

# INTEGRATION OF COMPLEX DETECTION DATA WITH CASE-SPECIFIC INTERACTIVE EXPERT KNOWLEDGE FEEDBACK FOR FRAILTY PREVENTION

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**Abstract:** *This paper describes an environment based on rich interactive diagrams, allowing the geriatricians and caregivers to access, analyze and precisely annotate or label specific granular cases of interest in a variety of heterogeneous data collected in order to identify “behaviour changes” through Smart City IoT and Open Data infrastructure. The overall goal is to detect and contextualize as early and precisely as possible negative behaviour changes that may lead to onset of MCI/frailty in the elderly population segment.*

*The environment is being developed and deployed in the context of City4Age, a project partially funded by the EU, within the Horizon 2020 programme.*

**Keywords:** *unobtrusive behaviour recognition, ambient-assisted active healthy ageing, data labelling, interactive assessments.*

## 1. INTRODUCTION

Numerous recent and ongoing projects, deployed systems and research initiatives in AAL (Ambient Assisted Living) and AFE (Age-Friendly Environments) development are acquiring, gathering and processing heterogeneous health and personal data, in growing volumes, variety, and input rates. In particular expansion in recent years is the cross-cutting field of AHA (Active and Healthy Aging) in Smart Cities and Communities, founded to a large extent on constant development and expansion of ICT and institutional infrastructure of many of the major Smart Cities worldwide during the last decade. The infrastructure is becoming well established, sustainable, and practically ubiquitous, with steadily growing inflow and increased reliability of monitoring, surveillance, and citizen feedback data. Additional and improved sensor types are being continuously integrated in IoT networks (wearable and mobile devices, sensors at homes and in the city public spaces – cultural, shopping, banking, transport/commuting etc.), available Open and/or Linked city datasets getting larger, more comprehensive and refined, and the challenge focus is shifting towards generating new services and added values from the acquired Big Data, through predictive analytics, interpretation, contextualization, and deployment of intelligent systems. In the area of health,

wellbeing and ageing, this translates to emphasis on public health and prevention, transforming the urban public health from reactive to a predictive and eventually risk-mitigating system.

## 2. DATA COMPLEXITY AND HETEROGENEITY FACTORS

Along with technology and infrastructure advancement, important social-technological factors are additionally driving the increase in complexity and heterogeneity of personal data to be obtained and processed:

- increased level of “digital” participation and influence of citizens on urban community issues, through social networks and local open-government platforms (“smarter communities”).
- the globally upcoming ageing population heading into retirement in metropolitan areas [1] is mostly the generation of “baby boomers”, born between 1946 and 1964. They are more active, more skilled, tech savvy and more discerning consumers than previous generations of seniors [2], with significantly increased digital interaction level and online “footprint”, and consequently more and more diverse personal data to be discerned and integrated into richer profiles.
- holistic integrated policy management approach increasingly adopted on regional and city level, based on “city-as-a-whole” model, integrating and processing data from various city administration sectors - health, environment, planning, transport. This again means increased number of correlations and links to be processed and detected within the data used by the tools developed for the health/social services and administration, and also partly for expert geriatricians/physicians in everyday monitoring of patients or care recipients (CRs).

In the City4Age research project (funded under the EC Horizon 2020 programme), aiming towards development of unobtrusive “sensing” systems for early detection of risks and precursors of physical & cognitive frailty, to enable fully ambient-assisted Age-friendly Cities, we face in this context the main “detection” challenge of identifying or reconstructing relevant behaviours of persons from input data streams, and assessing frailty risks from relevant behaviour changes. The project is

breaking new ground in expanding the concept of Ambient-assisted Environments from currently predominant implementations in residential and social indoor spaces (homes, elderly care/community centres...) to outdoor and public environments as well, and in redefining data-driven geriatrics in integration with domain knowledge.

### **3. City4Age HYBRID DETECTION APPROACH**

Human behaviours are complex, commonly represented via multi-level hierarchical structured models, with fundamental decomposition units (according to Activity Theory) being human activities, consisting further of sequences of human actions as simplest units, mostly associated with unitary events captured by a sensor or reported through external input [3]. The recognition and synthesis is thus performed on multiple model structure and aggregation levels (activities from actions, behaviours from activities etc), using different analytic techniques and algorithms. Higher-level variation measures, geriatric factors and sub-factors, have been introduced into the model to quantify the changes in specific behavioural domains relevant for active and healthy aged life and onset of frailty (both physical and cognitive).

Despite the significant advances achieved in the last decade, the complexity and sheer quantity of possible complex activities and their temporal interdependencies, and the relevance of semantics associated to activities and behaviours to represent meanings, nevertheless still make behaviour detection non trivial, and a major research challenge of data-driven geriatrics. Empirical evidence from project geriatricians' work indicates that the integration of various sensory data of high temporal resolution into geriatric and behavioural models developed over decades based on daily care, questionnaire assessments, and traditional medical exams of patients [4], practically introduces additional uncertainty in the models, and notably higher variations of behaviour measures on the individual level. Similar or same behaviour variation pattern can denote high risk for one person but low or no risk for another, and, as unobtrusive sensory layer is constantly ubiquitously capturing (nearly) all activity and behaviour changes that occur, it becomes crucially important to resolve and filter out the "false positives" - numerous transient variations caused by external environmental factors (unobservable heterogeneity, model "frailty" [5]) or sensor imprecision, not by onsets of physical frailty or mild cognitive impairment (MCI) targeted for recognition. Currently prevalently used knowledge-based models that generalize contextual real world observations into formal knowledge structures (computational rules, schemas or networks)

therefore need mechanisms for refinement and increased robustness, to integrate newly acquired and/or more granular case-specific expert knowledge into model structures.

City4Age adopts the hybrid combined knowledge-driven and data-driven approach on all detection/recognition levels, aiming to integrate the "best of both worlds" – data mining and machine learning to obtain most value from collected data (already adding value to the project and state of the art in the field due to data extent, scope and variety), supported and refined by ontology-based knowledge-driven recognition to associate contexts, overcome pattern granularity problems and boost performance [6]. Data-driven methods and techniques are also being referred to as "bottom-up" in the project, discovering frequency and similarity patterns in the data and synthesizing higher-level behaviours and geriatric factors from lower-level actions and activities, while knowledge-based methods are mostly "top-down", classifying the acquired data record, case, or pattern down the hierarchical category structure through multi-criteria decision making.

In the data-driven approach, generally most successful recognition solutions are based on supervised learning techniques, relying on relatively large significant datasets of annotated or labelled cases/patterns to be used for training different kinds of classifiers in ML techniques, and the required amount of annotations and labels in turn relies on manual input from the experts. This is not feasible for envisioned scale of City4Age scenarios, where tens of thousands of elderly persons may be monitored in subsequent city-wide deployments after the project piloting on limited numbers (50-80 people in each of the 6 testbed cities), and the heterogeneity of acquired data and observed unrecognized activities/behaviours is likely to increase still more notably with integration of new sensor types or other data sources [7]. Even for a single individual, the projected volume of sensory data, recognized activities, and possible behaviour variations in a timespan of a couple of years is so large that manual labelling is not viable. A combination of unsupervised learning techniques and knowledge-based models is therefore chosen as optimal, and there is exploration potential still in mechanisms for automatic or semi-automatic labelling of characterized behaviour patterns that denote "risk" warning and alerting.

### **4. COLLABORATIVE VISUAL DASHBOARDS WITH DATA ASSESSMENTS AS KNOWLEDGE INTEGRATION MECHANISM**

One of the main developed components of the City4Age system exposed to the end-users, monitoring and analytics

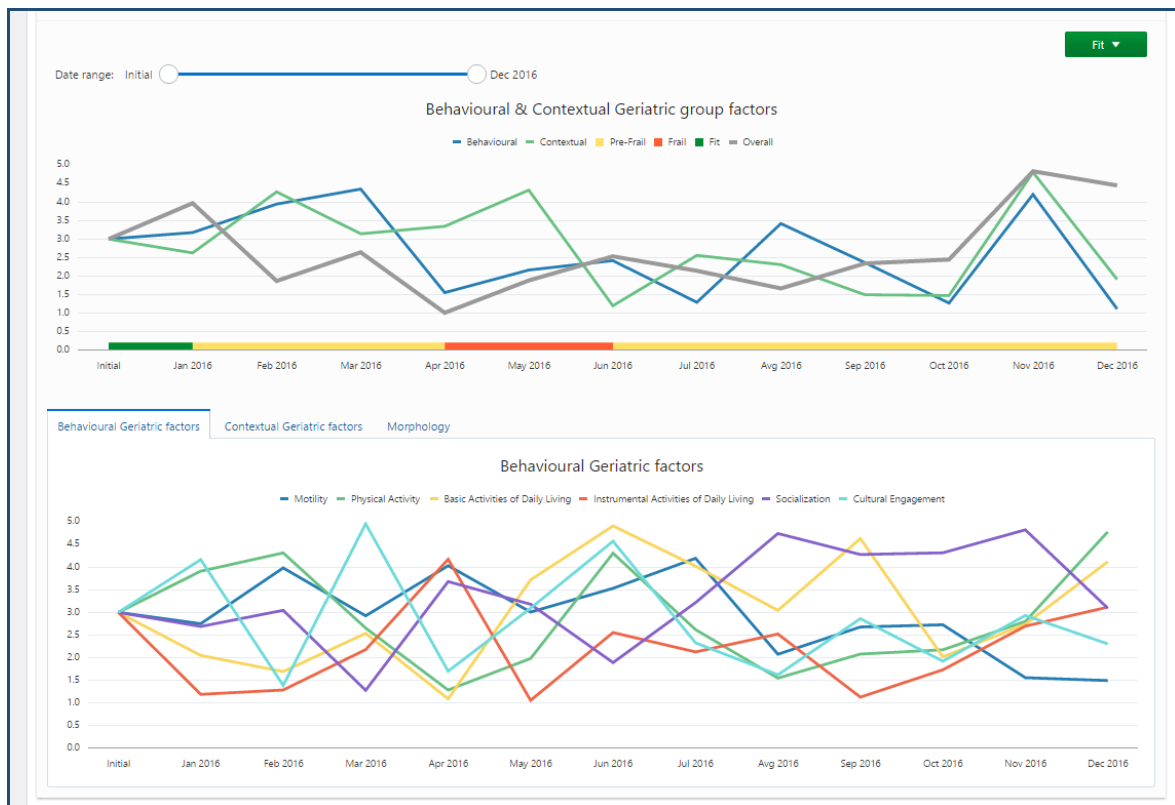
dashboards provide the primary functionalities of interactive visualization of behaviour data, and collaborative environment for expert assessments/annotations of data in detection. They are also supporting the input of various caregiver observations and indications for City4Age digital interventions [8], as well as of incentives and feedback on the effects and results of interventions. Baseline first prototyped version are the Individual Monitoring Dashboards (IMDs), focused on representation of aggregated data of a single selected CR, targeted for geriatric caregivers, primarily health-care professionals (geriatricians, general practitioners, intervention staff, etc.) to help them fully detect, contextualize and annotate

behavioural changes of the elderly people subject to their care.

Main visualization elements are rich composite diagrams – combined multi-line and stacked bar diagrams, and radar (“morphology”) diagrams, showing aggregated time-series data – as identified optimally understandable and intuitive by the project (and external consultant) geriatrician experts. Once the desired CR is selected through list/search in preceding screens, the dashboards present the data acquired on the person in selected or predefined time period in a general top-down flow, from high-level normalized aggregated model features (overall frailty status, geriatric domains, factor groups), supporting the drilling down to show specific granular data (sub-factor values, variation measures, activities).



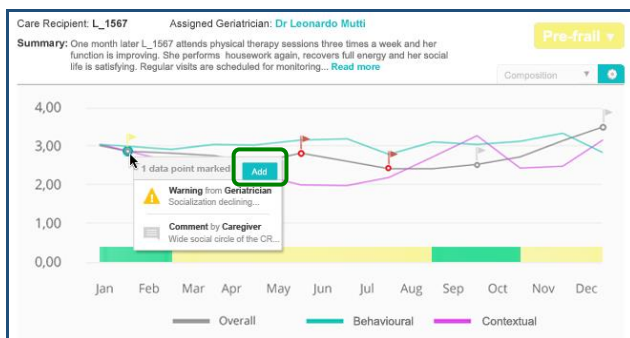
**Figure 1.** Individual Monitoring Dashboards – radar (factor “morphology”) diagrams



**Figure 2.** Individual Monitoring Dashboards - combined multi-line and stacked bar diagrams

A diagram aims to show the decomposed influence of the underlying constituting “child” variable values on each of the detected variables (geriatric factor, sub-factor, variation measure) over time. The composite multiline+bar diagrams can also show data on multiple model/aggregation levels at once on a single diagram, as exemplified by the top diagram on Figure 2 – timeline changes of overall frailty status (in Fried Index notation) are rendered as additional stacked bar below the multiple lines for each of the main geriatric domains (factor groups).

Basic interaction is a feature of the diagram UI elements (zooming in/out, showing/hiding specific series/groups, single/multiple point or window selection...), and the innovative advanced interaction is provided by the custom component for interactive data assessments/annotations on graphs. An assessment can be assigned to each granular point on a diagram, or any set of points selected by multiple-click or window selection, via a modal popup panel for assessment input, launched by the “Add” command from the informative pop-up panel shown on hover over selection (Figure 3).



**Figure 3.** Adding assessment on a selected data point or dataset on diagram

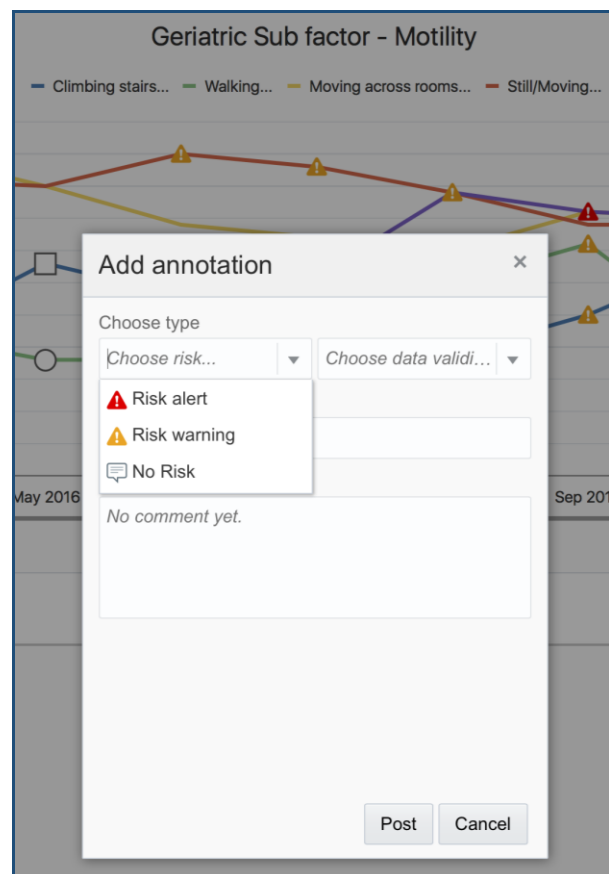
Each annotated data point or dataset can, in turn, have one or a thread of multiple assessments assigned to it in different times. In common use cases of collaborative daily practice of caregivers, this provides the functionalities of:

- accurately selecting
  - specific individual peak outlier value point(s) on the diagram, likely to denote significantly deviating anomalous behaviour, or
  - sets of points (on one or different series on the graph) commonly marking relatively longer-term steady increase or decrease of corresponding variables or factors over weeks/months.

This way, for example, on a diagram with decomposition of “Motility” geriatric factor, a geriatrician user can select 3 average monthly values of

“Still/Moving Time” in constant increase, together with one value of “Walking” sub-factor in spike decrease in the same (or different) period, and assign a single assessment to these total 4 important values of two different variables, attributing them to one same phenomenon and potential motility risk, and thus denoting their connection (temporal, locational, causal, or other).

- writing down and storing in the system annotations pinpointed to granular case-specific behaviour change values, and reading stored annotations (in freeform comments) provided by other colleague caregivers or different dashboard user roles. Common supported cases are writing indications for special attention to other caregivers, or indications for initiating or adapting an intervention. One or more target audience roles can be selected for each assessment in the input form panel (“For (select multiple)” field, Figure 5), so an assessment with instructions or recommendations for an intervention can be targeted by the author, for example, to intervention staff and informal caregivers, who are to perform the intended intervention.



**Figure 4.** Assessment/annotation input panel (1)

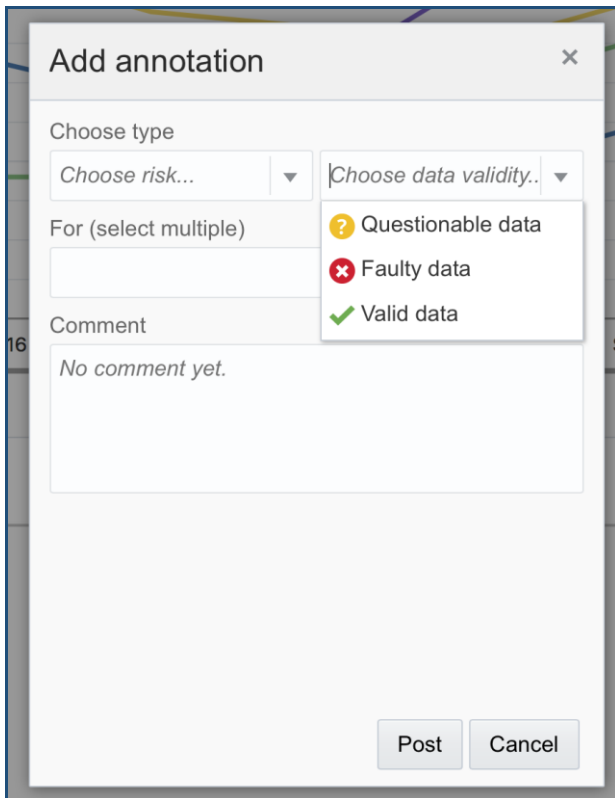


Figure 5. Assessment/annotation input panel (2)

- most important – **annotating the selected data point or dataset with structured categorized or quantifiable attributes** interpretable and usable for training/refining the targeted automatic reliable risk/attention assessment and alerting to be achieved by the City4Age analytics (practically labelling data on various temporal and aggregation levels). Primary in initial implementation is the basic risk assessment categorization (Warning - potential risk, Alert – evident risk), complemented by the detection confidence label,

also crucially important to account for inherent variable reliability rating of sensory acquisition data. In case a caregiver finds the specific detected value(s) dubious or inconsistent, or evidently wrong (determined by examining/interviewing the actual CR), due to specific sensor problem or interference, the problematic data can be categorized as questionable or faulty via assigned assessment (Figure 5). This data validity rating figures in the calculation of eventual risk ratios, modes and priorities denoted and/or assigned to the marked data values, according to the failure time and effect models for health/frailty domain utilized for risk evaluation in analytic framework. Overall dataset annotation process performed this way via the IMDs is still essentially manual, but leveraged and accelerated by the optimized UX and the workflow that multiple caregivers on all pilot locations perform simultaneously daily, and when a significant number of input annotations is reached, the categorical Multi-Criteria Decision Making (MCDM) methods in the analytics layer will be able to semi-automatically infer annotations for classes of similar cases to the manually input annotated ones (methods in analytics elaborated in separate dedicated work paper). Assessments of data validity by the dashboard users are of additional particular importance in the deployment, testing and piloting operation of the system, to capture and indicate to the project development and integration teams all eventual problems or faults in the sensory acquisition and machine estimations.

The categorized labelling attributes feature additional data marker icons for each of the categories, and these markers are rendered on the source diagrams, so the annotated points can be seen immediately on the graph.

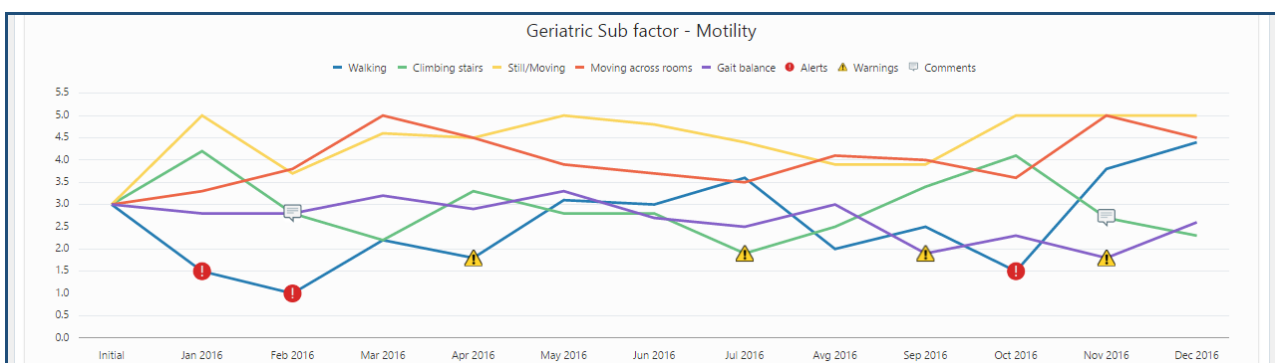


Figure 6. Markers on points with assigned assessments/annotations on diagram

By default the risk categorization markers are plotted, being of highest interest, but it is parameterized in the custom assessment component, allowing the setting of optional other categorization instead. For points that have assigned multiple assessments with different risk categorizations, the marker denoting highest criticality in the set is shown (criticality order: >> >> , Figure 6).

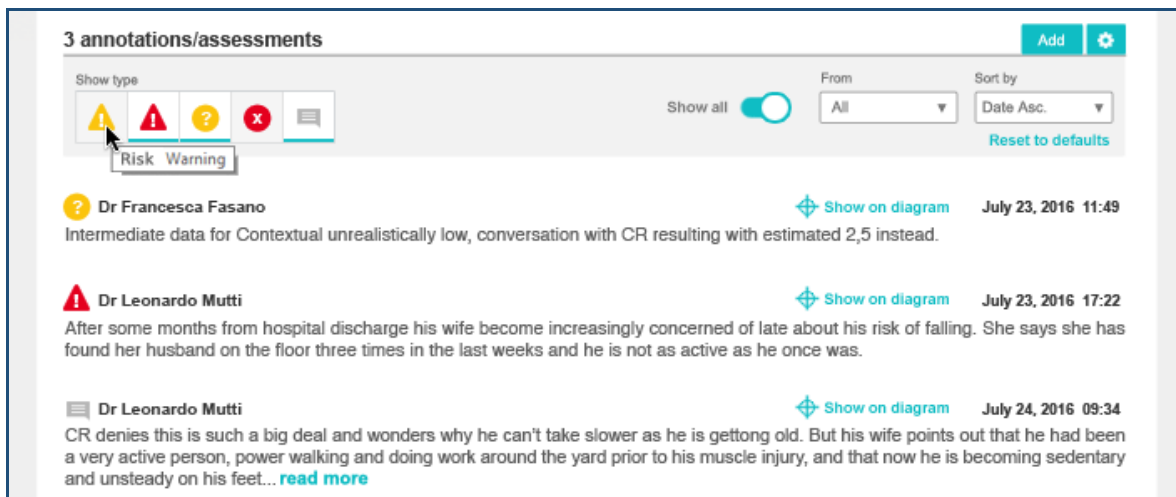


Figure 7. Summary view of all assessments on a selection/diagram

In case a user selection on the diagram comprises a data point or points that have assessments assigned, all assessments on selected points (or datasets the points belong to) are shown in the summary list view below the diagram, with expandable truncated comments, and a filter panel for easier management of long threads of assessments, and a repeated “Add” command.

## 5. DASHBOARD IMPLEMENTATION

The dashboards are implemented through components of responsive web (or hybrid mobile) application, exchanging data with the City4Age unified cloud data repository via a set of RESTful web services. The front-end components are implemented using a state-of-the-art modular open source JavaScript, CSS3 and HTML5 toolkit - Oracle JET (JavaScript Extension Toolkit) with extensive library of interactive graphic elements and visualizations (combined multiline+bar and radar diagram included). Assessment/annotation module has been developed as custom JET composite component, optionally following or wrapping a typified combined multiline diagram, providing it exposes the required annotation metadata in series and groups, and that required RESTful services for persisting and fetching assessments are in place and running.

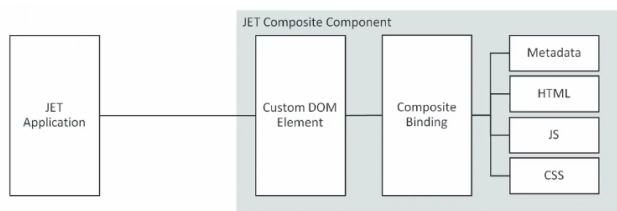


Figure 8. High-level architecture of Oracle JET custom composite component (©Oracle 2017)

The services are maximally modular and decoupled, with primary aims of:

- re-use of services across the City4Age project and its various other software modules (intervention subsystem, m-testing mobile application, personal data protection management toolkit...)
- extended and wider usage of the developed assessment/annotation component beyond the project, as a scalable parameterized tool for generic interactive dataset labelling/annotation with case-specific knowledge.

The dedicated services persist the assessments in the unified data repository in a many-to-many relation with values of detection variables they are assigned to, via the *assessed\_dataset* intermediate entity. The data structure for assessments is otherwise generic, and the assessment component is agnostic of the type and nature of data values (regardless whether it is geriatric factors, measures, frailty statuses...) passed to it via the source diagrams.

## 6. CONCLUSION

Integrating complex detection data with interactive case-specific expert knowledge feedback through “Detection” Dashboard front-end components has been presented, as additional mechanism for advancing dataset annotation/labelling in knowledge-based support to unsupervised learning for human behaviour recognition. The development of components and underlying data analytics framework for MCI/frailty risk detection and prevention is performed in the scope of the City4Age project for development and establishment of Age-friendly Smart Cities, funded under the EC Horizon 2020 programme (Grant Agreement No.689731). Crucial aspects of the overall City4Age hybrid detection approach have been provided in background context, as well as the

primary dashboard functionalities of interactive visualization of behaviour data, and collaborative-interactive environment for geriatric care provision and policy management experts.

Further work continues in the development of Group Analytics Dashboards for identifying, and annotating data, of particular subgroups or clusters of elderly individuals of interest in the population, as well as in augmenting the data-driven analytic algorithms with annotations obtained from dashboards.

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