals: a systematic review of its impact, Medical care (2000) 175–186.
[16] L. P. Fried, Y. Young, G. Rubin, K. Bandeen-Roche, W. I. C. R. Group, et al., Self-reported preclinical disability identifies older women with early declines in performance and early disease, Journal of clinical epidemiology 54 (2001) 889–901.
[17] B. J. Wakefield, J. E. Holman, Functional trajectories associated with hospitalization in older adults, Western Journal of Nursing Research 29 (2007) 161–177.
[18] G. L. Alexander, M. Rantz, M. Skubic, M. A. Aud, B. Wakefield, E. Florea, A. Paul, Sensor systems for monitoring functional status in assisted living facility residents, Research in Gerontological Nursing 1 (2008) 238–244. URL: https://journals.healio.com/doi/abs/10.3928/19404921-20081001-01. doi:10.3928/19404921-20081001-01.

arXiv:https://journals.healio.com/doi/pdf/10.3928/19404921-20081001-01.

[19] M. Fernández-López, A. Gómez-Pérez, N. Juristo, Methontology: from ontological art towards ontological engineering, in: Proc. Symposium on Ontological Engineering of AAAI, 1997.

[20] S. Michie, R. West, R. Campbell, J. Brown, H. Gainforth, ABC of Behaviour Change Theories, 2014.

[21] P. Hitzler, A. Gangemi, K. Janowicz, A. Krisnadhi, V. Presutti (Eds.), Ontology Engineering with Ontology Design Patterns - Foundations and Applications, volume 25 of *Studies on the Semantic Web*, IOS Press, 2016.

[22] A. Gangemi, N. Guarino, C. Masolo, A. Oltramari, L. Schneider, Sweetening ontologies with dolce, in: Proceedings of the 13th International Conference on Knowledge Engineering and Knowledge Management. Ontologies and the Semantic Web, Springer-Verlag, 2002, pp. 166–181. URL: http://dl.acm.org/citation.cfm?id=645362.650863.

[23] L. Chalaguine, E. Hadoux, F. Hamilton, A. Hayward, A. Hunter, S. Polberg, H. W. W. Potts, Domain modelling in computational persuasion for behaviour change in healthcare, 2018. arXiv:1802.10054.

[24] F. Corcoglioniti, M. Rospocher, M. Mostarda, M. Amadori, Processing billions of RDF triples on a single machine using streaming and sorting, in: ACM SAC, 2015, pp. 368–375.