Multi-criteria Modelling Approach for Ambient Assisted Coaching of Senior Adults

Martin Žnidaršič[1], Bernard Ženko[1], Aljaž Osojnik[1], Marko Bohanec[1], Panče Panov[1], Helena Burger[2], Zlatko Matjačić[2] and Mojca Debeljak[2]

[1]*Jožef Stefan Institute, Jamova cesta 39, Ljubljana, Slovenia*

[2]*University Rehabilitation Institute, Linhartova 51, Ljubljana, Slovenia*

{*martin.znidarsic, bernard.zenko, aljaz.osojnik, marko.bohanec, pance.panov*}*@ijs.si,*

{*helena.burger, zlatko.matjacic, mojca.debeljak*}*@ir-rs.si*

Keywords: Rule-based systems, Multi-criteria Modelling, Ambient Assisted Living, Elderly Care.

Abstract: This paper presents and critically discusses an approach for knowledge modelling and reasoning in a system for monitoring and coaching of senior adults. We present a modular architecture of the system and a detailed description of the modelling methodology which originates from the field of multi-criteria decision modelling and differs from the commonly used ones in this problem domain. The methodology has several characteristics that make it fit well to the purpose in this application and initial insights from potential users are positive. A discussion of the suitability of the proposed methodology for knowledge representation and reasoning in the given problem domain is provided, with an outline of its potential benefits and drawbacks and a comparison with the ontological approach.

1 INTRODUCTION

In this paper we describe and discuss an approach for knowledge modelling and reasoning in a system for multi-modal long-term monitoring and coaching for the elderly.

Demographic changes in most of the world are resulting in increased share of older people. An important aspect of quality of life of this population is independent living, which has many benefits, but also presents some risks. This gave rise to various technological solutions of ambient assisted living (AAL) for the elderly (Azimi et al., 2017; Li et al., 2015). AAL solutions usually consist of sensors and communication infrastructure, data management elements, modelling and reasoning tools and finally actuators or services. There is a need and recent trend to provide platforms that are capable of managing and exploiting multiple components and services of this kind, to combine multiple information and knowledge sources and corresponding reasoning on various levels.

In scope of an international collaborative project, we are tackling such a task and one of the main challenges is design of the modelling and reasoning components. Design of these components must allow representation of relevant data and domain knowledge in a transparent and understandable manner. At the same time it must be flexible and general enough to support updates and extensions of the system's functionalities and input/output devices.

Systems of this kind usually employ ontological (Chen et al., 2012; Yamada et al., 2007; Fides-Valero et al., 2008; Hervás et al., 2013), agent-based (Ayala et al., 2013), rule-based (Bikakis and Antoniou, 2010) or mixed (Rafferty et al., 2017; Bouznad et al., 2017) approaches for knowledge representation and reasoning. We have considered these types of approaches and opted for a rule-based approach that employs hierarchical multi-criteria models, which are commonly used in the field of multi-criteria decision support (Greco et al., 2016). These models are transparent and easy to interpret and manage. For each issue that we want to provide monitoring and coaching for, we use a cascade of three such models, which are responsible for: (I) situation assessment, (II) coaching action selection and (III) coaching action rendering. All the models rely on data transformation component for input data preprocessing and criteria construction. The three sequential models together with the data transformation component represent a modular pipeline architecture which enables decoupling of core reasoning components from those that are tied to the input and output devices. This ensures ease of maintenance and simplifies addition of new input and output devices.

We find this modelling methodology and architecture very suitable for the problem at hand, but to the best of our knowledge, hierarchical multi-criteria modelling methodology has not been used for such purposes yet. The methodology as such was used in AAL domain for decision support purposes, for example for quality evaluation of AAL systems (Zavadskas et al., 2008; Kara et al., 2017), but not for reasoning tasks in an automated system of this kind. In this paper we offer it for consideration through presentation of its characteristics and discussion of its knowledge representation and reasoning features that are relevant for the tackled problem domain.

2 MONITORING AND COACHING SYSTEM

The monitoring and coaching system for the elderly, which is being developed in the scope of the project, is aimed at continuous monitoring of users in their home environments, detection of relevant changes in their activity (for example: abandonment of cooking meals, disturbed sleeping patterns, potential loneliness etc.) and issuing of corresponding coaching actions.

2.1 Coaching Actions and Domains

The coaching actions are twofold: they can be issued to the user directly, or they can be indirect, issued to the members of the user's social circle, which then take part in executing the coaching action. An example of a direct coaching action is a context-dependent list of sleep improvement suggestions that is shown on the user's tablet screen. An indirect coaching action would be a suggestion to a family member to visit the user or to engage in an activity together (a walk for example).

In the scope of the project we are addressing four domains of monitoring and coaching, which were identified as important by the target population: (I) *Mobility*, (II) *Activity*, (III) *Sleep quality* and (IV) *Social activity*. For each of these domains we are implementing a continuous monitoring and coaching solution for one or more domain-specific phenomena. While the data processing, knowledge modelling and reasoning infrastructure is shared, each coaching solution relies on a specific set of sensoring devices and a specific set of coaching actions.

There is, however, a long and non-trivial information path from sensor readings and domain knowledge to the final high-level coaching action suggestions. It is described in the following subsection.

2.2 Coaching Pipeline

Each phenomenon that we intend to monitor and coach about demands a specific set of input information about its context and dedicated reasoning processes for automated triggering of actions. We denote one set of such elements that pertains to one coaching action as a *coaching pipeline* (see sketch in Figure 1).

The data-flow starts at the sensors that continuously send raw data to a database. In predefined time intervals, the coaching pipeline gets activated by an execution process on the server. This triggers the criteria estimation module to collect the relevant data from the database and calculate or estimate the values of all the criteria that are needed as inputs by any of the three models in the pipeline (the situation model, the coaching action model, and the coaching action rendering model).

There are three kinds of transformations that the criteria estimation module conducts in order to transform raw data into criteria for the models:

- Passing, without processing. There is actually no transformation in this simplest case. An example of it would be passing of the temperature as sensed by the environmental sensor directly to the models.
- Processing of data with simple explicit functions (use of filtering, equations, etc.). An example of this is heart rate calculation from the ECG signal of a wearable ECG device or a simple *noise* or *no noise* signal from a thresholded amplitude of an audio signal.
- Provision of output by a machine-learned model. An example of this kind is transformation of accelerometer data into activity, such as *walking*, *sitting*, etc. This is an example for the case of supervised models (in which we have the learning data about the target class). In unsupervised case, the machine-learned models can be used to transform specific data into criteria such as *usual* or *unusual* activity or situation.

The situation model is the first one that is executed. It conducts a focused situation assessment, the one which is relevant to the pipeline's target phenomena. Next, the coaching action model is used to select a suitable coaching action based on the outcome of the situation assessment and other relevant external factors that can influence the choice of action, such as the user's personal profile information that is provided by the criteria estimation module (forward ar-

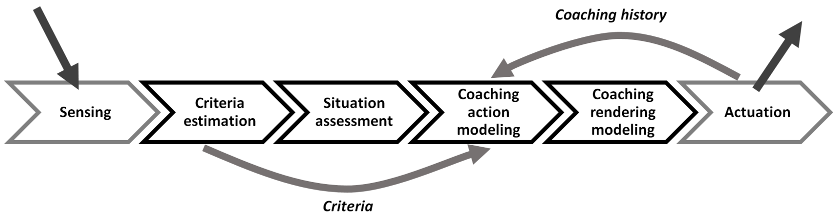

Figure 1: Coaching pipeline.

row in Figure 1) or the history and sucess of previous actions (backward arrow in Figure 1). Of course, the possible coaching actions are individualized and also strictly limited to only those accepted by the user. The selected action is then used as the main input in the action rendering model, which selects a suitable modality of presentation of the coaching action (the way it is presented to the user) based on the selected action and the context that is relevant for rendering, such as previous effectivness of various modalities in similar contexts. The coaching suggestion is then rendered through a corresponding coaching interface. The coaching interface is in most cases realised by an electronic device. In addition, in this project the coaching actions are also realised through people who are supporting the user and whom we denote as social circles or secondary users. In some sense, the interface is extended by the members of the user's social circles.

For example: an outcome of a situation model from the coaching pipeline that is dedicated to social activity might indicate a decrease in social activity in the past week. The coaching action model would take this information, together with some additional contextual information (as defined in the coaching action model) and would suggest a suitable coaching action, which might be: *Go for a visit*. However, this coaching action could be rendered or conveyed to the user via several modalities, such as a notification on the smartphone screen, specific audio, visual or tactile nudge, or it might be sent to a secondary user (a friend), who could convey this message to the user or accompany the user to a visit.

The three models that are used in the coaching pipeline are mainly based on expert knowledge, with some parts, such as some of the parameters, also estimated from available data with statistical and machine learning techniques. The elements of knowledge that need to be encoded in a form that is available for reasoning are:

- The criteria that must be taken into account in each particular model. What factors affect a specific phenomena and can be used to assess it?
- Collection of the possible outputs of each model. For example, what are the appropriate coaching actions in each given scenario?
- Definition of how the values of the input criteria affect the assessment of the outputs of each model. What rules govern the state of outcomes, based on the states of the inputs?

For the purposes of formalisation of expert knowledge and reasoning we use the multi-criteria modelling methodology, which is presented next.

3 MODELLING METHODOLOGY

The three models from the coaching pipeline (as described in Section 2.2) act as the main knowledge representation and reasoning components of the system. In ambient intelligence systems, the most commonly used knowledge representations are ontologies (Bouznad et al., 2017) as they offer rich knowledge representation capabilities. Our initial design of the modelling pipeline envisaged use of existing problem domain ontologies (e.g., *dogont*[1] and *universAAL*[2]) for description of sensor readings and contextual information. A collection of simple rules that would include elements from the ontologies was foreseen as the reasoning engine. However, the available existing ontologies from this field were found not to be focused on concepts that are important in our application, such as wearable sensors and coaching-related concepts. Instead of expected minor adaptations, significant additional ontology development would be needed. We therefore opted for a less demanding modelling solution with a more elaborate reasoning engine and weaker knowledge representation capabilities: the hierarchical multi-criteria decision models (MCDM), which are established in the field of decision making and decision support.

Multi-criteria decision models (MCDM) are used to evaluate, compare and study alternatives (Greco et al., 2016). Typical examples of alternatives are, for instance, cars, job candidates, office locations, etc. Usually the task is to select the most appropriate alternative for specific goals, the one with the highest

[1] http://iot-ontologies.github.io/dogont/
[2] https://github.com/universAAL/ontology

utility. Decision support with MCDM is based on a hierarchical decomposition of the problem. Alternatives are hierarchically decomposed into sub-concepts (or aggregate attributes) and finally to a finite set of basic attributes, which represent model inputs. Utility of aggregate attributes is evaluated with functions, which depend on the corresponding attributes located on the lower levels of the hierarchy. In view of the problem presented in this paper, the alternatives are situation assessments, coaching actions and their renderings in specific contexts. In case of coaching actions for example, their utility corresponds to the fitness of the coaching action in a given situation. Basic attributes describe the context and the topmost aggregate attribute represents the coaching action to be triggered in such a context.

Due to our past experience, we used the methodology DEX (Bohanec et al., 2013), which is a qualitative multi-criteria decision modelling methodology that is well established in practice and is supported by freely available software, primarily by DEXi[3]. Similarly as in many other methodologies of this kind, its models have a hierarchical structure of variables, which represent concepts relevant for solving the assessment problem at hand. The lowest level concepts are inputs for the model, which get hierarchically aggregated into higher-level concepts up to the outputs, which usually represent assessments of decision options. For example, in Figure 3 a hierarchical structure of such a model is shown in which the topmost concept *Mobility stand-up Coaching Action* depends on two sub-concepts: *Ability to stand-up* and *Relative change*. The latter further depends on *Ability to stand-up* and *Predicted ability to stand-up*.

A distinctive characteristic of DEX is its focus on qualitative modelling in which the inputs to the model are qualitative values and the value functions (the functions used for aggregation of criteria into higher level ones) are rule-based, usually represented in tabular form. In the exemplary model from Figure 3, the value scales are shown to the right of each concept and exemplary rules (a selection, not all) which are used for calculation of the higher-level concept from the lower-level concepts are shown in tables that overlay the arrows that indicate dependencies.

The qualitative nature of this methodology allows the models to be transparent, which is particularly useful in situations in which the operation of the model must lend itself to human understanding. Automated AAL solutions are a prime example of such a case. However, the use of qualitative values can also represent a limitation in situations in which relationships among the criteria are naturally numerical

[3]http://kt.ijs.si/MarkoBohanec/dexi.html

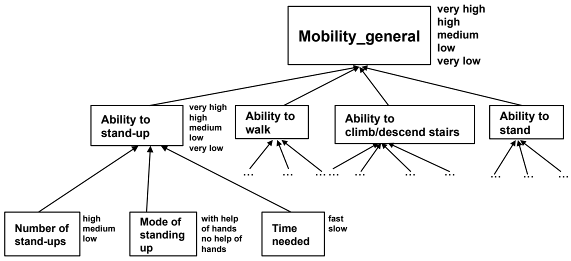

Figure 2: Structure of the situation model for the *Mobility* pipeline.

(summations, averages, etc.). Such relationships usually occur at the lower levels of models, thus, they are commonly left out of the main model and are separately computed as inputs. If a direct inclusion of such concepts in the models is necessary or beneficial, it can be done by using specific DEX methodology extensions (Trdin and Bohanec, 2018; Žnidaršič and Bohanec, 2010).

4 EXEMPLARY MODELS

In the following, we present selected models that were developed for the *Mobility* domain pipeline. This pipeline conducts an assessment of a person's physical mobility — the ability to move. It is executed daily and mostly uses the data of the past 24 hours. The models were developed in collaboration of computer modelling and domain experts, in this case domain experts for physical mobility and rehabilitation.

The structure of the situation assessment model for *Mobility* is shown in Figure 2. The topmost concept of *Mobility_general* is decomposed into four different aspects of physical mobility. For one of them, *Ability to stand-up*, further decomposition is shown, while for the others, their sub-hierarchies are omitted from the sketch.

Based on the input criteria, this model conducts an assessment of a person's mobility in general. As a side-result we also get the values of all intermediate concepts in the model, for example all the individual abilities that constitute *Mobility_general*. In the subsequent model of the cascade, which selects a coaching action, we usually consider the topmost concept of the situation model as one of the inputs. However, sometimes also intermediate concepts can be used as criteria. In case of *Mobility* pipeline it makes sense to separately coach for the general mobility, as well as for the individual abilities to move, as coaching actions for each of these are in some cases different. This way we can construct five coaching pipelines, which all share a situation model, but have different coaching action models.

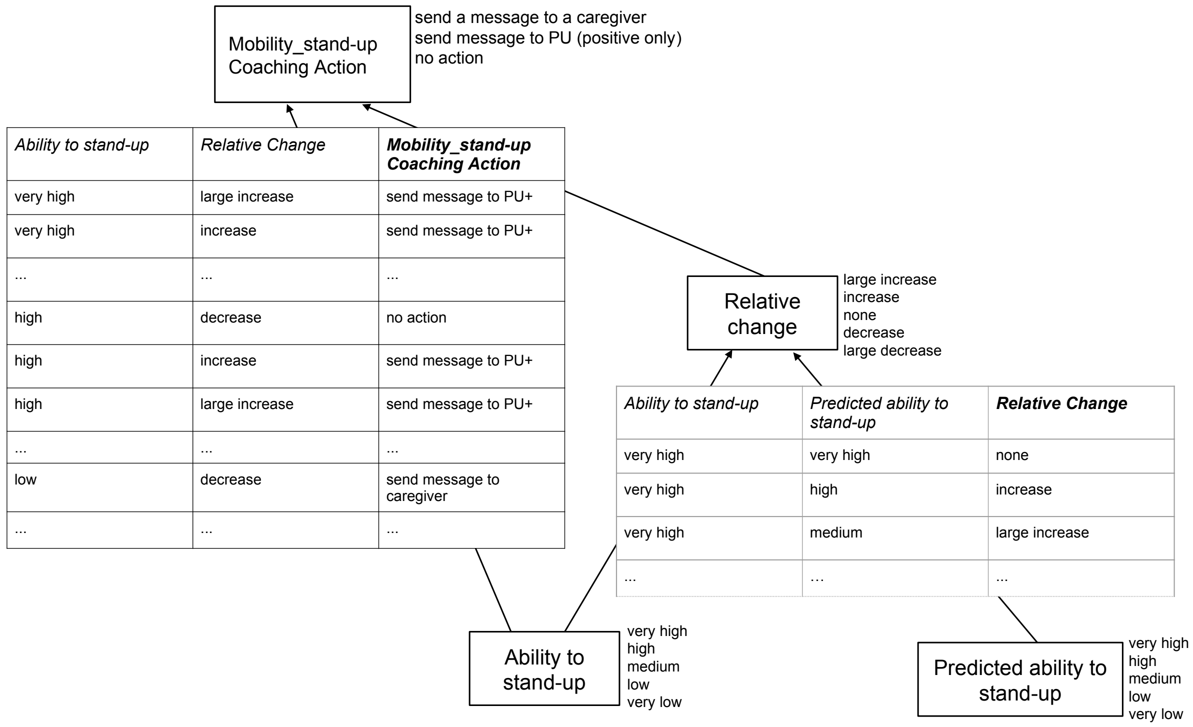

Figure 3: Structure and a preview of decision rules of the coaching action model for the *Mobility* pipeline.

A coaching action model for the person's ability to stand-up is shown in Figure 3, which shows the structure of relevant concepts and also some exemplary rules. There are only three coaching actions possible: (I) *send a message to a caregiver*, (II) *send a message to the primary user (positive only)* and (III) *no action*. A suitable coaching action is chosen based on the values of the *Ability to stand-up* and *Relative change*. The *Ability to stand-up* is an input that originates from the situation model (see Figure 2), while the *Relative change* is an aggregate concept that depends on the values of the *Ability to stand-up* and the *Predicted ability to stand-up*. The latter can be simply the most frequent value in a specific past time interval or a result of prediction with machine-learned tools, which can take into account past values as well as abundant contextual information (weather, day of the week, etc.).

The rules that are used to calculate the values of *Relative change* and *Mobility_stand-up Coaching Action* are shown in the tables that overlay the dependency arrows in Figure 3. The rules of *Relative change* are simply expressing how different is the current assessment of the ability to stand-up compared to the usual values of a particular person. The idea of the rules for *Mobility_stand-up Coaching Action* is to combine absolute and relative information in a way to primarily consider the relative change, but differently in case of some specific absolute values. For example, a small relative decrease in mobility does not trigger a coaching action if its absolute value is high.

5 DISCUSSION

In previous sections we presented an AAL problem and a system that tackles it by employing qualitative multi-criteria models in its knowledge modelling and reasoning infrastructure. Use of such a design and methodology is novel in the specific problem domain. Its effectiveness will be objectively evaluated in the scope of dedicated evaluation tasks in the corresponding project, but here we outline some of its qualitative characteristics and potential benefits and drawbacks, particularly in comparison to the entirely ontological approach.

Besides very fast execution and feasibility of serialization of the models (which makes them easy to store and update), the main benefit of MCDM approach, which was expressed as such also by several stakeholders that were presented with the proposed methodology, is the transparency and understandability of the models and their operation. This is a very important aspect in the targeted AAL domain. Some of the possible reasons for their understandability are: (I) use of (primarily) qualitative values and rules, (II) united representation of concepts and reasoning rules, (III) limited representation of concepts.

The qualitative variables used in the models and the corresponding (mostly) qualitative reasoning elements are transparent and easy to understand. There is no black-box model or complex calculation function included from the level of model inputs onwards. However, the qualitative nature of the models represents also a limitation when the natural representation of the variables is numerical. There are methodological extensions necessary (and some available) for this kind of modelling, but the corresponding software tools are only experimental. There is another negative consequence of qualitative modelling: given a large number of criteria to aggregate, the rule-sets can become too large to grasp and manage. This is to some extent alleviated by the use of hierarchical structures and possibility of using rule summarization tools, but could still represent a problem in some situations.

The MCDM models represent relevant knowledge (concepts, their value scales and dependencies) and at the same time function as reasoning tools (as they incorporate operational rules). This importantly simplifies understaning of the system's operation. On the other hand, consequently there is no separation of knowledge from its use, which limits the reusability of the models for other purposes. Ontological approach is very different in this respect, with clearly separate knowledge base and reasoning components. In some sense, the MCDM models represent concepts in a specific way (their specific aspect or interpretation), which is subjected to the model's purpose or output. This makes them more easily understandable, but at the same time also less general.

The concepts in MCDM models are represented with very limited information: name, description, value scales, structure and rules that govern dependencies of their values. Limited information and limited amount of relations among them (essentialy ony one among each two) constrain the knowledge representation and reasoning options to only the purposes in line with the main purpose of the model. This is another example of a generality versus understandability tradeoff.

Difference among the ontological and MCDM approach to modelling is also in the assumption of the open versus closed world. The ontologies assume an open world and allow reasoning also about concepts that are not represented in an ontology (e.g., having an ontology of animals with only birds defined, a condition on not being a bird can be formed). On the other hand, the MCDM models only contain what is necessary for their reasoning purposes and for example need options of none-existance explicitly defined (e.g., as a specific value in the value scale of a concept).

The MCDM modelling methodology seems to clearly have some important benefits in tackling the problem presented in this paper, but also some limitations. Likewise, the ontological approach is very general and powerfull, but has drawbacks for its use. There is, however, also a possibility of combined use and there were some attempts of it in some domains (Bastinos and Krisper, 2013; Brahimi et al., 2017). In AAL and similar problems, the two approaches could be used in combination on different levels — ontological on the level closer to data and MCDM on higher levels that are more important for the people to find them easy to comprehend. We intend to experiment with such a hybrid approach, starting with the use of ontologies for data fusion, in our future work.

6 CONCLUSIONS

Knowledge modelling and reasoning parts of an AAL system were presented in the paper, which differ from the common purely ontological approach, but seem to fit well to the purpose of the application and the needs of its users. We presented the architecture of the solution and the details of the applied multi-criteria decision modelling methodology, with a discussion of its potential benefits and limitations in the context of application in the given problem domain. The characteristics of this methodology somewhat limit its general reusability, but make it very suitable for implementation of the reasoning components that are close to human users.

ACKNOWLEDGEMENTS

The authors acknowledge the financial support from the Slovenian Research Agency for research core funding for the programme Knowledge Technologies (No. P2-0103) and the project SAAM – Supporting Active Ageing through Multimodal coaching which has received funding from the European Union's Horizon 2020 research and innovation programme, Horizon 2020 SC1-PM-15-2017 Personalised coaching for well-being and care of people as they age (RIA), grant agreement no. 769661.

REFERENCES

Ayala, I., Amor, M., and Fuentes, L. (2013). Self-configuring agents for ambient assisted living applications. *Personal and ubiquitous computing*, 17(6):1159–1169.

Azimi, I., Rahmani, A. M., Liljeberg, P., and Tenhunen, H. (2017). Internet of things for remote elderly monitoring: a study from user-centered perspective. *Journal of Ambient Intelligence and Humanized Computing*, 8(2):273–289.

Bastinos, A. Š. and Krisper, M. (2013). Multi-criteria decision making in ontologies. *Information Sciences*, 222:593–610.

Bikakis, A. and Antoniou, G. (2010). Rule-based contextual reasoning in ambient intelligence. In *International Workshop on Rules and Rule Markup Languages for the Semantic Web*, pages 74–88. Springer.

Bohanec, M., Žnidaršič, M., Rajkovič, V., Bratko, I., and Zupan, B. (2013). DEX methodology: three decades of qualitative multi-attribute modeling. *Informatica*, 37(1).

Bouznad, S., Chibani, A., Amirat, Y., Lyazid, S., Prestes, E., Sebbak, F., and Fiorini, S. (2017). Context-aware monitoring agents for ambient assisted living applications. In *European Conference on Ambient Intelligence*, pages 225–240. Springer.

Brahimi, L., Bellatreche, L., and Ouhammou, Y. (2017). Coupling multi-criteria decision making and ontologies for recommending dbms. In *22nd International Conference on Management of Data, COMAD*, pages 08–10.

Chen, L., Nugent, C. D., and Wang, H. (2012). A knowledge-driven approach to activity recognition in smart homes. *IEEE Transactions on Knowledge and Data Engineering*, 24(6):961–974.

Fides-Valero, Á., Freddi, M., Furfari, F., and Tazari, M.-R. (2008). The persona framework for supporting context-awareness in open distributed systems. In *European Conference on Ambient Intelligence*, pages 91–108. Springer.

Greco, S., Figueira, J., and Ehrgott, M. (2016). *Multiple criteria decision analysis*. Springer.

Hervás, R., Bravo, J., Fontecha, J., and Villarreal, V. (2013). Achieving adaptive augmented reality through ontological context-awareness applied to aal scenarios.

Kara, M., Lamouchi, O., and Ramdane-Cherif, A. (2017). A quality model for the evaluation aal systems. *Procedia Computer Science*, 113:392 – 399. The 8th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN 2017) / The 7th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH-2017) / Affiliated Workshops.

Li, R., Lu, B., and McDonald-Maier, K. D. (2015). Cognitive assisted living ambient system: a survey. *Digital Communications and Networks*, 1(4):229–252.

Rafferty, J., Nugent, C. D., Liu, J., and Chen, L. (2017). From activity recognition to intention recognition for assisted living within smart homes. *IEEE Transactions on Human-Machine Systems*, 47(3):368–379.

Trdin, N. and Bohanec, M. (2018). Extending the multi-criteria decision making method DEX with numeric attributes, value distributions and relational models. *Central European Journal of Operations Research*, 26(1):1–41.

Yamada, N., Sakamoto, K., Kunito, G., Isoda, Y., Yamazaki, K., and Tanaka, S. (2007). Applying ontology and probabilistic model to human activity recognition from surrounding things. *IPSJ Digital Courier*, 3:506–517.

Zavadskas, E. K., Naimavičienė, J., Kaklauskas, A., Krutinis, M., and Vainiūnas, P. (2008). Multi-criteria decision support system of intelligent ambient assisted living environment.

Žnidaršič, M. and Bohanec, M. (2010). Handling uncertainty in DEX methodology. In *URPDM 2010: Proceedings of the 25th Mini-EURO Conference*.