Artificial Intelligence in Support of Individual Assessment of Support Needs for People with Disabilities

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Abstract

Intelligence aids in choosing which data to analyze and how to do so, ensuring that users have accurate, timely, and easily accessible information when making decisions. The use of intelligent solutions enables businesses to make well-informed decisions, gain competitive advantages, and utilize information to respond quickly and effectively to changes. Why couldn't the same principles be applied to assessing the specific needs of people with disabilities? Modern systems can ensure the availability of relevant data for determining the individual needs of a person with disabilities. Based on these data, accurate analyses can be conducted, providing the opportunity to identify impairments attributable to the disabilities. The report proposes an approach to extracting knowledge based on data collected through the application of the Methodology for Conducting Individual Assessments of Support Needs for People with Disabilities and extracting knowledge from the experts working in the social support agency. Software tools have been proposed to combine the two types of knowledge.

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Introduction

The interest in artificial intelligence is entirely understandable in the modern technological world, given its involvement in various aspects of both public and personal life. The use of artificial intelligence in information systems enables organizations to make well-informed decisions, gain competitive advantages, and utilize information to respond quickly and appropriately to changes in the surrounding environment, even predicting and preparing for them in a timely manner. Intelligence aids in selecting what data to analyze and in what manner, ensuring that decision-makers have accurate, timely, and easily accessible information. Employing intelligent solutions enables businesses to make well-informed decisions, gain competitive advantages, and utilize information to respond quickly and appropriately to changes. Why couldn't this also happen when assessing the specific needs of individuals with disabilities? Modern systems can provide relevant data to determine the individual needs of a person with a disability, on which accurate analyses can be conducted, and the identification of impairments due to disabilities can be ensured. The report proposes an approach to extract knowledge based on data collected during the application of the Methodology for Conducting Individual Needs Assessment for People with Disabilities.

1. Literature review

Despite the advancements in technology, several areas of public life remain inaccessible to a significant portion of people with disabilities. Examining the regulatory framework in Bulgaria over the past 20 years reveals numerous legislative documents that, in one way or another, address individuals with disabilities. However, the support measures for people with disabilities outlined in these documents are often too general and do not account for their individual needs. It was only in 2019 that the Methodology for Conducting an Individual Assessment of Support Needs for People with Disabilities was developed and adopted. Two annexes were created alongside this methodology: Annex 1, “Individual Assessment of Needs for People with Disabilities“ and Annex

2, “Form to be completed by the case manager“. The amount of data collected through the completion of Annex 2 is substantial. If this data is digitized, knowledge extraction techniques can be applied to obtain clear and accurate information about the individual's condition and specific needs.

Data is one of the most crucial components of information systems because, without a sufficient volume of accurate data, the system cannot provide the required information. Artificial intelligence-based systems, even more so, heavily rely on the quality of the data.

However, a distinction must be made between knowledge derived from the processing of data recorded in Annex 2 and the knowledge held by employees in the “Social Assistance“ department, accumulated during their training and practical work.

The knowledge, by its nature, is information about the properties of objects and phenomena within a considered domain and the relationships between them. For the purposes of this study, we distinguish two categories of knowledge – "raw knowledge" and "expert knowledge". By "raw knowledge“, we refer to knowledge obtained as a result of the data mining process; therefore, it is information that has been analyzed using algorithms, techniques, and tools for knowledge extraction. The application of knowledge extraction algorithms represents an analytical process involving artificial intelligence, statistics, optimization, and other mathematical algorithms to perform in-depth analysis. The transformation of data into "raw knowledge" encompasses the following stages: 1) pre-processing – converting data into information; 2) analysis – transforming information into raw knowledge.

The characteristics of "raw knowledge" include:

- rawness – without further refinement, "raw knowledge" contains a lot of redundancies, biases, or even incorrect information.
- diversity – knowledge needs to be represented through a specific model for decision-making. There are various forms of presenting "raw knowledge" – associative rules, decision trees, neural networks, probability maps, clusters, formulas, etc. Some representations are easy to understand (such as decision trees), while others are challenging to interpret (like neural networks).
- source identification – these are results from analyses.
- time of acquisition – "raw knowledge" is extracted at a specific moment in time. Therefore, conflicts may arise between knowledge generated at different periods.
- partial ease of use – there is a possibility to support the organization's activities.

The main tasks of extracting "raw knowledge" involve characterization, differentiation, relevance, classification, clustering, identification of unusual dependencies, anomaly detection, similarity finding, etc. The technologies used in this process include statistical analysis, optimization, machine learning, visualization, data storage, and more. The following types of representation of "raw knowledge" can be distinguished: rules, classification markers, clustering tags, etc.

"Expert knowledge" is the knowledge held by specialists in a specific field. It relies on individual skills acquired through training, daily work, and overcoming critical situations. This knowledge has strict boundaries in terms of its applicability. Within a specific domain, it is necessary and valuable, but beyond those boundaries, its application diminishes. The quality of "expert knowledge" to some extent depends on the professional experience of the individuals. We can attribute facts and rules that do not require proof to "expert knowledge."

2. Knowledge extraction through Data Mining

For the extraction of “raw knowledge“ it is necessary to choose an appropriate methodology tailored to the characteristics of the subject area. In this context, a detailed analysis of knowledge extraction is required, as it is a fundamental element of artificial intelligence applications. Research has primarily focused on obtaining accurate models through the practical application of knowledge extraction methods. The result of this process is numerous models and rules.

Knowledge extraction, by its nature, applies specific algorithms to extract models from data and represents a step in the process of knowledge discovery in databases (KDD). The KDD process (Fayyad, 1996) consists of 9 steps: 1) domain understanding; 2) creation of a target data subset; 3) data cleaning and preprocessing; 4) data reduction and selection; 5) choice of Data Mining (DM) technique (e.g., classification, clustering, association, prediction); 6) selection of a DM algorithm; 7) knowledge extraction; 8) interpretation of results; 9) use of the discovered knowledge.

Any methodology, related to KDD and DM must include the following steps: 1) problem analysis; 2) data preparation; 3) data exploration; 4) model generation (DM); 5) model evaluation; 6) model deployment (Han and Kamber, 2006).

Authors in the KDD field view the process as interactive and iterative, requiring continuous coordination and integration of acquired knowledge into the system. The most crucial step in the process is knowledge extraction. DM tasks can be conditionally divided into two categories: descriptive and predictive. Descriptive tasks characterize and describe the general properties of data in the database, while predictive tasks make forecasts by examining current data.

In summary, the main stages in the knowledge extraction process are: 1) application of knowledge extraction algorithms; 2) evaluation of discovered models; 3) presentation of obtained models in suitable formats.

The CRISP-DM (Cross Industry Standard Process for Data Mining) methodology is regarded as a standard for Data Mining (DM). The workflow in CRISP-DM is not significantly different from the framework proposed by Fayyad or that suggested by Han and Kamber, meaning they actually apply to the entire Knowledge Discovery in Databases (KDD) process rather than specifically to DM.

In CRISP-DM, the DM process is considered to consist of six phases[1]:

- Business Understanding: This phase focuses on defining the project goals and requirements from the perspective of the specific activity.
- Data Understanding: The phase starts with the initial collection of data and continues with activities related to data analysis.
- Data Preparation: This phase involves all activities related to the selection of subsets from raw data.
- Modeling: Different techniques are chosen for creating models in this phase.
- Evaluation: The model or models obtained are carefully evaluated. The steps of the model are reviewed to ensure the precise achievement of the goals.
- Deployment: Creating the model is not the end of the process officially.

The acquired knowledge must be organized and presented in a way that the user can utilize it. The knowledge extraction methodology suitable for use in the discussed subject area is CRISP-DM. It provides a reliable and repeatable process for knowledge extraction, accessible even to individuals without specialized knowledge in the field. Furthermore, it is flexible enough to account for differences in conducting diverse activities and solving specific problems requiring particular data.

However, there is rarely an evaluation or formalization of DM results to support the decision-making process. Therefore, the obtained models and rules may not represent useful knowledge. In the essence of the DM process, the discovered models are considered its endpoint. There is a lack of in-depth examination of the transformation of data into information and knowledge, and the cycle of accumulating and creating new knowledge is not explored.

Based on the presented information, the models discovered through DM are referred to as “raw knowledge”. The evaluation of the model and the representation of the knowledge obtained

[1] IBM SPSS Modeler CRISP-DM Guide <https://www.ibm.com/docs/it/SS3RA7_18.3.0/pdf/ModelerCRISPDM.pdf>

through DM depend on the algorithm used—association, classification, clustering, etc. Modern DM tools have a complex interface that does not allow experts in the social assistance agency to actively participate in the knowledge extraction process. Additionally, both information and knowledge depend on specific scenarios and the social interactions of individuals. Therefore, models or rules obtained from DM must be combined with the specific context to be used in the organization. The context includes external and internal factors that are a key element for a comprehensive understanding of knowledge, reflecting on people's assessment of knowledge. Hence, context is critical for the DM process and its results.

However, a method is needed to integrate knowledge about the domain that is outside the database, the knowledge decision-makers use in their daily work, user experiences, and their assessments (perspectives). Currently, there is no software tool that supports the analysis of “raw knowledge” and ways to integrate it with “expert knowledge”. As a result, a large set of models obtained from the knowledge extraction process is maintained, which is not connected to the specific environment for solving problems. There is also an observation of the disregard for “raw knowledge” with a reliance only on “expert knowledge” as a valuable knowledge base. Therefore, a framework for integrating the two categories of knowledge is necessary to obtain truly valuable and useful knowledge.

3. Knowledge extraction from experts

The extraction of “expert knowledge” is associated with knowledge engineering, which represents the process of selection and structuring of knowledge and the relationships between them to build knowledge bases (Atanasova, 2011). The primary goal of knowledge engineering is to structure the development and use of knowledge bases (Auer and Herre, 2007). In a broad sense, knowledge extraction can be defined as extracting additional value from the existing intellectual potential (Panayotova, 2010).

In the development of the early knowledge-based systems, only one expert in the field was used, as it was believed that in this case, knowledge extraction is easier, and contentious issues and conflicting opinions are avoided (Nasuti, 2000). However, soon specialists realized that knowledge extraction is rarely within the capabilities of a single expert. The expertise of each expert is limited only to their specific area, and if that area does not align with the problem domain, incorrect solutions can be obtained. Additionally, mistrust or lack of knowledge can lead to errors. Upon discovering these issues, the practice of involving multiple experts in the field began.

The use of multiple experts, in turn, helps overcome mistrust and lack of knowledge, as well as avoiding inaccurate knowledge. The presence of multiple experts can provide a blend of knowledge, which is essential for complex tasks, such as those related to the individual assessment of the needs of people with disabilities.

In general, the benefits of creating a team of experts can be described by providing positive effects on the results of the system's work, and they are:

- guarantee of the completeness of the knowledge base;
- increased likelihood of obtaining specialized knowledge in subdomains of the problem;
- improved quality and reliability of acquired knowledge;
- confidence that the facts included in the knowledge base are genuinely important;
- better understanding of knowledge in the field through discussions, debates, and exchange of hypotheses among members of the expert team;
- interaction between experts and the creation of synergy (knowledge gained from the group is greater than the sum of the knowledge of individual experts).

Techniques primarily used for obtaining knowledge from a group of experts include brainstorming, the Delphi method (Linstone and Turoff, 1975), focus group interviews, voting, and others.

On the other hand, acquiring knowledge from multiple experts is fraught with many problems related to coordinating the work of individual experts and integrating multiple knowledge into the knowledge base. Generating a set of knowledge that does not originate from a single expert but results from the collaborative effort of several experts is challenging. Numerous issues are also associated with conflicts between experts and the cognitive inability to express the relationship between different perspectives in desired specifications, as these opinions can overlap, complement, and contradict each other.

Possible ways to avoid conflicts and disagreements include:

- requiring documents from experts as evidence for their claims;
- using probabilities to express the degree of agreement and disagreement among experts;
- creating the system based on individual modules so that different experts are utilized for specific parts and consultations.

Just as conventional systems need to be tested, knowledge-based systems also need to be verified and validated, usually through the processes of verification and validation. Experts, cognitologists, and users typically participate in these processes.

The primary methodologies used in knowledge engineering are CommonKADS, SPEDE, and MOKA. CommonKADS is an evolution of the methodology for creating knowledge-based systems – KADS. Its goal is to assist cognitologists in choosing a scheme for representing knowledge (Davis et al., 1993) and programming techniques. In Europe, CommonKADS has become a standard in the development of knowledge-based systems. The SPEDE methodology is a combination of principles, techniques, and tools for knowledge engineering, successfully adapted in the knowledge management process. MOKA is a methodology for developing knowledge-based engineering applications, primarily focused on discovering and applying knowledge in the automotive and aviation industries during the design of complex mechanical products. The development of these methodologies is attributed to several factors related to the knowledge extraction process:

- Experts are not good at explaining everything they know. They possess implicit knowledge that operates at a subconscious level and cannot be easily explained.
- Experts have different experiences and opinions, necessitating their integration to provide a unified representation.
- Experts use jargon, assuming that most people understand the terminology they employ.

To assist cognitive scientists, the use of software tools for knowledge extraction and representation is appropriate. One such tool is Protégé[2], a free, open-source software platform that supports the creation of knowledge bases, ontologies, and the acquisition of expertise from domain experts. It provides two forms of knowledge representation—using frames and ontologies—through two standalone applications: Protégé-Frames and Protégé-OWL.

Ontologies created using Protégé applications can be exported in various formats such as RDF(S), OWL, and XML schema. Protégé applications are written in Java, and their advantages include the ability to extend functionality through plugins and the availability of ontologies for this platform.

The key advantages of Protégé can be summarized as follows:

- user-friendly interface;
- scalability;
- flexibility in adding additional plugins.

[2] https://protege.stanford.edu/

PCPACK[3] is an integrated package comprising 10 tools designed to facilitate the acquisition and utilization of knowledge. It supports various methodologies, including those discussed above. The tools included in the package perform activities such as:

- knowledge analysis from textual documents;
- knowledge structuring using various knowledge representation models;
- knowledge acquisition and validation from experts;
- publication and implementation of acquired knowledge;
- knowledge reuse in different domains.

These activities are crucial for all projects related to knowledge engineering and management, and the use of software tools enhances their effectiveness.

By using PCPACK, knowledge bases are created, allowing remote access for multiple users with predefined access rights. In the latest version, PCPACK6, RDF functionality has been added, enabling the import and export of files in RDFS and OWL RDF formats.

The use of software such as PCPACK makes the process of acquiring, modeling, and storing knowledge more efficient and less prone to errors (Van Der Elst and Van Tooren, 2008).

4. Knowledge representation

The presentation of knowledge is one of the fundamental concepts in the field of artificial intelligence. The knowledge base is developed over a significant period using various techniques for knowledge acquisition (ranging from interactive sessions with experts to the automatic generation of new facts), some of which have been discussed above. The choice of a knowledge representation scheme influences the system's operation. In fact, this is one of the most important and challenging phases in creating knowledge-based systems (Naydenov N., Sima Navasardyan, 2009). Domain experts actively participate during testing. The real need for using knowledge can be divided into three subcategories:

- acquiring more knowledge;
- extracting facts from knowledge related to the problem;
- reasoning about these facts and seeking a solution.

In knowledge-based systems, knowledge is presented as a combination of data structures and procedures that interpret them. Before choosing a knowledge representation model, it must be determined whether it is suitable and useful for solving the problem in a given area. Knowledge representation models in symbolic systems are procedural, declarative, and procedural-declarative. Declarative models are further divided into modular and network models. Logical models (representing knowledge through propositional logic and first-order predicate logic) and production rules belong to modular models.

The representation of production rules makes them easy to understand and modify. Semantic networks are representatives of network models. They consist of nodes representing objects, concepts, states, or events and links between them. In this case, the knowledge base can be changed by deleting or adding new nodes and corresponding links. The advantage of semantic networks is the ability to be presented graphically, significantly facilitating explanations and understanding of the reasoning process.

Procedural models are characterized by the construction of the knowledge base and the inference mechanism as a whole. Procedures, whose disadvantage is difficult verification and modification, belong to these models.

As an attempt to combine the advantages of both model types, procedural-declarative models have been created. Their representatives are frames and scripts. In the development of knowledge-based systems, models that use hypertext and web pages, where links between concepts and other types of knowledge are represented through hyperlinks, have been created. This allows

[3] https://www.tacitconnexions.com/index-9.html

the creation and use of templates from structured text, using a separate template for different types of knowledge.

Each model has strengths and weaknesses depending on the characteristics of the knowledge that needs to be represented in the knowledge base. For example, declarative representation of knowledge is used to represent logical relationships with many descriptive conditions, while procedural representation is used mainly in areas with prevailing algorithmic knowledge. The model chosen to represent knowledge in this research must meet the following requirements:

- provide the ability to express all the knowledge necessary to solve the problem;
- be as close as possible to the problem, providing an easy representation of relationships and the ability to check the correctness of knowledge. A small change in the problem should lead to a small change in its representation.
- have the ability to evolve and improve.

The knowledge representation models aim to encompass the process of human reasoning. However, complex tasks (most tasks that experts from the social support agency need to solve) require different types of knowledge as well as different models for knowledge representation to facilitate reasoning. But still, none of the models considered is able to fully represent the real world and simulate human reasoning. For this reason, in many areas, it is necessary to use more than one knowledge representation model. In this sense, for knowledge representation in the context considered, a combination of production rules, semantic networks, and frames is appropriate.

Conclusion

In recent years, artificial intelligence has been actively applied by companies to assist people with disabilities. Various forms of integration using different methods and tools from the field of artificial intelligence are employed in tackling this challenging task, as individuals with disabilities have diverse and specific needs. The emphasis is on machine learning, computer vision, natural language processing, and speech recognition. People with disabilities stand to benefit significantly from AI – powered solutions, which will help them with dailytasks and provide them with the chance to learn new skills (Samim, 2023).

The essence of the proposed approach is the combination of “raw” and “expert” knowledge to acquire information that is necessary and genuinely useful for conducting an individual assessment of support needs for people with disabilities. In this process, the source being investigated is the knowledge base, and deductive approaches are employed. This way, not only knowledge about facts is discovered but also the relationships between them, which is related to organizing the knowledge base. The means applied for reasoning can also involve various logical levels.

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