Neuro-Symbolic AI Approaches for the Study of the GENCAT Quality of Life Scale

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Abstract

This paper presents and discusses two neuro-symbolic AI methodologies, previously published, for studying and explaining the quality of life of individuals with intellectual disabilities, as assessed by the GENCAT scale, a tool widely used in Catalonia's Social Services. The first technique is based on logic-based belief merging, which integrates expert knowledge using the Horn fragment of signed logic. The second one leverages Logic Explained Networks, an interpretable family of deep learning models capable of generating explanations.

Keywords

Disability, Real-world based case, Neurosymbolic AI, Explainable AI

1. Introduction: Bridging real-world challenges and logic-based methods

For several years, our research group has been actively engaged with institutions focused on supporting individuals with intellectual disabilities. A core aspect of the work of Social Services in Catalonia involves using the GENCAT scale [1, 2] to assess and understand the quality of life (QOL) of these individuals. Some of the main challenges are related to a comprehensive understanding of the relationships between various dimensions of QOL, the structure of the GENCAT scale and its associated databases, and the key factors that contribute to the varying levels of QOL of Social Services users. This paper presents ongoing research to address these empirical problems, subsequently bridging real-world challenges and AI symbolic or hybrid methodologies.

In line with other approaches from formal explainable artificial intelligence such as [3, 4, 5], our proposal is fundamentally rooted in logical approaches. We argue that significant contributions can be made from this approach and exemplify it in the social challenge of assessing and improving the QOL of individuals with intellectual disabilities. In this way, we leverage both classical contributions in knowledge representation, such as merging [6, 7], and more recent and hybrid advancements like Logic Explained Networks (LENs) [8, 9].

2. Quality of Life Assessment and the GENCAT Scale

The concept of Quality of Life (QOL) emerged in the early 1980s in various fields, including healthcare, education, and social services [10]. During the past four decades, it has become a cornerstone in guiding quality improvement strategies, evaluating effectiveness, and facilitating person-centered planning [10, 2]. This evolving understanding of QOL aligns with the principles of the United Nations Convention on the Rights of Persons with Disabilities (2006), which views disability as an aspect of human diversity rather than a defining characteristic. Similarly, the American Association on Intellectual and Developmental Disabilities (AAIDD) has changed its definition of disability from a

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Table 1
Dimensions and core indicators of quality of life

Dimensions	Variable	Indicators
Emotional well-being	p_1	Satisfaction. Self-concept. Lack of stress or negative feelings. *Questions 1-8.*
Interpersonal relations	p_2	Social, familiar and affective relationships. Positive and gratifying social contacts. Satisfying sex life. *Questions 9-18.*
Material well-being	p_3	Housing, workplace, and service conditions. Employment. Incomes/salary. Possessions. *Questions 19-26.*
Personal development	p_4	Education. Learning opportunities. Work and functional abilities. New technologies. *Questions 27-34.*
Physical well-being	p_5	Health care access and consequences. Functional diet, sleep, mobility. Technical assistance. *Questions 35-42.*
Self-determination	p_6	Autonomy. Goals and personal preferences. *Questions 43-51.*
Social inclusion	p_7	Integration- Access. Supports. *Questions 52-59.*
Rights	p_8	Knowledge, defense, and exercise of rights. Privacy. Respect. *Questions 60-69.*

static, individual trait to an interaction between an individual's skills (performance competence) and the support structures within their environment (integration facilities) [10].

In line with these principles, Schalock and Verdugo [10] introduced a multidimensional QOL model. This model assesses and intervenes based on a person's situation on eight operationally defined dimensions, each with core indicators [1]. These dimensions are: emotional well-being (EW), interpersonal relations (IR), material well-being (MW), personal development (PD), physical well-being (PW), self-determination (SD), social inclusion (SI), and rights (RI).

In 2008, the Institute on Community Integration (University of Salamanca) and the Catalonian Institute of Assistance and Social Services (Government of Catalonia) collaboratively developed and introduced the GENCAT scale [1, 2]. The GENCAT scale is a widely used questionnaire designed for users of social services. It comprises 69 questions, organized into eight blocks, with each block corresponding to one of the aforementioned QOL dimensions. In general, the answers to the questionnaire permit five response options: *very-low*, *low*, *medium*, *high*, and *very high*.

AI research using the GENCAT scale has explored various aspects of QOL. Armengol, Dellunde and Ratto [11] employed decision trees to estimate correlations between dimensions, although this initial work considered only 90 records. This was later expanded in [12], which used a filtered tree and analyzed 5158 records from the GENCAT scale. This research concluded that SI, SD, and IR are the most relevant dimensions for the level of QOL and yielded rules, such as *if SD is medium or high, the QOL level is never low*. However, these studies often restricted QOL level classes to *low*, *medium*, and *high*, resulting in less detailed explanations.

The GENCAT scale continues to be a subject of interdisciplinary debate and improvement efforts [13, 14]. Furthermore, there is a growing consensus on the utility of Artificial Intelligence (AI) in psychological assessment and test construction [15]. Moreover, the demand for explainable AI, particularly in ethically sensitive domains, is undeniable.

3. Two methodologies to studying the GENCAT QOL Scale

In this section, we present the two methodologies we adopted to study the GENCAT QOL Scale.

3.1. The merging approach

As a first step, in [16], we presented some theoretical results. In particular, we introduced a set of logical postulates for belief merging under constraints for the Horn fragment of signed logic [17] and obtained a sufficient condition for a merging operator to satisfy these postulates. Furthermore, an

Table 2
GMAX-aggregation and cardinality distance ($d_c(w, K_1), d_c(w, K_2), d_c(w, K_3)$, and $d_c(w, K_4)$)

Models	$d_C(w, K_1)$	$d_C(w, K_2)$	$d_C(w, K_3)$	$d_C(w, K_4)$	GMAX
10001000	0	0	4	4	(4,4,0,0)
10001100	3	0	5	5	(5,5,3,0)
10001110	4	4	6	6	(6,6,4,4)
10001111	5	5	7	7	(7,7,5,5)
11001000	0	0	5	5	(5,5,0,0)
11001100	4	0	0	0	(4,0,0,0)
11001110	5	5	7	7	(7,7,5,5)
11001111	6	6	8	8	(8,8,6,6)
11101000	0	0	6	6	(6,6,0,0)
11101100	0	0	7	7	(7,7,0,0)
11101110	0	0	8	8	(8,8,0,0)
11101111	0	0	9	9	(9,9,0,0)
11111000	0	0	7	7	(7,7,0,0)
11111100	0	0	8	8	(8,8,0,0)
11111110	0	0	9	9	(9,9,0,0)
11111111	0	0	10	10	(10,10,0,0)

implementation of the belief merging process in this fragment, based on the example of the GENCAT scale, was presented. The Horn fragment of signed logic was considered as an adequate formalism to represent the knowledge of this field and to implement the operators.

We started with rules previously obtained by machine learning techniques (see [12]) and organized different interviews with social practitioners in which they provided their own rules, representing their experience of decades working with people with intellectually functional diversity. Experts' evaluations were represented as knowledge bases. We noticed that these bases were not always consistent with the results obtained by applying machine learning techniques. Therefore, an interesting open question was how to merge all these possibly mutually inconsistent knowledge bases not in a purely numerical aggregation approach but a qualitative one, which was the motivation of the research presented in [16]. There, the knowledge bases were represented by signed formulas.

As an illustrative example, let us consider the case of four practitioners analyzing the QOL of the same Social Services user. The main goal is to merge all of the experts' opinions in order to obtain a consolidated evaluation ($p_1, \ldots, p_8$ are defined in Table 1 and q_v indicates the QOL level). So consider the profile $E = \{K_1, K_2, K_3, K_4\}$, where $K_1 =\uparrow 0.75 : p_5 \vee \downarrow 0.25 : q_v$, $K_2 =\uparrow 0.75 : p_5 \vee \downarrow 0.5 : q_v$, and $K_3 = K_4 =\uparrow 0.5 : p_5 \wedge \downarrow 0.5 : p_5 \wedge \uparrow 0.5 : q_v \wedge \downarrow 0.5 : q_v$. That is, in this case, the practitioners established a relation between the dimension of physical well-being (see Table 1) and the QOL level. Let us briefly present the semantics of the formulas in the profile and refer to [16, Section 2] for more details. A set of values N is a nonempty finite set $N = i_0, \ldots, i_N$, where $i_0 = 0$ and $i_n = 1$, and a sign S is a subset of N. A signed interpretation I of the set of propositional variables P is a function $I : P \to N$, and a signed interpretation I satisfies a signed literal $S{:}p$ if $I(p) \in S$. The connectives appearing in the profile are interpreted as in classical logic.

The outcome of a merging process for the profile E using the GMAX Horn Merging Operator [18] was (see Table 2 and [16, Example 4.3] for more details): $\uparrow 0.25 : p_5 \wedge \uparrow 0.5 : p_5 \wedge \downarrow 0.5 : p_5 \wedge \downarrow 0.75 : p_5 \wedge \uparrow 0.25 : q_v \wedge \downarrow 0.5 : q_v \wedge \downarrow 0.75 : q_v$, that is, the dimension of physical well-being is *medium* and the QOL level is *low* or *medium*.

3.2. An approach from neurosymbolic AI: Logic explained networks

The need for explainability in AI, especially in domain applications with ethical implications, is beyond doubt. In response to this need, neurosymbolic AI emerges as a highly appropriate framework to integrate the value of symbolic AI and to overcome the limitations of deep learning that have become increasingly evident in recent years [19]. Within this context, Ciravegna et al. [8] introduced logic explained networks (LENs), a family of interpretable DL models that provide explanations for their predictions. The functions computed by LENs are of the form $f : C \to E$, where $C = \{0, 1\}^k$ is the space of activations of the k-input, $E = \{0, 1\}^r$ relates to the activations of the r-outputs, and so that the inputs are cognitively understandable notions. In our case, all the explainable models perform categorical tasks, specifically predicting the QOL level or assessing one of the eight dimensions.

Interdisciplinary debates on reviewing and improving the GENCAT scale, where societal and ethical aspects and strands related to psychology converge, are still open ([13, 14]). Furthermore, there is some consensus on the convenience of using AI in the psychological assessment and test construction domains [15]. In line of these proposals, as we explain next, we studied in [20, 21] the GENCAT scale using LENs and focused on the generation and analysis of explanations regarding the dimensions of QOL.[1]

First, we used the IntDisCat database, introduced in [20], whose content was provided to us by the Catalonian Institute of Assistance and Social Services. This database contains records corresponding to 6104 Social Services users, indicating responses to the GENCAT scale of multiple practitioners in diverse institutions. With these data, scores of the eight dimensions of QOL were calculated and then categorized into the five levels mentioned above[2].

In classical logic, the interpretations of the variables corresponding to the dimensions (Table 1) as well as q_v cannot allow the nuances of the five evaluations considered. Thus, this formalism was extended to include the five evaluations. Hence, $p_1, \ldots, p_8$ were extended to $p_{11}, \ldots, p_{15}, p_{21}, \ldots, q_5$, where q_j is related to the QOL level, the j, with $1 \leq j \leq 5$, indicates the evaluation (1 stands for *very low*, and so on), and the first subindex i in p, with $1 \leq i \leq 8$, indicates dimension. For example, p_{72} expresses that social inclusion is *low*.

We designed a LEN-based model for each QOL level[3], using the entropy-based LEN framework proposed in [9]. This enabled us to obtain a global explanation for each QOL level considered. Recall that a global explanation [22] is defined as the disjunction of the most frequent local explanations in the training set. Next, we present the two illustrative global explanations obtained using the IntDisCat database.

QOL level *very low*

A very low value for IR or PD, or the absence of a high value for SI together with meeting one of the following conditions: the EW is very low, the IR is very low, or the MW is low. That is:

$$p_{21} \vee p_{41} \vee (\neg p_{74} \wedge p_{11} \wedge p_{21} \wedge p_{12}).$$

QOL level *very high*

MW and RI are medium, EW is not low, and SD and PW are at least high. That is:

$$p_{33} \wedge p_{83} \wedge \neg p_{12} \wedge (p_{54} \vee p_{55}) \wedge (p_{64} \vee p_{65}).$$

In [21], we extended our analysis of the GENCAT scale by using LENs to study the relationships between the QOL dimensions In this way, we applied the previously explained formalism to design different models aimed at generating global explanations of the correlations among these dimensions. To this end, each model was designed to predict one dimension from the remaining seven. As a result, the experimentation produced 37 global explanations; no explanations resulted for the level *very high* of MW, PD, and RI dimensions since the data from the IntDisCat database were insufficient to generate an explanation. Next, we present some illustrative examples of the global explanations obtained.

[1] In parallel, we proposed a first step towards designing a reduced version of the GENCAT scale with 23 questions (from the original 69) and made a twofold analysis of it (regarding the accuracy metrics, and comparing the global explanations generated when using the two questionnaires). Certainly, let us observe that practitioners using the scale at present have to answer 69 questions for each interviewee to obtain the QOL level, so in some situations (depending on the time resources and labor force available), it could be desirable to have a reduced, and thus faster-to-do (see [20] for more details on this reduction).

[2] See https://github.com/dfp97/LENsIntDisCatQOLDimensions.

[3] See https://github.com/dfp97/LENsQoLIntDisability_ReducedGencat.

***Medium* level of emotional well-being (p_1).**
Interpersonal relations are low, self-determination is very low, social inclusion is very high, and rights are low. That is:
$p_{22} \wedge p_{61} \wedge p_{75} \wedge \neg p_{82}$.

***Very low* level of interpersonal relations (p_2).**
Self-determination is very low, emotional well-being, material well-being, and personal development are low, and physical well-being and social inclusion are medium. That is:
$p_{61} \wedge p_{12} \wedge p_{32} \wedge p_{42} \wedge p_{53} \wedge p_{73}$.

***Very high* level of self-determination (p_6).**
Personal development and social inclusion are high, physical well-being is not high, rights are not low, and interpersonal relations are not medium. That is:
$p_{45} \wedge p_{75} \wedge \neg p_{54} \wedge \neg p_{82} \wedge \neg p_{23}$.

4. Discussion, conclusions, and future lines of research

This research underscores the critical importance of practically applying existing AI techniques to real-world problems, moving beyond theoretical *toy examples*. Our work with the GENCAT scale and individuals with intellectual disabilities presented numerous challenges, from the complexities of understanding quality of life dimensions to navigating the intricacies of real-world data. Instead of confining ourselves to a single, specific technique, we learned the need for adopting a multi-faceted approach, exploring and implementing various methods.

For the sake of clarity, this paper focuses on a real-world application concerning the quality of life of individuals with intellectual disabilities. Nonetheless, it is worth noting that we have also developed explainable models for a different application domain, namely, the categorization of art paintings by style and genre, using a range of symbolic and neurosymbolic approaches, including logic-based systems [23, 24, 25, 26], logic aggregators [27], and logic explained networks [28].

Ultimately, engaging with these complex, real-world scenarios is essential not only for achieving tangible social impact but also for driving the advancement of AI itself. Such applications inevitably give rise to new theoretical questions and push the boundaries of current methodologies. To truly elevate the role and relevance of AI, we find that the field must continue to embrace these practical deployments as well as rigorously testing and comparing diverse AI approaches on the same real-world problems.

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Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT-4 to check grammar and spelling.

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