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Explainable Ontology-Based Intelligent Decision Support System for Business Model Design and Sustainability

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Abstract: Background: Case-Based Reasoning (CBR) is a problem-solving paradigm that uses knowledge of relevant past experiences (cases) to interpret or solve new problems. CBR systems allow generating explanations easily, as they typically organize and represent knowledge in a way that makes it possible to reason about and thereby generate explanations. An improvement of this paradigm is ontology-based CBR, an approach that combines, in the form of formal ontologies, case-specific knowledge with domain one in order to improve the effectiveness and explanation capability of the system. Intelligent systems make daily activities more easily, efficiently, and represent a real support for sustainable economic development. On the one hand, they improve efficiency, productivity, and quality, and, on the other hand, can reduce costs and cut waste. In this way, intelligent systems facilitate sustainable development, economic growth, societal progress, and improve efficiency. Aim: In this vision, the purpose of this paper is to propose a new generation of intelligent decision support systems for Business Model having the ability to provide explanations to increase confidence in proposed solutions. Findings/result: The performance results obtained show the benefits of the proposed solution with different requirements of an explanatory decision support system. Consequently, applying this paradigm for software tools of business model development will make a great promise for supporting business model design, sustainability, and innovation.

Keywords: decision support system; business model; case-based reasoning; sustainability; explanation; ontology

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1. Introduction

Sustainability is fast becoming a need that has to be seriously confronted by decision-makers, enterprises, and consumers [1,2]. With the growing human population, environmental and social degradation is getting more severe and our options are diminishing [3,4]. However, technological advances towards sustainability are increasing rapidly, and many companies find it difficult to meet their sustainability goals. Therefore, to leverage sustainable solutions innovation on the business model level, it is indispensable to align incentives and revenue mechanisms [3,5].

Today, decision-making requires taking into account an increasing amount of data, information, and knowledge of different kinds and qualities in the various activities of the company; competitiveness depends on their analysis and optimal exploitation. As a result, managers are increasingly using Decision Support Systems (DSS), which are interactive computer-based systems planned to help decision-makers using communications technologies, data, documents, knowledge, and models to identify and solve problems, complete decision process tasks, and help make decisions; this is for the purpose to enhance a person or a group's ability to make decisions [6]. Decision support methods are designed to support decision-making processes concerning an extensive range of problems. When the challenge is the analysis of many often conflicting decision criteria [7–9], multicriteria decision analysis (MCDA) methods are used to help making the choice of the best compromise [7–9]. The Multicriteria Decision Aid (MCDA) is a field of the operational research discipline that manipulates complex decision-making problems handling high uncertainty and conflicting objectives [10]. Recently, the integration of MCDA tools into DSS has provided decision-makers with powerful capabilities in analyzing, exploring, and comparing a set of alternatives. Many studies have presented Multicriteria Decision Support Systems [7,11,12]. In fact, this paper suggests Intelligent Decision support systems that are the result of the fusion of Artificial Intelligence (AI) with DSSs. The intelligent decision support systems (IDSS) has helped in widening the window of current research and application in information processing and analysis. As a result, the systems are smarter, quite efficient, adaptable, and better able to aid human decision-making. The IDSSs are part of the AI with the main objective of filling the gap between decision-making tools and human interactions [13].

The power of Information and Communications Technology (ICT) is increased by AI and its constitutive elements of data, algorithms, hardware, connectivity, and storage, and this is a major opportunity for Sustainable Development. Recently, ICT branch is making the world's energy infrastructure more efficient, that is demonstrated in the Global e-Sustainability Initiative (GeSI) 2008. This initiative concluded that buildings and transport, smart grids, along with travel substitution could reduce global carbon emissions by a net 15% and save up to €600 billion by 2020 [14].

In 2020, the GeSI Smarter 2020 study found that the total abatement potential of ICT-enabled solutions in 2020 was about 9.1 gigatons of carbon dioxide equivalent (GtCO2e), a saving of ~16.5% of global GHG emissions by 2020. This is a saving of 21.6 billion barrels of oil and approximately equivalent as USD 1.9 trillion in gross energy and fuel savings [15,16].

In another view, digitization and dematerialization, depending fundamentally on existing technologies, substitute the need for a carbon-intensive product achieved 0.5 GtCO2e. Research mentioned that the reduction of emissions is 1.5 GtCO2e from the use of social media and networking (data collection and communication) and intelligent simulation, the automation of infrastructure, and industrial processes more broadly were shown to save 4.7 GtCO2e, while Systems integration—primarily building or industrial management systems and the use of less-carbon intensive, renewable energy technologies—saved 2.4 GtCO2e [16].

Artificial Intelligence has received increased interest from academic scholars. Therefore, it has to be understood as the ability of a system to act intelligently and to do so in ever-wider regions [17,18]. The arrival of AI is modifying a number of sectors, and it is expected to affect global productivity [19], environmental outcomes [20], and other areas, both in the short- and long-term. The authors of [21] argued that AI can enable the accomplishment of 134 targets across all the United Nations Sustainable Development Goals (SDGs).

The aim is to provide and manage intelligent products, services, and experiences through the sharing of information for cooperation or creation of optimal and sustainable value [22]. This branch of computer science can influence production and consumption patterns to achieve sustainable resource management according to SDGs outlined in the UN 2030 Agenda [18]. The growing of AI and the significant potential of development in the different sectors of society determine the evaluation of its effects on sustainable development [21]. For this reason, companies have to face the challenge of sustainability by improving innovations to preserve the use of natural resources and the integrity of the ecosystem [23–25].

In the past few years, the business model literature gave little importance to the social and environmental challenges facing the world today. The concentration was on market sustainability instead of social and environmental sustainability [26]. For instance, the authors of [27] argued that the "understanding of sustainable business models and how sustainable development is operationalized in firms is weak" [28]. Consequently, recent researches argued that developing sustainable business models is a strong way to combine the benefits of using business models and to search for the performance at the financial, social, and environmental levels. To integrate sustainability at their business, managers need instruments to perform change in their current business models [26]. This question of how managers can reflect on their business model has gained more interest in recent years [29]. Therefore, companies should benefit from existing methodologies developed over recent decades in operations research, complex systems analysis, and artificial intelligence. These techniques are increasingly used to develop sustainable solutions [30].

Many researchers have contributed to the area of business model design [31–33], innovation [34,35], and start-ups BMs [25]. They concluded that additional tools are needed to support the design and evaluation of BM, which has led to the development of computer-based tools. This potential is reflected not only in recent calls for business model development tools (BMDT) in the Information System (IS) discipline, but also in adjunct disciplines [36], in which the introduction of software-based tools has already successfully contributed to an improvement, among others, of the development of strategies and products. Software-based tools for strategy making enable easily to integrate and document information from various sources during the process of ideating and progressing such strategies [37].

While software-based BMDTs are said to have great potential to support their users in innovating BMs [38–40], especially with the use of AI techniques as machine learning [41], little attention has been given to providing highly accurate decisional guidance by creating trust in these AI-based DSSs [41]. The capability of an intelligent system to provide a meaningful explanation of its actions is a crucial factor affecting the acceptance of the system [42]. Consequently, this explanation is important to enable end users to understand, trust, and effectively manage their systems. Furthermore, the BMDTs have to focus on providing assistance to the user in being creative, which was neglected by existing BM design tools. The author of [37] suggested that BMDTs could incorporate functions for exploring business model patterns. The author of [43] has argued that the challenges of BM-related education involve the limits to creativity imposed by existing frameworks and the difficulty in prototyping new business models. The solution is to combine explanation and experience-based learning approaches into a virtuous learning cycle. Given such explanation capability, the user is more likely to accept the decisions, suggestions, or results provided by the system.

Therefore, with regard to business applications, the use of the BM ontology in an ontology-based CBR approach can be regarded as the next logical step. Unfortunately, no significant attention has thus far been paid to ontology-based CBR concerning the inclusion of BM ontologies. For this reason, this paper proposes an intelligent decision support for business models that offer highly accurate decisional guidance into account by integrating explanations for designing and innovating BMs, with a case-based reasoning approach that uses domain knowledge from the BM domain.

The remainder of this paper is organized as follows. Section 2 presents key concepts and definitions. Section 3 outlines literature on related works. Section 4 introduces the overall proposed system and main contributions of this paper and discusses the architecture of the proposed solution. Section 5 is devoted to the CBR process. Section 6 explains the implementation of the proposed solution, and its performance evaluation is depicted in Section 7. The last section concludes the paper and gives some perspectives for future enhancements of this solution.

2. Background

2.1. Decision Support Systems

Many types of computer-based information systems (IS) have been developed to support decision-making, including decision support systems [44]. DSSs were first developed in the 1970s, and have been used widely since the personal computer revolution in the 1980s. DSSs can be described as "computer-based systems that help decision-makers confront ill-structured problems through direct interaction with data and analysis models" [45]. They are designed to increase the speed and accuracy of data analysis, while reducing costs, enabling the effective and efficient analysis of large volumes of quantitative data. They were originally developed as tools for managers, but they are now also used by many non-management employees such as sales people and purchasing officers. They are particularly valuable tools in complex situations, where decision-makers need to analyze multiple sources of data [44].

Decision support methods are designed to support decision-making processes concerning an extensive range of problems. When the challenge is the analysis of many often conflicting decision criteria [7–9], multicriteria decision analysis (MCDA) methods are used to help the decision to make the choice of the best compromise [7–9]. The Multicriteria Decision Aid (MCDA) is a field of the operational research discipline that manipulates complex decision-making problems handling high uncertainty and conflicting objectives [10]. Recently, the integration of the MCDA tools into DSS has provided decision-makers with powerful capabilities in analyzing, exploring, and comparing a set of alternatives, many studies have presented Multicriteria Decision Support Systems [7,11,12].

Multicriteria Decision Analysis (MCDA) methods use an approach in which an expert in a given field defines the model, and then the decision variants are evaluated [10,13]. The author of [11] proposed a decision-making model based on already evaluated alternatives and stochastic optimization techniques, without the need to expert's interfering with the process. Classic methods of multicriteria decision analysis are used to analyze alternatives described by using numerical values, to solve the problem in decision-making methods in which the decision-maker makes decisions based on partially incomplete data. The author of [7] proposed a fuzzy models with partially incomplete data and in [12] proposed a technique for selecting and evaluating suppliers in an incomplete fuzzy using the fuzzy MCDM method, that provide more acceptable and efficient outcomes to select the best alternatives without the affection by the experts' inclinations.

The fusion of AI with DSSs has helped in widening the window of current research and application in information processing and analysis. As a result, the systems are smarter, quite efficient, adaptable, and better able to aid human decision-making. In order to develop systems, the most usable possible, in the 1990s, DSSs were enriched by techniques rooted in AI, particularly the introduction of a knowledge base into their architecture, so as to give the system the capacity for reasoning [46]. The literature survey in [47] presents the broad historical progression of DSS research. A number of DSSs were presented such as Model-driven DSS and Data-driven DSS, then the emergence of Communication-Driven DSS, Web-based DSS, and Knowledge-driven or Knowledge Based DSS (KB-DSS) that can suggest actions to the manager. The authors of [48] discussed recent advances, challenges, and evolution perspectives of KB-DSS.

2.2. Case-Based Reasoning

Case-based reasoning is a common methodology for humans to solve problems. Therefore, this methodology is well applied in business, while people do not know that they use this approach by default. Scholars highlighted that the case-based reasoning methodology, implemented in information systems, can be successfully applied in business [49]. It is an adequate methodology for experience management to support people who have to perform complex and knowledge intensive tasks. Case-based reasoning (CBR) is an AI approach that solves a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation [50]. CBR is based on the human cognitive model and is meant to mimic our way to think, predict, and comprehend. It has been used in many successful applications due to its psychological plausibility [51]. The principal idea of CBR systems is to store the experiences of people in the knowledge base as cases. When there is a new problem, we can search the knowledge base, finding the result of the past similar problem and the process of problem solution. Then, we can have an acceptable case as a reference. If the user is unsatisfied with the case, it can adjust the case to suit the current situation. Finally, this revised case will be stored in the case base [52]. CBR can be considered as a five-step problem solving process:

1. Case representation: a description of the current problem is input to the system;
2. Case retrieval: the system retrieves (similar) past cases from the case base relevant to solving the current problem.
3. Case adaptation: the system uses solution used for the previous case to generate target situation to the current problem.
4. Case Revising: the solution is validated through feedback from the environment or the user. It is tested in the real-world or using simulation.
5. Case Retaining: if appropriate, the validated solution is added to the case base for use in future problem solving.

The retrieve step consists of subtasks such as treat identifying features, initial match, search, and select [50]. Choosing indices is a critical step to CBR system, and three types of case indexing are used. In nearest neighbor approach, the retrieval system searches similar cases based on a weighted sum of features between cases. The inductive approach is based on the most important features. It indexes past cases affecting the outcome as induced from the data itself. In knowledge-guided approach, existing domain and experimental knowledge is applied to locate relevant cases [53]. Guidelines suggested for selecting indexing features include predictiveness, abstractness, concreteness, and usefulness [54].

2.3. Explanation of System Decisions

Furthermore, it is commonly known that in everyday human–human interactions, explanations are an important vehicle to convey information in order to understand one another. Explanations enhance the knowledge of the communication partners in such a way that they accept certain statements and allowing them to make informed decisions. It has long been recognized that increased user understanding of system reasoning may increase user confidence in an intelligent system's decisions [55]. CBR systems cases provide a natural vehicle for explanation. Unlike more opaque methods such as neural networks, CBR systems present the cases on which decisions are based, in this way the outputs are intuitively explained. Users can then compare the current situation to the prior cases to assess their applicability. Some CBR work considered the case as a sufficient explanation; recent work is developing a richer view [56]. In addition to providing arguments for the relevance of a case and a conclusion in the form of comparisons and contrasts [57], other research examines the facets affecting system conclusions, such as how features of a case contribute to similarity calculations to fulfill explanation [58].

2.4. Business Model

Today, research on business models is a rapidly growing field that is still in search of a strong theoretical foundation. The business model concept can be broadly defined as an abstract representation of business logic [59] that supports practitioners in conceiving, designing, and communicating business ideas, and serving as a reference framework [40,60,61]. The business model literature finds its roots in many research branches such as strategic management [62], technology and innovation management [63], or information systems [60]. Business models are considered by many as purposefully designed systems focus on identifying principles, patterns, elements, or configurations of successful business models [52].

IT Support Software and tools that support BM management have already been developed but are still in the earliest state of immaturity and are largely restricted to the design phase, by supporting the visualization of a BM [40,61]. However, recent research highlights that such "computer-aided business modeling tools should go beyond simple design tools and evolve into an own class of high-level decision support tools" [39,61]. This implies that software tools not only support design, but the overall process. Business model knowledge was represented by informal text [40,64], structured text [40,65], morphological representation [66], ad hoc graphical representation [67], conceptual models with defined semantics and dedicated graphical representations [33], and ontologies [32,40].

3. Related Work

Various research works have been carried out on information systems. In this paper, we are interested in research devoted to approaches used for DSSs. We focus more particularly our review on existing studies that aim at integrating explanation in DSSs and satisfying the design requirements. The reading of the literature review of our problematic case reveals that research in this area has taken a big step in the DSS domain. However, only few studies have focused on intelligent decision support system for the Business Model. To our knowledge, there is no DSS for BM that have the ability of providing explanations. In this section, we limit our review to the existing studies adopting the CBR approach and DSS having the ability to provide explanations, as our proposed solution combines these concepts.

3.1. DSS for Business Model

The first stream of BMDT scholars in the context of BM design and innovation focuses on modeling languages [37]. These languages facilitate analysis, communication, and documentation of business model ideas, especially using graphical notations to represent the basic logic and the most important elements of a business model. The "e3-value" language was proposed in [33]. It allows to capture and evaluate BMs from a financial point of view. The authors of [68] presented a toolbox design that offers a set of soft and hard methods for designing BMs. Business Model Canvas is a visual chart for developing new or documenting existing BMs [69]. Strategic Business Model Ontology (SBMO) is defined as a layer on top of the goal-oriented modeling framework. The authors of [70] proposed a framework composed principally of the strategic business model ontology (SBMO) for representing and analyzing business models and strategies. Moreover, scholars suggested a switch from the well-known business model canvas to a novel form of ontology that contain more in-depth information on a company's Business Model [71].

Further research focused on the use of analogies for product or process innovations to stimulate the generation of business model ideas, and researches noted that most "new" business models are a recombination of existing ideas, concepts, and patterns [72]. The authors of [73,74], generate BM in the form of catalogs of business model examples. Business model patterns was proposed in [72]. A set of four tools were developed by the INSPIRE project related to business model archetypes, which uses 55 Business Model patterns and serves as an inspirational tool to consider innovative value propositions and revenue models [75]. Scholars highlighted that these IT tools supporting the process of designing, innovating, and evaluating a company's business model are currently not leveraging the full potential of tool support [38].

Another research stream focused on validating the BM with analytical methods such as using modeling and simulation [60,76–78]. Simulations provide a time-efficient and cost-efficient way to help decision makers understand the consequences of business model adaptions without endangering an organization [79]. In [71,80,81], quantitative and qualitative scenarios analysis was applied to predict the viability of design decisions in the context of business model innovation. Other researches were interested by stochastic analysis of financial models to identify the most important drivers of financial performance [78].

A third research stream scholars used Artificial Intelligence techniques as machine learning with collective intelligence to validate the BM [41]. However, little attention has been given to provide highly accurate decisional guidance by creating trust in these AI-based DSSs [41,82]. If explanations about the decision process are given, the user is more likely to accept the decisions and understand the solution provided by the system. In addition, understanding the reasons behind decisions of black box decision systems is nowadays a crucial topic [83].

3.2. DSS and Explanation

During the last two years, the awareness for explanation-aware computing increased rapidly as a result of the growing call for providing an explanation to support the decision made [84]. The capability of a knowledge-based system to provide a meaningful explanation of its actions is a crucial factor affecting its acceptance [42]. Since the earliest promises of computing and artificial intelligence, the explanation power of intelligent systems has attracted growing interest in recent decades. In the late 1970s and 1980s, expert systems using knowledge bases [85] and production rules [86] were the first to integrate the explanation dimension, especially for medical decisions. Rule extraction was developed to interpret artificial neural networks (ANN) and support vector machines (SVM) from the 1990s to 2000s [87,88].

For recommender systems in the 2000s, researches showed that the acceptance of the recommendations was increased with explaining to the user why a recommendation was made [89–91]. Recent research focused on explanation methods for Bayesian Belief Networks [92], ontology-based explanation for ANN [93], and explanation in Case-Based Reasoning systems [56].

Explanation in Expert Systems, Bayesian Networks, and Case-Based Reasoning influenced later research on explaining intelligent systems. Furthermore, the recent interest in interpretable Machine Learning is not well connected to this body of work [91].

AI techniques and algorithms which generate explanations are characterized by the way they support human reasoning and how to represent explanations with visualization methods, data structures, and atomic elements. Similarity-based modeling technique seeks to group similar objects and identify distinguishing features to differentiate between objects. This technique uses the same method as people learning general concepts [94]. Various AI approaches have been developed, including similarity modeling with distance-based methods such as case-based reasoning [50] and clustering models [95], classification into different kinds as in supervised models [96], nearest neighbors [97], dimensionality reduction to find latent relationships such as collaborative filtering [98], principal components analysis [99], and matrix factorization [100]. Many of these methods are data-driven to match candidate objects with previously seen data (training set), where characterization depends on the features engineered and the model which frames an assumed structure of the concepts. Explanations of these mechanisms are driven by inductive and analogical reasoning to understand why certain objects are considered [94].

The growing field of eXplainable AI (XAI) in recent years was driven by DARPA's initiative to fund XAI in the 1970s [101]. There has been interest in explanations of intelligent systems with expert systems [85,102], Bayesian networks (for a review, refer to the work in [87]) and artificial neural networks in the 1980s [87], and recommender systems in the 2000s [89,90]. Recently, AI and machine learning are achieving major successes for several applications. However, machine learning algorithms need to be able to explain how they arrive at their decisions. Consequently, there has been increased attention into interpretable and eXplainable AI.

3.3. DSS and Case-Based Reasoning

Case-based reasoning (CBR) is a nature-inspired paradigm of machine learning capable of continuously learning from past experiences [103]. It uses already solved problems to solve a new one, and its working principle is reasoning by remembering. This principle implies that the reasoning used to solve a target problem is remembered. Thanks to the advantages offered by the CBR method, such as being able to deal with data with noise, missing data, unstructured data, and being closer to the human decision-making process than rule-based systems, CBR applications are various in almost every field of knowledge. In addition to medical diagnosis [104], e-commerce [105], bankruptcy prediction [106], scheduling and process planning [107,108], customer classification [109], fault diagnosis [110,111], prediction of information system outsourcing success [112], concurrent product design [113], risk analysis [114], knowledge management [115], and military control [110], CBR can also be applied to mine big data [116].

The CBR system can use three types of ontologies [117]:

1. Domain ontologies providing the vocabulary for describing a domain and interpreting a description of a problem in that domain,
2. Task ontologies providing the vocabulary for describing terms involved in the problem solving processes,
3. Common sense ontologies including a wide range of foundational knowledge as time, space, or causality [118].

To the best of our knowledge, CBR systems have not been used in DSS for Business Model. However, CBR is well adapted to this context because it leads itself easily to reasoning about context and situations by storing and remembering specific episodes (situations), and it has been suggested as a candidate for computational reasoning about situations [119]. Due to the creativity and diversity of Business Model cases and the lack of associated knowledge retrieving and intelligent systems, this paper aims at the design and implementation of a CBR system for Business Model design and validation. The structure of CBR systems allows the user to consider the relation between cases, which is important for an explanation [120]. The CBR technique is based on examples and a means of assessing the similarity or differences between examples. Consequently, the explanation of the recommendation given by the decision support system is done by presenting similar cases that motivate the recommendation.

In summary, there were three major limitations in the previous studies:

1. The few proposed DSSs for BM do not assist the user in the first idea of the project.
2. The DSSs for BM lack of explanation about how the system reaches the solution. Based on the preliminary review on the various scholars, this study aimed to develop a CBR-based decision support system for the design and validation of the BM.
3. Scholars indicated that such IT-based guidance might be perceived as missing the in-depth support of personal mentors [41]. For that, the proposed knowledge based system includes all in-depth knowledge about BM in the form of ontology.

3.4. Intelligent DSS and Sustainable Development

For the social impact, AI enables all the targets by supporting the provision of water, food, health, and energy services to the population. Moreover, it supports low-carbon systems, for instance, by underpinning the creation of circular economies and smart cities that efficiently use their resources [121,122]. AI integrates variable renewables by facilitating smart grids that partially match electrical demand to times when the sun is shining and the wind is blowing [121]. For the economic outcomes of, the AI has positive impact associated to increased productivity and consumption reduction.

Environmental benefits of IA are that with analyzing large-scale interconnected databases enabling to develop joint actions aimed at preserving the environment. AI advances can support the understanding of climate change and the modeling of its possible impacts. Furthermore, it can support low-carbon energy systems with high integration of renewable energy and energy efficiency, which are all needed to address climate change [121,123,124]. Neural networks improve the classification of vegetation cover types based on satellite images, with the possibility of processing large amounts of images in a short time [21].

AI has revolutionized the ways of doing business [125]. It has influenced trade and management practices in number of sectors that offer increasingly competitive and sustainable products or services [18,126]. Indeed, the interaction between artificial technologies and human intelligence is based on algorithms that should help managers make the right decisions, generating a cultural drift in which a large number of data, connections, and interactions become part of the standard management of organizations [125]. They have well-cataloged and organized information sets, so much so that previous research has even shown that in many situations, these models are more efficient than human decisions [127]. These mathematical models simplify the work of managers [18].

Knowledge Management Systems (KMS) promote the management of intelligent work [128], as they put together organizational, human, and technological factors in the process of creating value through the sharing of knowledge [129]. KMS exploits AI for the improvement of operational processes and business models [130].

From a business model view, sustainable change can be reassured through the renewal of the corporate purpose and organization, oriented by innovation strategies that point toward the creation of long-term value [131,132]. A business model provides a "concise representation of how a related set of decision variables in the areas of business strategy, architecture and economics are addressed to create a sustainable competitive advantage in markets" [133]. A BM draws the boundaries of the operational and physical structure of the company, presaging the consequences of corporate operations in the system architecture, encouraging sustainable choices through innovative strategies for the creation of value [134].

Thus, profitability and sustainability at the business level represent two major objectives that have to be integrated into company's strategy. They are not antagonistic concepts; they can work together in order to develop and improve business models. Moreover, considering the state-of-the-art in the field of business models, during the last 20 years, the BMs were reinvented based on the challenges generated by the international business environment [135].

The use of AI in Sustainable BMs (SBMs) can support managers' choices in decision-making and management processes through the use of data to make forecasts and reducing the cost of projections themselves, encouraging a change in the culture and behavior of organizations [136]. Thus, profitability and sustainability at business level represent two major objectives that have to be integrated into company's strategy. They are not antagonistic concepts; they can work together in order to develop and improve business models. Moreover, considering state of the art in the field of business models, during the last 20 years, BMs were reinvented based on the challenges generated by the international business environment [135].

4. The Overall Structure of EIDSS-BM

Most enterprises agree that knowledge is an essential asset for success and survival on an increasingly competitive and global market. This awareness is one of the main reasons for the exponential growth of knowledge management in the past decade. Our approach to BM design is based on ontologies, and makes knowledge assets intelligently accessible to people in organizations, that knowledge resided only in the heads of people.

The system allows decision-makers to assess, understand, measure, change, communicate, or even simulate their business models and allow them to introduce changes and experiment with it in order to learn about business opportunities. The system allows offers a visualization tool of the actual business model of a firm and, on the other hand, equally allows the representation of virtually possible business models. This would facilitate innovation and could also help managers understand the business models of competitors. The past cases of BM are well cataloged and organized that simplify the design of the BM by decision makers. Then, based on the adaptation phase of the CBR system, a new business model could be suggested. By using a number of iterations for learning, managers can do risk-free experiments without endangering their organization.

The system assists decision-makers by providing knowledge about environmental production and reverse logistics processes, hybrid products (integrated and associated services) focusing on sustainability ideas in order to open up new markets for sustainable products, innovations about how companies preserved, and improve the use of natural resources and the integrity of the ecosystem.

This is a pioneering work for creating a case base ontology of Business domain (Business Models) for CBR systems. The initial idea of the Intelligent Decision Support System for Business Models (IDSS-BM) has been discussed in [82].

Our contribution consists of an explainable and Intelligent DSS (EIDSS-BM) for BM design. This is motivated by the fact that unstructured intangible experiences and knowledge are usually difficult to represent and instantiate, which engenders the hardship of knowledge transfer and sharing. This system presents a new paradigm of the CBR based on ontology. It consists of retrieving, reusing, revising, and retaining cases and has been proved effective in retrieving information and knowledge from prior situations. The system handles well the integration of the prediction of the success of the BM to more explanation and guidance for the decision-maker.

Ontology-based CBR is an approach that combines, in the form of formal ontologies, case-specific knowledge with domain one in order to improve the effectiveness and explanation of the system. The authors of [137] combined CBR, Rule-Based Reasoning (RBR), and ontology to develop a solution retrieval system for fault diagnosis. An ontology-based CBR information retrieval system method that integrates CBR and natural language processing (NLP) techniques for metro accident case retrieval has been proposed in [138].

Consequently, case-based reasoning system can benefit from ontology-based knowledge representation. This gives the possibility to reuse existing domain knowledge about business models during the execution of the case-based reasoning cycle. Applying this paradigm to software tools of business model development has great promise for supporting business model design and innovation. Moreover, case semantic retrieval algorithms can be improved by using case-base and domain background knowledge in the form of ontologies, and our approach uses the Business Model Canvas for this purpose.

4.1. Architecture of EIDSS-BM

Many CBR architectures have been presented in the literature [50,139]. Inspired by these architectures, EIDSS-BM architecture is composed of three layers: a data layer, a processing layer, and an application layer as shown in Figure 1.

The data layer contains three main containers: vocabulary, case base, and similarity measures. In knowledge-intensive CBR Systems, ontologies play an important role in representing these containers. They can be used as the vocabulary to describe cases and/or queries, as a knowledge structure where the cases are located, and as the knowledge source to achieve semantic reasoning methods for similarity assessment [140]. The vocabulary and the case base rely on two knowledge models, the domain and case models are respectively presented above.

The processing layer is the core part of the system. The proposed system aims to design BM and aid managers in their decisions. Many types of contextual information cannot be easily inferred [141]. Based on the BM ontology model, the CBR module is used for suggesting the design of BM following four steps which are feature selection, case retrieval, case matching, and case updating. The CBR module is able to obtain the different alternatives of the BM because it exploits historical cases being actually happened.

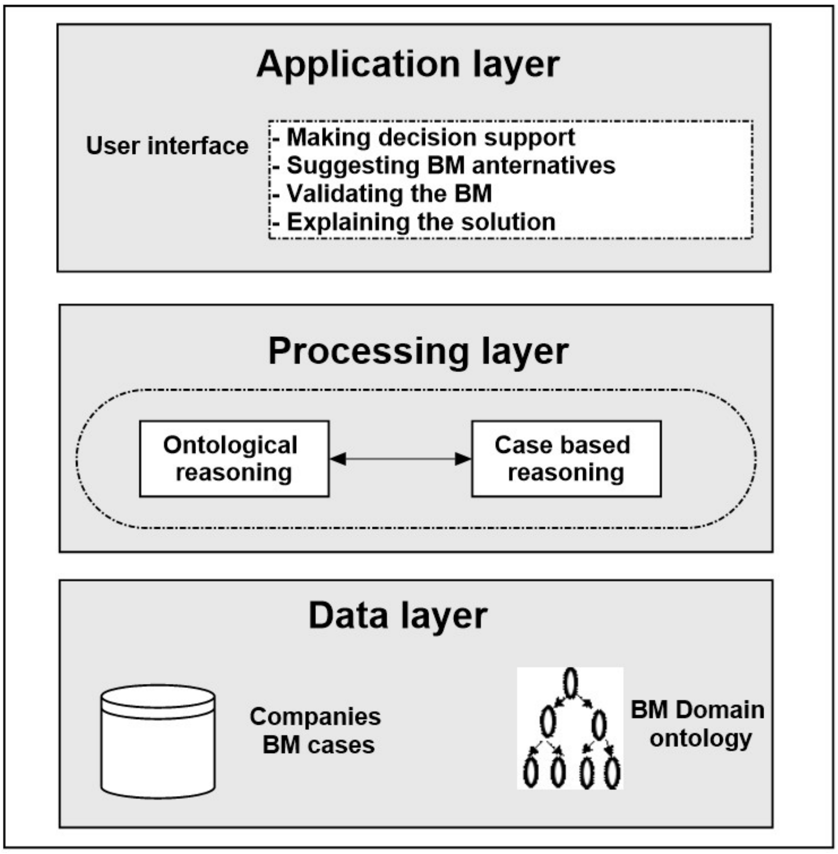

Figure 1. EIDSS-BM architecture.

4.2. Domain Model

In the CBR system, ontology plays two main roles: the first as case base and the second as domain ontology. The combination of ontologies for domain and case base will achieve the Knowledge-Intensive CBR (KICBR) [31].

The domain model is represented by ontologies which contain the vocabularies, concepts, and relations for representing knowledge concerning Business Models. Following the classification proposed in [142], we have developed two types of ontologies: a core ontology that contains the different parts of the business model in more detail for a deeper understanding such as the value proposition that is the central characteristic of a business model. This ontology provides the formalization of elements, relationships, vocabulary, and semantics of the essential knowledge about BM domain. This ontology is built on BMO illustrated in Figure 2. It contains knowledge about the four main pillars of a BM which are the products and services that a firm offers, the infrastructure and the network of partners, the relationship capital, and the financial aspects [143].

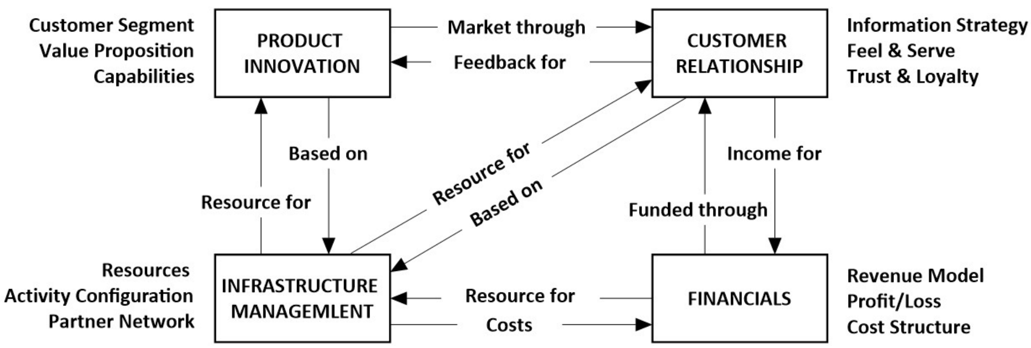

Figure 2. E-Business Model Ontology e-BMO [143].

The value proposition settles the value that is delivered to the customer, which can be a product, a service, or a combination of both [144]. Nevertheless, when choosing which value should be delivered, the customer and provider have to rely on their competences and resources. The organization model analyzes the capabilities or skills and the firms role in the value chain. If the provider is not able to take over the tasks or services he is obliged to by the value proposition, he cannot offer a certain business model. Therefore, value proposition and organization model have to be considered at the same time as they form the backbone of a business model [145].

A domain ontology describes the domain of BM Components. This part of the ontology is built on the BM ontology BMO [32], which is an important contribution to the theory and practice of business models. Its concepts are specializations of other concepts of the core ontology, after collecting information about the business model of startups and technology companies, including attributes and relations of companies, people, and investments. Moreover, the reuse of ontologies from a library also benefits from their reliability and consistency. The more knowledge is embedded into the system, the more effective is expected to be.

4.3. Case Model

The present paper considers BM experience as cases in the sense of case-based reasoning. The CBR framework can be used to retrieve historic BM from a knowledge base, the case base, which is represented as an ontology. It is built on the business model ontology BMO [32] which is an important contributions to the theory and practice of business models.

The proposed BM-ontology includes the important terminology used for the representation of cases in CBR systems according to the methodology described in [118]. A case, in general, is described by a pair (problem, solution) containing problem attributes and solution attributes. Accordingly, the enterprise description part of our model corresponds to the problem part, and the BM part corresponds to the solution part. Therefore, the two main parts are a description part describing the context and the enterprise and a BM part describing the different possible values of the components of a BM. Inspired from the approach of CBR ONTO [118], in order to enhance the communication between the case base and the domain model, the case model is represented within an ontology that integrates the domain model.

This ontology, illustrated in Figure 3, contains the main following concepts:

1. CBR-CASE that subsumes the various case types that may exist in the System;
2. CBR-DESCRIPTION that subsumes the case main parts company description (name, number of employees, country), and BM components (value proposition, customer segment, key resources, customer relationship, key activities, cost structure, key partners, revenue stream).
3. CBR-INDEX allows to integrate the domain model concepts used to describe cases. The central characteristic of a business model which was identified in the literature is the value proposition. It is analyzed by the majority of scholars that regard business model components [146]. The value proposition settles the value that is delivered to the customer, which can be a product, a service or a combination of both. Nevertheless, when choosing which value should be delivered customer and provider have to rely on their competences and resources [32,145].

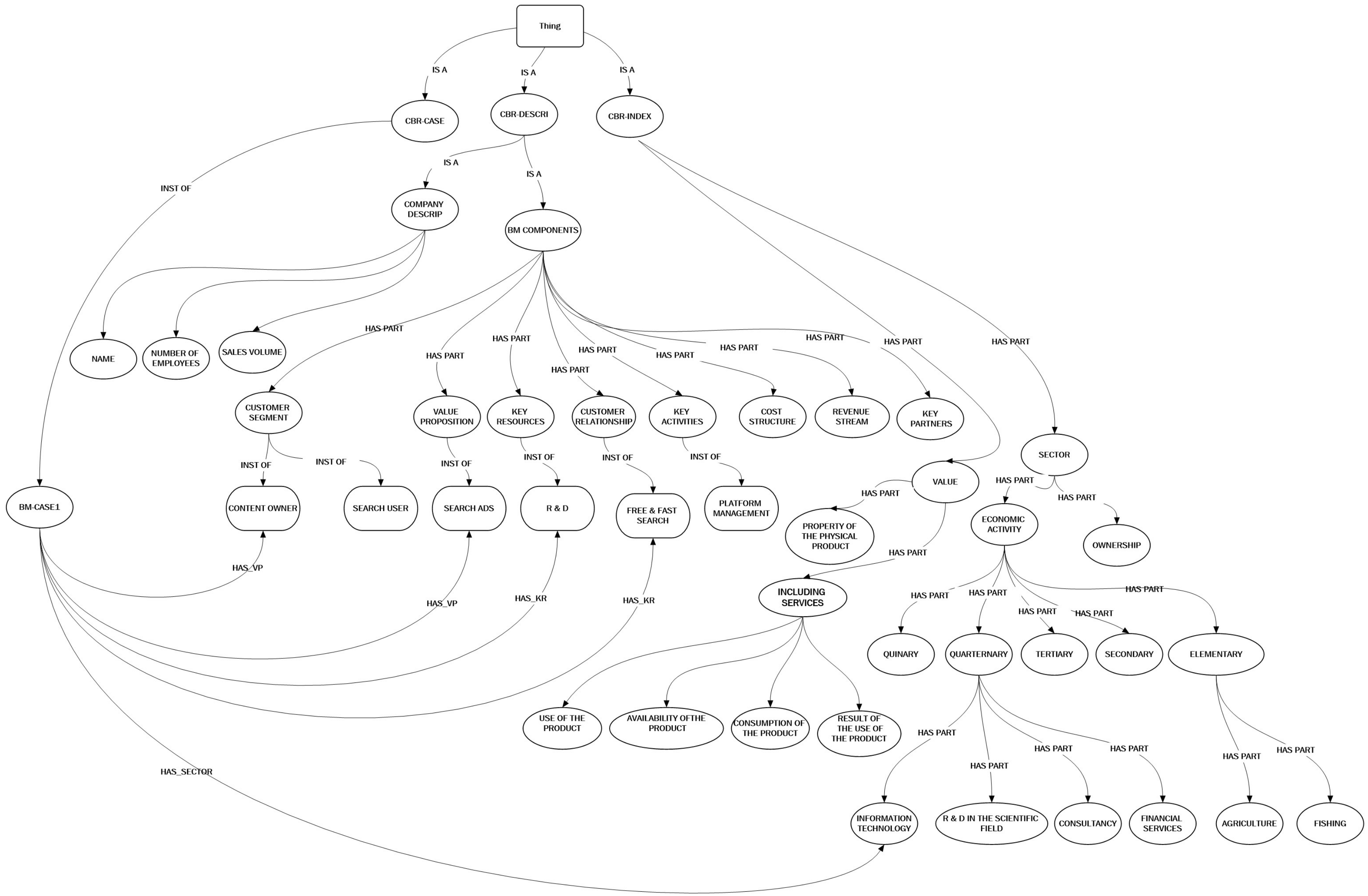

Figure 3. The case model ontology.

5. The CBR Process

The CBR, proposed in [147], can simulate human cognitive processes and integrates empirical knowledge of different fields into a unified format [45]. The CBR can achieve effective and accurate BM design. This is because that CBR can obtain and suggest BM components and innovation methods as long as cases are able to be matched successfully in the case base. Furthermore, CBR can also exploit historical cases which have actually happened and have been solved, to ensure accuracy.

The process of CBR-based EIDSS-BM is shown in Figure 4. Industry, Year of foundation, Number of employees, and Country are selected as feature indexes for calculating case similarities in the case base. The project is selected as an essential feature if case matching is successful then the BM components of the matched case are displayed directly. Then case updating is evaluated, and if successful then the case base will be updated, else the CBR process will end. When the similarity value is less than the desired value, the system will fail and the process will end.

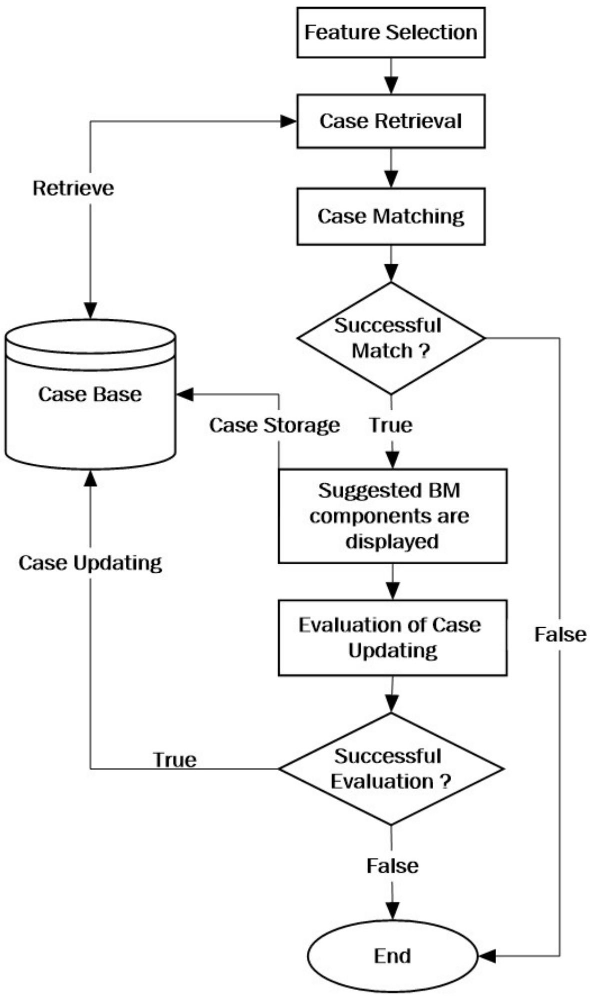

Figure 4. The CBR Process in EIDSS-BM.

5.1. Case Retrieval

Case retrieval refers to searching the business model case base based on Industry, Country, and Year of foundation. The system uses ontologies as a persistent media for the cases. The ontology defines the type and values of the attribute of the case. User defines the problem by entering information regarding Industry, Country and Year of foundation. The case retrieval engine module takes the created semantic query vector generated and searches for the most similar *k* cases in the case base ontology. The solution space consists of a list of alternatives of business models for the current project type, results and benefits with each of them.

5.2. Case Matching

The nearest neighbor algorithm was used to calculate the similarity value [46]. Its formula is given in Equation (1).

$$Sim(C_i) = \sum_{j=1}^{m} (w_j * Sim(C_{ij})) \tag{1}$$

where i is the sequence number of the case in the case base. $Sim(C_i)$ is the similarity value between the target case and the ith case. j is the sequence number of the feature index. m represents the numbers of all feature indexes. w_j is the weight of the jth feature index. $Sim(C_{ij})$ is the similarity value between the jth feature of the ith case and the target case.

The threshold of $Sim(C_i)$ is set as $Sim(C)$, which means that the case-matching is invalid when $Sim(C_i) < Sim(C)$; otherwise, case-matching is successful. The value, w_j, is directly defined by system experts together with domain experts.

5.3. Case Updating

When case matching is achieved successfully, the actual business model results can be saved into the case base.

5.4. Explanation

The ability of any software system is improved by increasing its understandability, which in turn can be supported by appropriate explanation capabilities [120]. We follow Schank [148] in considering explanations the most common method used by humans to support understanding and their decision making. In everyday human–human interactions explanations are an important vehicle to convey information in order to understand one another. Explanations enhance the knowledge of the communication partners in such a way that they accept certain statements. They understand more, allowing them to make informed decisions.

Ease-of-use is of high priority for the development of myCBR applications integrating explanations into the user interface. In order to increase transparency and trust in the retrieval process [149], myCBR creates an explanation object for each case during similarity calculation.

Increased user understanding of system reasoning may increase user confidence in an intelligent system's decisions, thanks to CBR systems cases that provide a natural vehicle for explanation.

In case-based reasoning, conceptual explanations are used to explain the vocabulary knowledge container. Backward explanations make clearer and justify the outcome of a particular retrieval result and provide means for understanding the results of a similarity calculation [150].

5.4.1. Conceptualization Goal

A conceptual explanation is a comprehensive description of a concept. It answers questions about concepts, about terms and concepts of ten arise for the end user when he or she is not familiar with the application domain. It consists of a definition, some examples, and references to further characterizations, for which any kind of medium can be used (e.g., text, images, audio, and video). Conceptual explanations are inherently static, because concepts usually do not change. However, there are good reasons to consider the context in which the concept is used and the user's personal level of knowledge [151].

5.4.2. Transparency Goal

The user could ask how the system reached the conclusion presented, and an explanation in the form of a reasoning trace from the system would be presented. This allows the users to check the system by examining the way it reasons and allows them to look for explanations for why the system has reached a surprising or anomalous result. The use can ask the question "How did the system come to the similarity assessment of a particular case?" when he/she wants to retrace the procedure of similarity assessment, thus achieving the transparency goal.

5.4.3. Justification Goal

The justification goal is closely related to the transparency goal. Where transparency is concerned with presenting the reasoning trace, justification deals with the ability to explain why an answer is good. Justification is often preferable over transparency, as simply displaying the reasoning trace is not always sufficient and can even be counter productive [74,119]. With regard to Explainable Artificial Intelligence (XAI), CBR is particularly interesting because similar cases can be used as examples for justifying the reasoning of the system. This can be considered as an interpretable model.

However, in terms of explanations, most CBR systems are limited to the display of similar cases. Compared to "black box" algorithms such as deep learning, the responses of CBR systems can be justified easily using similar cases as examples. The user can have in mind the question "Which are the most similar aspects of a case? Which are the least?", so the answer explains in which way the case is similar to the query and thus achieving the transparency goal.

6. EIDSS-BM Implementation

6.1. Overview

myCBR is an open-source plug-in for the open-source ontology editor Protégé [152]. Protégé is an extensible Java-based tool that provides a plug-and-play environment making it a flexible base for rapid prototyping and application development [153]. It allows defining classes and attributes in an object-oriented way. Furthermore, it manages instances of these classes, which myCBR interprets as cases [151]. Therefore, the handling of vocabulary and case base is already provided by Protégé. The myCBR plug-in provides several editors to define similarity measures for an ontology and a retrieval interface for testing [154]. The main goal of myCBR is to minimize the effort for building CBR applications that require knowledge-intensive similarity measures.

To develop a CBR system, various programming tools are available both freely and commercially. Among these, myCBR and jCOLIBRI are the most widely used and known frameworks for teaching and academic research purposes. myCBR has a number of features and provides a very easy way to develop case-based reasoning applications. It supports fast prototyping and combining state-of-the-art CBR functionalities. It can work as a standalone and also as a plugin of Protégé.

6.2. Implementation

Three steps are required to develop a CBR application:

- Generation of case representations.
- Modeling similarity measures.
- Testing of retrieval functionality.

Generation of case representations:

One powerful feature provided by myCBR is the easiness of the case representation by CSV data import module [154]. CSV files are widely used to store attribute-value based raw data in pure ASCII format. Using the CSV importer, the user has the choice to import data instances into an existing Protégé data model, or to create a new model automatically based on the raw data. Figure 5 shows how Business Model dataset is arranged in a CSV file. myCBR allows also slots to be added manually using Protégé. Figure 6 shows myCBR screen after importing the dataset into a new class Business Model which will be used as query and case values for retrieval step.

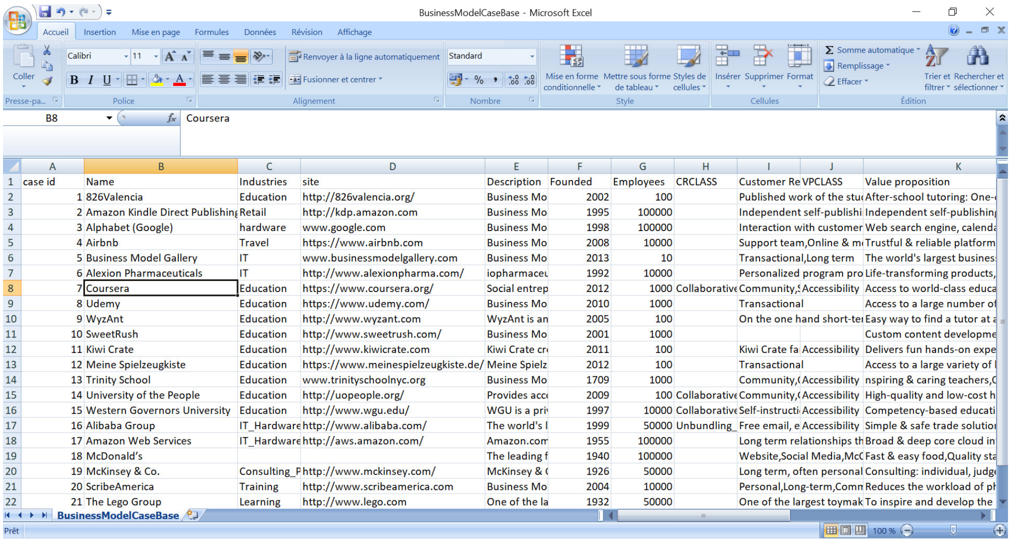

Figure 5. Business Model Dataset in a CSV File.

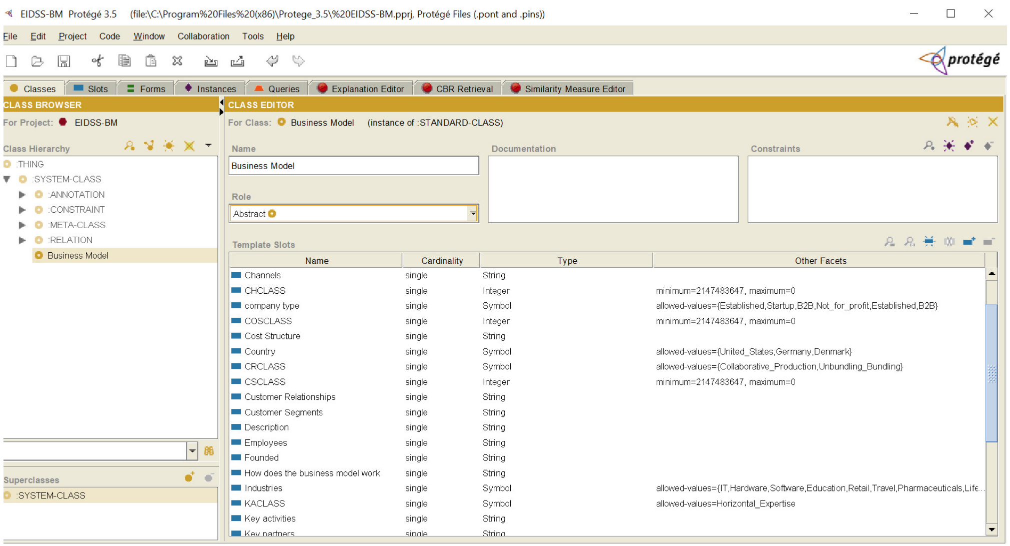

Figure 6. Business model Case Data Representation in myCBR.

Modeling similarity measures:

After having generated the case representation by using the CSV importer, the main task for creating a CBR application with myCBR is the definition of an appropriate similarity measure. Here, myCBR follows the local-global approach which divides the similarity definition into a set of local similarity measures for each attribute, a set of weights, and a global similarity measure for calculating the final similarity value. Figure 7 shows one of the implemented similarity measures.

There are several similarity modes, to choose between depending on the type of the slot. In our example, the slots values of the industry can be arranged in a hierarchical form and the taxonomy as similarity mode was used.

The resultant structure specifies parent–child relations through the position of the objects in the taxonomy. This means that a node has at least the same attributes its parent node has. For instance, "Learning" is also "education" and the real-world sectors are "learning" and "training". Therefore, "education" is an abbreviation for all companies with "industries" being "Learning" or "Training". This choice enhances the retrieval results.

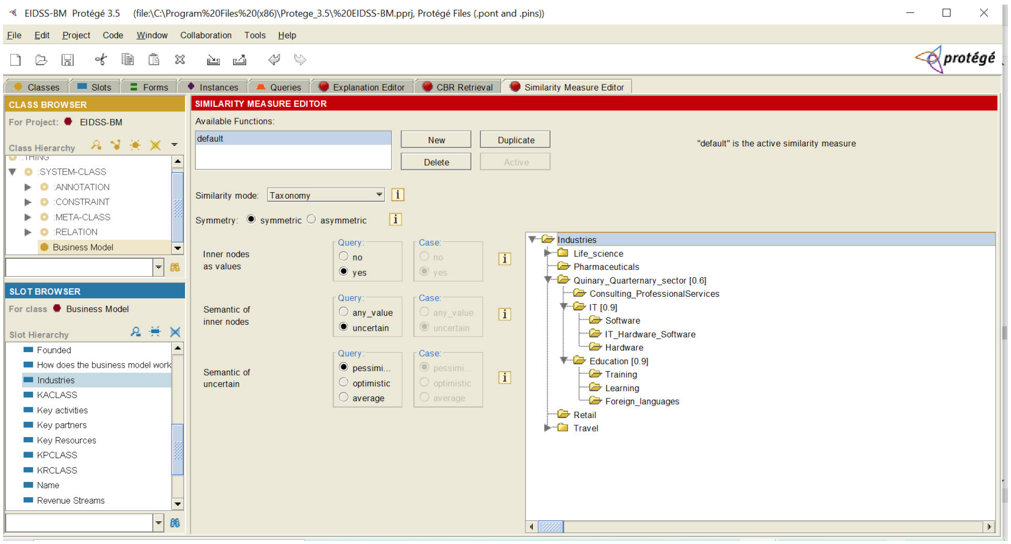

Figure 7. Similarity editors for symbolic attributes with taxonomy editor.

Testing of retrieval functionality:

Figure 8 gives a schematic overview of the Retrieval GUI. The names of the classes' attributes are presented with the rows of the table. The area is divided into several columns. The left most column is used for query specification. The others are used to show the retrieval results. The rightmost column lists all cases of the case base ordered by their similarity to the query.

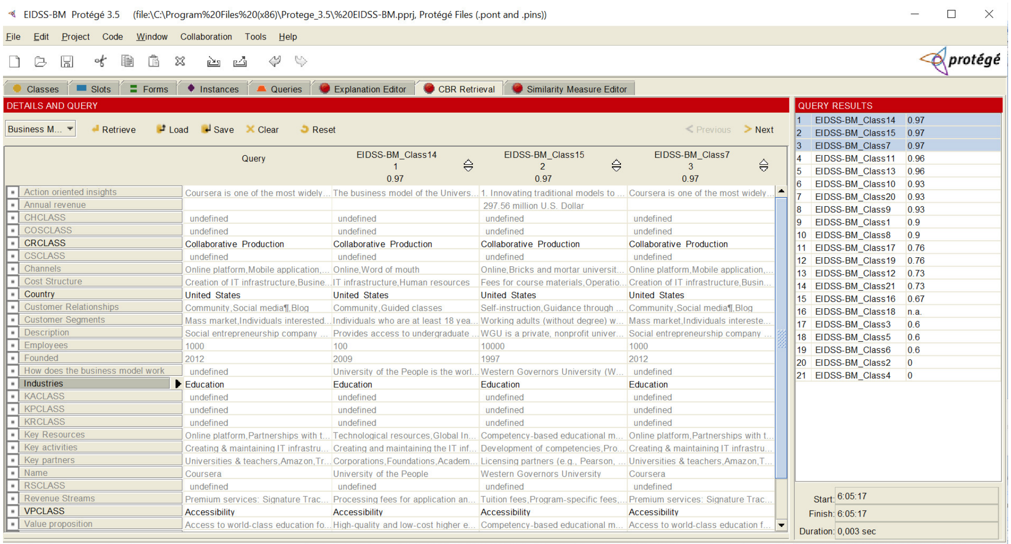

Figure 8. Retrieval of a case query.

myCBR includes an easy to use GUI for performing retrievals and for analyzing the corresponding results. By providing similarity highlighting and explanation functionality, after the initial knowledge model was created, a number of retrieval experiments using the myCBR were performed. We tested the 22 records that are in the case base and only one missed case is obtained. Figure 8 shows one query of these records after retrieving the most similar cases.

Enhanced retrieve using ontology:

A domain-specific ontology or user-defined ontology represents specific domain knowledge or relation between words using class and subclass [155]. Terms of a case can be compared with other cases by exact matching. However, some slots like the "industries" of the company can have a relationship with other synonyms or industries. The weight of such terms can be increased automatically using a domain specific ontology defined by experts. For example, the term "education" is related to "learning" and "training", and it is more similar to some industries, so that enhance the result of the user query.

6.3. Implementation of Conceptual Explanations

Conceptual explanations are addressing the system end users. They are interested in retrieving the most similar cases to their queries. At the bottom of the retrieval GUI, conceptual explanations are shown when the user hovers the mouse over a table cell. Figure 9 shows a snapshot. Conceptual explanations do not involve complicated algorithms. The required functionality at its core is a static mapping from concepts to explanations.

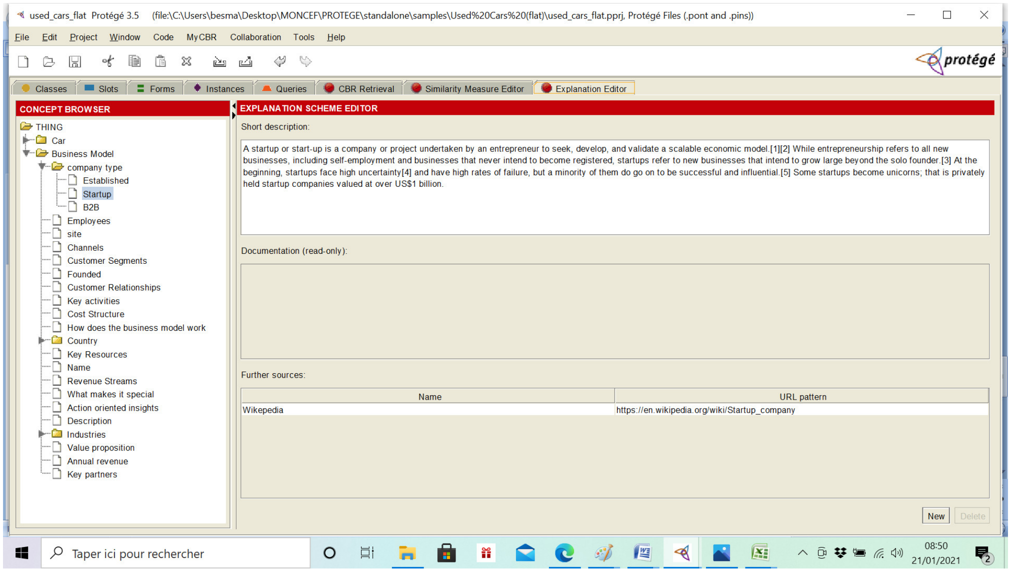

Figure 9. Conceptual explanations.

The figure displays all concepts of the ontology. On the right-hand side, one can edit its explanation like a short description and a list of URLs of further documents. For example, the "start up" in companies can be explained via Wikipedia or Google define.

6.4. Implementation of Backward Explanations

6.4.1. Implementation of Transparency Goal

For a query, the system delivers a ranking of the case base. However, the retrieval result may be quite surprising and need some explanation. To answer this question "How did the system come to the similarity assessment of a particular case?" The system offers a detailed recording of the retrieval process. Therefore, every step of similarity calculation can be traced. To increase transparency, myCBR creates an explanation object for each case during the retrieval. This tree-like data structure stores global and local similarity values as comments for each attribute.

6.4.2. Implementation of Justification Goal

The answer of the question "Which are the most similar aspects of a case? Which are the least?" The notion of aspect must be clarified, an aspect is one single attribute. The similarity of an aspect is then a local similarity value and can be displayed with myCBR.

7. Testing and Evaluation

After implementing the proposed EIDSS-BM, its performance has been evaluated. The purpose of the evaluation process is to get the end user's views on the significance and usefulness of the system.

The primary data used in this research are based on the dataset of the “Business Model Gallery” [156] that is a publicly available database on business models, as a resource for learning about different BM designs. In this database, BMs from all kinds of industries are explained allowing to learn about various patterns. This project aspires to capture the power of analogies by being a place for inspiration but this system do not use the case-based reasoning. It provides a variety of details including the company information about the industry, employees, foundation, country, company type, the annual revenue, and the different values of the BM components.

7.1. Performance Metrics

We use the following performance metrics for the evaluation of the system:

NCases: The number of cases contained in the case base over time is very important. It is desirable to enrich the case base while preserving or even increasing precision.

As in [157], for effectiveness, we examined the relevance of the retrieved cases given a test case. The retrieval effectiveness can be defined in terms of *precision* and *recall* rates.

Precision: The percent of retrieved cases that are similar to the new case ($N_{Correct}$) among the total number of retrieved cases ($N_{Correct} + N_{false}$).

Recall: The percent of retrieved cases by the system, which are similar to the new case ($N_{Correct}$), among the total number of cases actually similar to the new case in the case base (N_{Total}).

$$precision = \frac{N_{Correct}}{N_{Correct} + N_{false}} \tag{2}$$

$$recall = \frac{N_{Correct}}{N_{Total}} \tag{3}$$

where $N_{Total} = N_{Correct} + N_{Missed}$ denotes the total number of tagged cases that are similar to the new case and $N_{Correct}$ denotes the number of retrieved cases that are similar to the new case. N_{false} is the number of retrieved cases that are dissimilar to the new case and N_{Missed} is the number of tagged cases that are similar to the new case but not retrieved.

7.2. Comparison between the EIDSS-BM and the Business Model Gallery

The system’s performance has been evaluated in terms of *precision* and *recall*, which are two common metrics used to estimate the efficiency of the information retrieval in a CBR system. *Precision* is the fraction of a searched output that is relevant to a particular query. It represents the proportion of the relevant retrieved cases to all the retrieved cases and the less irrelevant cases are retrieved the better the precision will be. Therefore, the calculation requires knowledge of the relevant and non-relevant hits in the evaluation set of cases. *Recall*, on the other hand, measures the ability of a retrieval system to obtain all or most of the relevant cases from a collection of cases (case base). It represents the proportion of relevant cases retrieved to all the relevant cases in the case base. The more relevant cases are retrieved the better the recall will be. Thus recall requires knowledge not just for the relevant and retrieved cases but also those are not retrieved yet relevant.

To evaluate the correctness of the retrieval function, the CBR retrieval test is performed. For that test, relevant BM cases (from the case base) should be identified for each test case. For identification of relevant cases, test cases are given to the domain expert in order to assign possible relevant cases (from the case base) for each one. Then, the precision and recall are evaluated. Table 1 summarizes the results of this process where test cases are {Case 7, Case 40, Case 51 and Case 62} and for each one, the set of relevant cases identified by the expert (from the case base).

Table 1. Relevant cases assigned by domain experts for sample test case.

Test Case	Relevant Cases from the Case Base
Case 7	Case 9, Case 10, Case 8
Case 40	Case 18, Case 22, Case 7, Case 8, Case 9, Case 10, Case 11, Case 12, Case 13, Case 14, Case 15, Case 20, Case 21, Case 3, Case 5, Case 6 , Case 16, Case 17, Case 19
Case 51	Case 53, Case 54, Case 61, Case 68, Case 75, Case 81
Case 62	Case 55, Case 57, Case 69, Case 72, Case 71, Case 59

Once the relevant cases are identified and assigned to the test cases, the next step is the performance evaluation of the retrieval function. The *precision* and *recall* values of the CBR system retrieval function are calculated according to a threshold value. For this study, the similarity interval [0.6, 1.0] is adopted. This means threshold = 0.6 and cases with global similarity score greater than 60% are retrieved.

In the second phase, the evaluation has been done to judge the system performance on retrieving relevant cases. The *precision* and *recall* are calculated comparing the Business Model Gallery against our retrieval method enhanced with knowledge. For the evaluation, four test cases as query are created. The comparison results between the two systems in terms of *precision* and *recall* are stated in Table 2 where 0.6 is considered as a threshold value. The results from Table 2 indicate that the *average precision* of four test cases for the Business Model Gallery is 81.5%, whereas our enhanced system has better *average precision* of 95%. In the same way, the *average recall* for EIDSS-BM is 95.5%, whereas the Business Model Gallery has a lower value of 46%. On the whole, the results suggest that the enhanced system performs better in terms of *precision* and *recall* in this CBR system. Results demonstrated that CBR provides an effective approach to solving and suggesting BM. Further research in this particular area will continue to investigate more advanced features.

Table 2. Experimental results comparing two systems in terms of precision and recall.

	EIDSS-BM		Business Model Gallery	
	Recall	*Precision*	*Recall*	*Precision*
Problem 1	94%	100%	52%	100%
Problem 2	94%	100%	31%	33%
Problem 3	94%	100%	68%	93%
Problem 4	100%	80%	33%	100%
Average	95.5%	95%	46%	81.5%

8. Conclusions

In this paper, we are interested in the AI contributions to the Sustainable Development through an explainable intelligent system for BM design. Therefore, digital technologies can help designing BMs, increasing productivity, reducing production costs and emissions, decreasing the intensity of production process resources and improving correspondence in markets.

This paper has presented the first version of the CBR-based EIDSS BM. Our approach to the explainable decision support system for BM design is based on ontologies, and makes knowledge assets intelligently accessible to people in organizations, that knowledge resided in the heads of people only. The valuable knowledge of experts in past business models for many case studies is capitalized, which enables reusing existing domain knowledge as well as the transferring and sharing of knowledge. Consequently, applying this paradigm for software tools of business model development will make great promise for supporting business model design and innovation sustainability.

We presented our contribution which led to the development of new generation of intelligent decision support systems for Business called "Explainable Intelligent Decision Support System for Business Model" that takes highly accurate decisional guidance into account by integrating explanations for designing and innovating business models. We presented also a domain-independent CBR platform. The development of a new CBR system is done by providing its domain ontology. Our proposed solution can be used for two parallel objectives: to capitalize knowledge about BM, and to provide support to experts and Business students to design, innovate, and validate their BMs. Experts can use any concept or instance of the domain model to describe their cases.

Future work: For future research direction, we plan to develop a Rule-Based Reasoning module to predict the success of early-stage BMs. The SWRL language could be used to express the determinants of success of companies' rules, based on the analysis of classes and properties in the BM ontology model. Furthermore, the ontology development is a time-consuming task, and initial work is done. A significant future manual effort is required to extend the ontology model with knowledge about management and sustainable product, services, and strategies.

Moreover, we want to extend the intelligent system by a module of the Balanced Scorecard for Business model designed from the understanding of the organization's strategy. The indicators measure the performance of each of the choices of each block of the Business Model case. This module of the Balanced Scorecard allows the decision maker to monitor and visualization the performance of the Business Model case.

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Abbreviations

The following abbreviations are used in this manuscript:

BM	Business Model
CBR	Case-Based Reasoning
DSS	Decision Support Systems
BMDT	Business Model Development Tools
IS	Information System
AI	artificial intelligence
XAI	Explainable Artificial Intelligence
SDG	Sustainable Development Goal
SBMO	Strategic Business Model Ontology
KICBR	Knowledge Intensive Case Based Reasoning
ANN	Artificial Neural Networks

SVM	Support Vector Machines
KMS	Knowledge Management Systems
SBM	Sustainable Business Model
RBR	Rule-Based Reasoning
NLP	Natural Language Processing

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