Development of a Productive Credit Decision-Making System Based on the Ontology Model

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Abstract

The functioning of the banking system, which occurs in the aftermath of a pandemic, leads to changes in credit risk patterns around the world. Therefore, there is a need to adapt credit decision-making models to new conditions. The purpose of the work - The main result of the work is a light ontology based on the analysis of bank documents in the OWL language in the Protégé editor and the production system to support credit decision-making in banking institutions of Ukraine. The problem of adaptation to the bank documentation of the formalization method of Ukrainian-language content for the production system of fuzzy output is also determined. The application of the developed credit decision-making system based on the ontology model in banking practice will be able to provide early warning signals about the credit quality of the debtor and mitigate credit risk.

Keywords

Decision-making, bank, credit risk, Ukrainian-language content, ontology, fuzzy production system

1. Introduction

The new banking environment during the COVID-19 pandemic makes adjustments to credit risk management associated with a number of defaults and bankruptcies in vulnerable sectors of the economy: energy, travel, leisure and hospitality. The US Federal Reserve and the European Central Bank (ECB) have recommended that central banks and governments jointly provide additional support to promote economic stability. The ECB stressed that banks need to improve processes and controls, ensure data relevance and increase the use of promising lending measures: actively assess financial performance and quantify the probability of default [1]. The NBU joined the process of strengthening regulation by adopting a new version of Resolution №64 [2], taking into account the updated norms of European legislation and domestic practice of implementing a risk management system by banks.

There are different models for internal risk management, depending on the size of the banks, the type of products, the geographical presence and, to some extent, the way the business is run. Using of the latest information technologies will allow faster adaptation of risk management models to new conditions, generating new types of banking products and changing the way banks carry out their internal processes. An important subtask of adaptation of management models is timely forecasting of changes in external conditions, as suggested by the authors, for example in [3].

The ECB's banking supervision [4] constantly assesses risks and can adapt its supervisory priorities and actions to develop the economic environment. For 2021, the ECB's Banking Supervision focuses on four priority areas that have been significantly affected by the current crisis:

- credit risk management
- strength of capital
- sustainability of the business model
- management.

COLINS-2021: 5th International Conference on Computational Linguistics and Intelligent Systems, April 22–23, 2021, Kharkiv, Ukraine
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The ECB's banking supervision will focus its efforts on the adequacy of credit risk management, operations, monitoring and reporting of banks: on the ability of banks to detect any deterioration in asset quality at an early stage; make appropriate timely and adequate reserves; on the ability to continue to take the necessary steps to properly manage credits and loan arrears.

To meet such requirements, the bank needs to develop a risk management information system, which by definition is a set of technical means, methods and procedures that ensure registration, storage, processing, monitoring and timely formation of reliable information for reporting (informing), analysis and adoption of timely and adequate management decisions on risk management [2].

It is common for the development of information systems to use ontological models, which allows to respond to changes in operating conditions, possible changes and additions to the ontological model of the object, analyze the consequences of decisions and form a new a posteriori model to provide credit analytics at the level of debtors and liabilities portfolio, providing early warning signals about the credit quality of the debtor, as well as a wide range of credit analytics and scenario analysis for companies.

Therefore, the aim of this work is to develop an intelligent system for credit decision support by the bank based on the ontology model in OWL in the Protégé editor, which will form a common knowledge base for credit decision making in the new environment.

2. Related works

Of the existing ontologies of risk management should be noted electronic resource - Ontology of risk functions [5] - is a structure that aims to represent and classify knowledge about the functions of risk management using semantic web information technology. The code-named RFO codifies the relationship between the various components of a risk management organization. In banking institutions, there are units responsible for risk management. The ontology allows to more accurately identify risk management roles that can be used to better structure actual job descriptions, more accurately describe internal processes, and simplify risk assessment verification. The accepted language of web ontology is OWL, a semantic web language designed to present rich and complex knowledge. As a global standard, there is the possibility of built-in compatibility and reuse.

In [6], the author Khaoula Ben Addi draws attention to the specifics of credit risk management during a pandemic in financial institutions outside the banking system - microfinance institutions - in developing countries. In the context of mobilizing microfinance institutions to support the activities of their most vulnerable customers, the main task is emphasized - to minimize credit risk by adopting the most reliable scoring system. The main result of the work is the construction of an ontological model that represents the dimensions that affect the credit rating and their relationship. But such an ontological model solves one problem of making decisions on lending to customers only at the micro level of non-banking institutions and does not consider the use of existing risk management ontologies.

In contrast, in [7-8] group of authors conducts research on coordination and exchange of information groups, emphasizing that to date, information and communication technologies have made less progress. The authors emphasize that one of the several causes of the financial crisis of 2008 was the data architecture and information technology infrastructure. To address this issue, the Basel Committee on Banking Supervision (BCBS) has outlined a set of principles called BCBS 239. Using ontology design schemes (ODP) and BCBS 239, the authors propose a map of credit risk indicators and applicants' ontologies to improve decision-making on credit loan. It was also emphasized that future scenarios can be assessed and behavior predicted by adding artificial intelligence mechanisms. But artificial intelligence is not enough to achieve the desired results, because a good theory of domain content is not implemented, as shown in [9].

The following work [10] presents a model for credit risk management in two aspects. The first concerns methods of reducing investment risk using standard methods of a commercial bank to assess customers. The second concerns the social, political and investment components. The authors developed an integrated ontological model for evaluating client applications, which includes the default investment risk and the investment development component. In this case, the ontology is used to ensure the implementation of domain knowledge to support decision-making and customer evaluation in public development funds, but not in banking institutions.

The authors [11] focus on analyzing the performance of the Indian banking sector during the pandemic by creating and evaluating the knowledge base of the Covid 19-IBO ontology in order to obtain semantic information for decision-making in the Indian economy.

One of the steps in ontology building is using capabilities of existing ontologies. The above review indicates that all existing credit risk management ontologies are in English. But banking documents in Ukraine are in Ukrainian. Thus, a separate problem is the adaptation to the bank documentation of the method of formalization of Ukrainian-language content for the model of ontology and production system of fuzzy inference. In [12] the constant growth of interest in the use of intelligent systems in various fields is emphasized. Modern intelligent systems use knowledge bases that are formed in accordance with the subject area. One of the main results of [12] is the development of a method of data extraction based on the ontological knowledge base of parsing of Ukrainian-language text documents, which opens up prospects for solving the outlined problem.

3. Our approach

The purpose of this article on building an ontology for the development of DSS is provoked by reviews of the effects of the pandemic on the global banking system and work [13], which emphasizes the relationship and support between business and banks and the need for rapid response of banks to ensure a reliable customer experience business. It is recommended that banks review their overall risk appetite and portfolio thresholds.

It is possible to achieve such acceleration of decision-making on the basis of its automation, which is based on the general ontology of credit risk management in combination with methods of artificial intelligence. This will allow to: quickly assess the costs of risk and the impact of the crisis; clearly understand customers and data about them, better and faster to intervene to support them; prompt forecasting of financial statements and better monitoring of the effects of the recession.

Preliminary results presented by the authors in [14, 15] allowed to determine the model and stages of building a knowledge base for deciding on a loan in the new conditions and according to the updated relevant legislation in Ukraine.

In [14], a system of models based on neural network modeling and fuzzy inference was proposed to manage the bank's credit risk. It takes into account both external factors (customer self-organization) and internal (fraud, inefficient organization) and involves assessing the creditworthiness of the bank's customers, the overall assessment of credit risk and the identification of doubtful loans. To form a system of counteracting credit risk, a hybrid system for determining the bank's reserve level has been proposed.

The work of the authors [15] is devoted to the development of a method for building an intelligent decision support system based on the ontology model for justice field. This method is universal and can be applied to another subject area, as will be shown below.

Based on the results [14, 15], the representation of knowledge in the form of an ontology and a production model of fuzzy inference was chosen.

The development of the knowledge base according to the method proposed in [15] takes place in four stages:

1. At the first stage it is necessary to form the structure of the ontology of credit decision-making in the banking sector of risk management with the possibility of its further modernization in accordance with changing conditions of the financial sector of society. It is obvious that the decision-making ontology in banking risk management is a component of the general ontology "Banking".
2. In the second stage, a fuzzy derivation system is built to decision support system (DSS) of credit decisions in banking institutions of Ukraine. The ontology of credit decision-making is the basis for developing a model of such DSS.
3. The peculiarity of production systems is that the information at the input of the system is text, and the output must be information that contains both qualitative and quantitative components. Therefore, at the third stage it is necessary to build a model of concepts, developed ontology, which requires the creation of algorithms for processing banking documents.
4. Then at the fourth stage it is necessary to build a base of product rules and optimize it.

In this paper we perform the development of the first two stages.

The first stage is the development of ontologies.

The purpose of the ontological model is to determine the body of knowledge in the field of risk management in the banking system in general and separately in the field of credit risk. The ontological model clarifies the vocabulary by defining the terms needed to share knowledge related to banking risk management.

The concept of credit risk and credit decision in banking institutions of Ukraine is formulated in Chapter 18 of [2].

At the first stage it is necessary to form the structure of the ontology of credit decision-making.

Let's build a meta-ontology of risk management in banking with such a structure

$$O = \langle O^{form}, \{\langle O^{risk}, O^{alternative}, O^{choice}\rangle\}, SC^{agr}\rangle$$

where O^{form} - ontology of formalization of risk management related tasks and includes $\{\langle O^{risk}, O^{alternative}, O^{choice}\rangle\}$ - a set of decision-making ontologies for a particular type of risk, consisting of triplets, where O^{risk} - ontology of formalization of the task of risk management of a certain type; $O^{alternative}$ – ontology of alternatives generation of possible decisions on risk management of a certain kind; O^{choice}- ontology of the decision choice from set of alternatives of possible decisions on risk management of a certain kind.

Ontologies of task formalization of risk managing a certain type O^{form} and O^{risk}contain superclasses "Situation" and "Formal Task", which are related "Formalization".

The ontology of generating alternatives to possible solutions O^{altern} contains the superclasses "Formal Problem" and "Multiple Alternatives" in relation "Products".

The ontology O^{choice} solution selection set from a set of alternatives contains the superclasses "Set of alternatives", "Solver", "Decision made", "Risk assessment" and the relationships "Analysis", "Solution selection", "Testing".

To provide feedback in decision-making, we additionally define the relationship "Adjustment" between the superclasses "Risk Assessment" and "Formal Task" for each of the ontologies of decision-making for a particular type of risk.

SC^{agr} - superclass "Assessment" of formalization of the risk management task related to "Aggregation" with superclass "Risk Assessment" for all types of risks and the ratio "Adjustment" between superclasses "Assessment" and "Formal task".

Consider the content of the built ontology of decision-making in the field of risk management in banking, based on the concepts defined in the Resolution [2].

Superclass "Situation" = "Risk Management in Banking" contains information on the terminology of banking, defined as the probability of losses or additional losses or loss of income, or non-performance of contractual obligations by the party due to negative internal and external factors. To formalize this situation, it is necessary to develop a risk management system. The "Formal Task" superclass defines the types of risks that the bank will accept or avoid in order to achieve its business goals. Superclasses "Risk situation" contains the definition of risk of a certain type of risk, critical situations.

Resolution [2] defines significant types of risks:

1. credit risk;
2. liquidity risk;
3. interest rate risk of the banking book;
4. market risk;
5. operational risk;
6. compliance risk;
7. other significant types of risks to which the bank is exposed during its activities.

Superclass "Formal Task" defines indicators for assessing the bank's vulnerability to a particular type of risk, contains a set of properly documented and approved policies, methods that determine the procedure for implementing a systematic process of detection, measurement, monitoring, control, reporting at all organizational levels.

At this stage, the decision problem has the form of a tuple $\langle X, opt\_rule\rangle$, where *X* is the type of risk, *opt_rule* is the risk assessment criterion.

The "Multiple Alternatives" superclass contains many mitigation procedures for certain types of risk at all organizational levels. The "Solver" superclass contains rigorous and heuristic methods for constructing *solv_rule* decision rules on multiple alternatives, as well as the "Decision Subject" class with the “ATS” and “Automatic” subclasses. Superclass “Adopted decision” consists of many classes that describe the decision, procedures for its implementation, monitoring, control, reporting at all organizational levels.

The decision-making mechanism of the bank for risk management is determined by the relations that are schematically shown in Figure 1.

SC “Situation”	Risk Managing							
	Formalization							
SC “Formal Task”	Risk management system							
	Includes							
SC “Situation”	Risk Managing 1		Risk Managing 2	…		Risk Managing n		
	Formalization		Formalization	…		Formalization		
SC “Formal Task”	Risk management system 1		Risk management system 2	…		Risk management system n		
	Production		Production	…		Production		
SC “Multiple Alternatives”	Risk mitigation procedures 1 at all organizational levels	Adjustment	Risk mitigation procedures 2 at all organizational levels	…	Adjustment	Risk mitigation procedures n at all organizational levels	Adjustment	Adjustment
	Analysis		Analysis	…		Analysis		
SC “Solver”				…				
	Choice		Choice	…		Choice		
SC “Decision”	Decision-making by responsible persons involved in the risk management system. Carrying out specific actions of the Order on establishment		Decision-making by responsible persons involved in the risk management system. Carrying out specific actions of the Order on establishment	…		Decision-making by responsible persons involved in the risk management system. Carrying out specific actions of the Order on establishment		
	Testing		Testing	…		Testing		
SC “Assessment”	Risk stress testing 1		Risk stress testing 2	…		Risk stress testing n		
	Aggregation							
SC “Risk Assessment”	Assessment of the bank's vulnerability to risk							

Figure 1: Risk management scheme in banking institutions of Ukraine

Next, building a meta-ontology of credit decision approval which is shown in Figure 2.

Credit risk - the probability of losses or additional losses, or loss of planned income due to default by the debtor/counterparty of its obligations under the terms of the contract. Credit risk arises for all active banking operations, except for debt securities and other financial instruments in the trading book of the bank [2].

An effective credit risk management system provides for the identification, measurement, monitoring, reporting, control and mitigation of credit risk on both an individual and portfolio basis.

We build metaontology O for decision on risk management according to the following structure:

$$O = \langle O^{risk}, O^{alternative}, O^{choice} \rangle$$

where O^{risk}– ontology of formalization of the risk management task; $O^{alternative}$ - an ontology of generating alternatives to possible risk management solutions; O^{choice}- ontology of the decision choice from set of possible decisions alternatives on risk management.

SC “Situation”		SC “Formal Task”		SC “Multiple Alternatives		SC “Solver”		SC “Decision”		SC “Assessment”
Risk Managing	Formalization	Risk management system	Production	Credit risk mitigation procedures at all organizational levels	Analysis		Choice	Decision-making by responsible persons involved in the risk management system. Carrying out specific	Testing	Credit risk stress testing
		← Adjustment								

Figure 2: Credit risk management scheme in banking institutions of Ukraine

The O^{choice}-ontology contains the superclasses “Situation” and “Formal Task”, which are related “Formalization”. The ontology of generating alternatives of possible solutions $O^{alternative}$contains superclasses "Formal problem" and "Set of alternatives", which are in relation “Products”. The O^{choice} solution selection set from a set of alternatives contains the superclasses “Set of alternatives”, “Solver”, “Decision made”, “Risk assessment” and the relationship “Analysis”, “Solution selection”, “Testing”.

To provide feedback in decision-making, we additionally define the relationship “Adjustment” between the superclasses “Risk Assessment” and “Formal Task”.

To build a conceptual model, we choose the OWL language with implementation in the Protégé ontology editor.

Figure 3 shows the ontology of meta-ontology O, developed using the tools of the Protégé editor.

Consider the content of the meta-ontology O for the case of credit decision-making, based on the concepts defined in [2].

The Bank establishes and implements a clear credit decision-making process, including automatic credit decision-making, both for granting new loans and for making changes to the terms of existing / existing loans.

The Bank has the right to automate the process of automatic credit decision-making on standardized credit products or to carry out automatic credit decision-making without automation in accordance with the algorithm described in the internal bank documents.

The Bank determines the list of documents and information required for making credit decisions both on new loans and changes in terms of existing / existing loans.

When approving a loan decision (in Figure 4), the bank takes into account the following factors, which can be divided into groups:

1. group BUSINESS VIABILITY - viability of the business model, which contains components: CREDIT PURPOSES - the purpose of obtaining a loan and FUNDING SOURCE - sources of its repayment; VIABILITY - the viability of the business model of the debtor - a legal entity, an individual - a business entity, as well as the presence of sufficient COMPETENCE and

RESOURCES, for its implementation; EXPERTISE practical experience of the debtor's economic activity, the state of the economy in which the debtor operates and its position in it, markets for products / services produced / provided by the debtor, COMPETITIVENESS of the debtor; acceptability and sufficiency of ENSURE provision, possibility of its realization.

2. group REPUTATION - consists of elements: CREDIT HISTORY - credit history and current solvency of the debtor, based on financial trends of previous periods and cash flow forecasts for different scenarios; BEHAVIOR PATTERN behavioral models of debtors of individuals; PERSONAL REPUTATION the reputation of the debtor and his ability/willingness to legal responsibility and cooperate with the bank on all issues that may arise during the period of use of the loan; the structure of the group of related counterparties and the credit history and current solvency of these counterparties. To do this, the bank must develop a mechanism for identifying situations where it is appropriate to classify debtors as a COUNTERPARTY GROUP of related counterparties and as INDIVIDUAL DEBTORS of an individual debtor.

3. group DECISION - decisions of persons responsible for managing a legal entity and exercising control over its activities to obtain a loan, their authority to make such a decision CREDIT RISK DECISION contains components: CREDIT TERMS - additional terms of the loan agreement to limit the increase in future credit risk; CREDIT RISK - forecast data on the required amount of provisions for expected credit losses and the amount of credit risk at the time of the loan; reliability and sufficiency of LEGAL POSITION of the bank regarding the terms of the loan agreement and security/pledge agreements to ensure proper cooperation with debtors/counterparties/mortgagors.

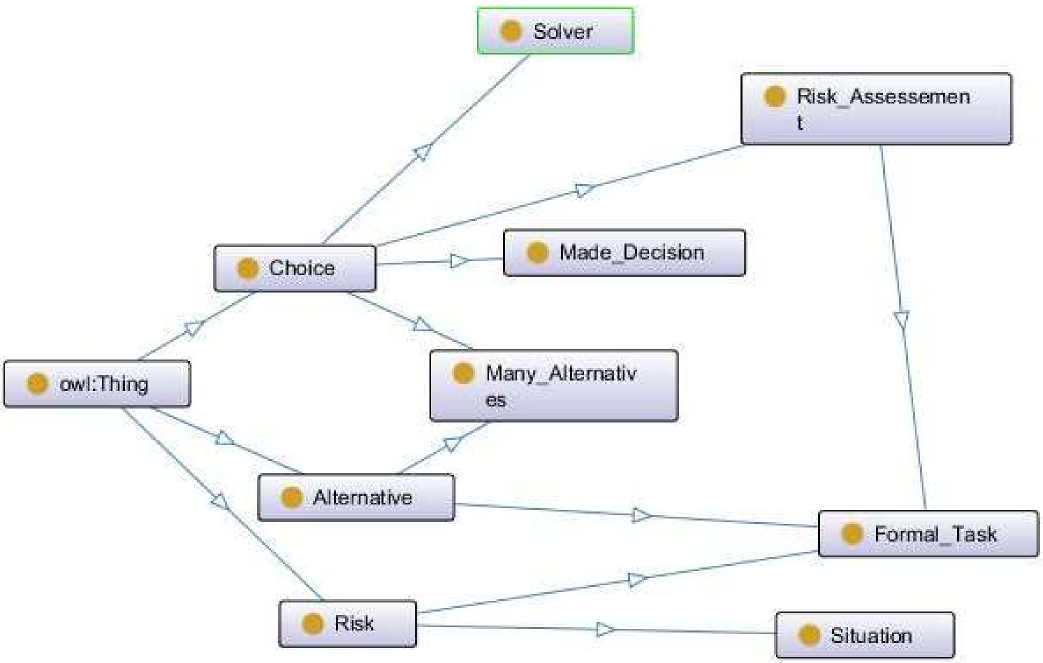

Figure 3: Decision-making ontograph on risk management in banking institutions

The loan decision must contain: LOAN AMOUNT loan amount / limit and loan repayment period (repayment schedule); INTEREST RATE interest rate / margin (in case of variable rate), loan usage fee and interest / commission payment terms; OBLIGATION - obligations of the debtor, which he must fulfill to obtain a loan (if necessary); REQUIREMENT loan collateral requirements (if required); TERMS conditions to be met by the debtor during the term of the loan agreement.

If the loan decision is not automatic, in addition to this information must also take into account: PERSONS list of persons involved in the decision, their powers and personal position of each person; PERIOD OF CONTRACT VALIDITY - the term of the loan decision (the period during which the bank has the right to enter into an agreement and issue a loan / guarantee / grant aval / open a letter of credit, and in the case of a credit line - the period during which the bank has the right to enter into an agreement bank loan obligations).

The second stage is the development of DSS production model.

In the second stage, a fuzzy inference system [16] is built to support decision-making (DSS) of credit decisions in banking institutions of Ukraine on the basis of the ontology of credit decision-making. The generalized DSS model has the form:

$$\begin{aligned}&(\textit{loan amount, interest rate, obligation, requirement, persons, period of contract validity}) =\\ &= F(\textit{credit risk decision, business viability, reputation}),\end{aligned} \quad (1)$$

where *credit risk decision* = F1 (credit terms, credit risk, legal position),

business viability = F2 (credit purposes, funding source, viability, competence, resources, expertise, competitiveness, ensure),

reputation = F3 (credit history , behavior pattern, reputation, counterparty group, individual debtors, decision).

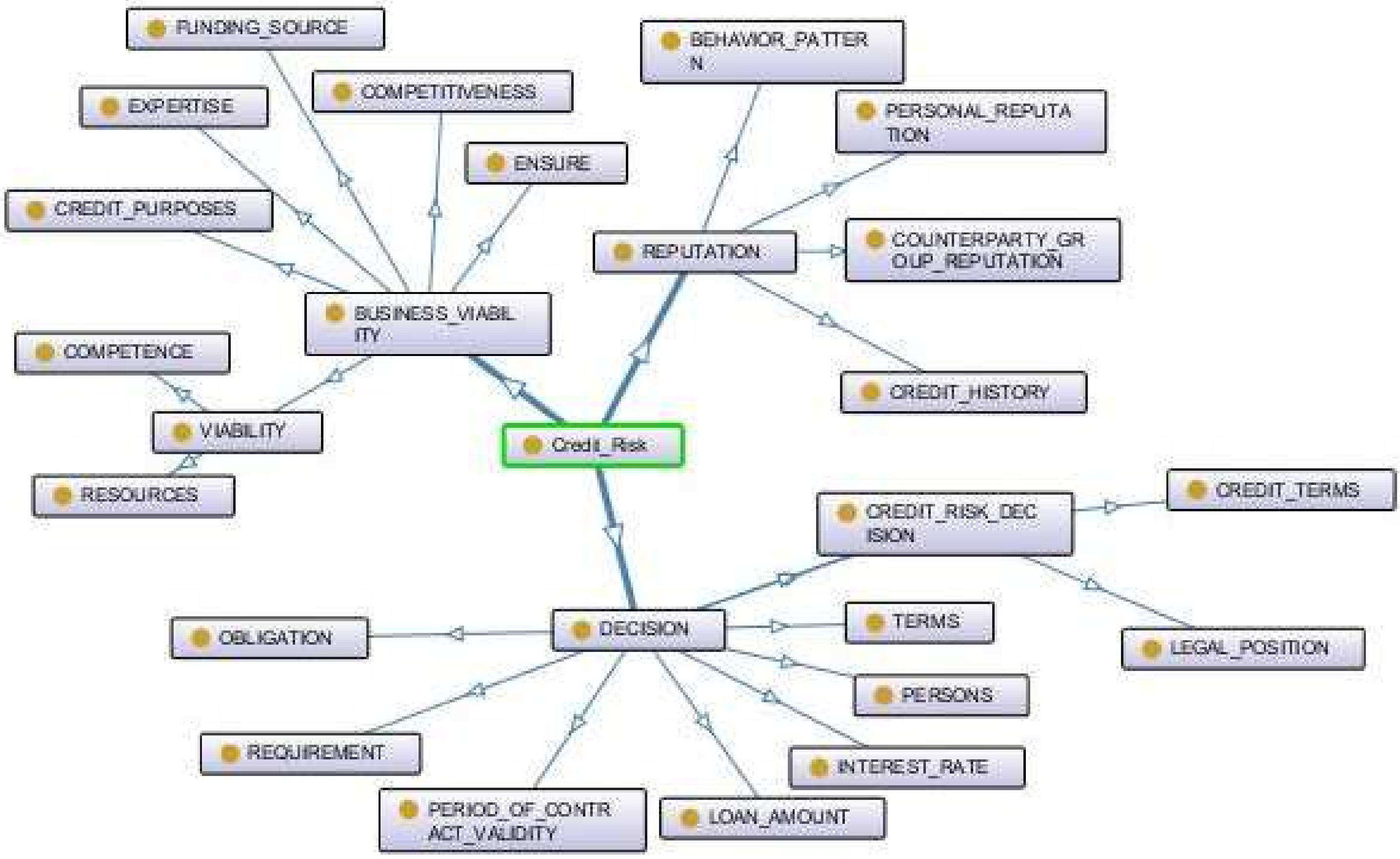

Figure 4: Credit decision-making ontograph in banking institutions of Ukraine

The result of the second stage is a model (1) of the production decision support system (DSS) of credit decision in banking institutions of Ukraine.

Consider schematically the construction of subsystems F1, F2, F3. Subsystem F1- CREDIT RISK. The grounds for calculating credit risk are intrabank provisions, which are regulated by the NBU Regulation № 351 [17]. In order to calculate the amount of credit risk on an asset in accordance with the requirements [17] and internal regulations, the bank determines the value of each of the components of credit risk (PD, LGD and EAD) depending on the type of debtor/counterparty [legal entity (except bank and budgetary institution), person, budgetary institution, bank, debtor - issuer of securities], type of asset, type of collateral, debt currency (national or foreign), method of asset valuation (on an individual or group basis). The Bank calculates an integrated indicator using a logistics model, the parameters of which are updated annually by the NBU on the basis of financial statements of debtors - legal entities. To update the logistics model, the Bank submits to the NBU data on the classification of debtors - legal entities, as well as data on their financial statements, in the form and within the time limits set by the NBU. The formal credit risk assessment procedure allows the introduction of linguistic variables based on quantitative characteristics.

To develop the subsystems F2- BUSINESS VIABILITY and F3- REPUTATION, it is necessary to build linguistic variables based on qualitative assessments of the debtor or bank employee. It is possible to formalize the procedure of providing assessments of qualitative criteria with the help of the model of concepts of the developed ontology, the information on which is presented in the Ukrainian-language content. To construct linguistic variables, it is necessary to determine the terms of fuzzy sets and the type of membership function. To initialize the input vectors of the fuzzy production system, according to the method [15], it is necessary to build digraphs on the basis of the model of concepts, to determine the order relationship in the digraph; calculate the membership functions for the constructed vectors of the variables that make up the term set. The result of the second stage is the model (1) of the decision support system production (DSS) for credit risk management in banking institutions of Ukraine.

4. Discussions and further researches

The developed ontology lays the foundation of the knowledge base for an intelligent decision support system for credit risk administration. In terms of further research - assessment of ontology quality, detailed construction of subsystems F1, F2, F3, as well as the implementation of the third and fourth stages of the production system development of credit decision-making according to the method presented in [15].

At the third stage, for the processing of credit decisions documents, it is necessary to create appropriate algorithms for the initialization of qualitative variables, which are characterized in natural language. It is necessary to build a model of concepts developed by the ontology. For example, in accordance with [2], the bank determines the list of documents and information required to make credit decisions on both new loans and changes in terms of existing loans. At the fourth stage it is necessary to build a base of product rules and optimize it. By optimization we mean ensuring the achievement of conflicting goals, namely - increasing the accuracy of the output while reducing the complexity of the system.

5. Conclusions and acknowledgment

The scientific novelty is determined by the developed general Base of knowledge of credit risk and credit decision-making of banking institutions of Ukraine, which are reflected in the DSS model of credit decision, based on the approach to structuring information contained in banking documents and ways to formalize data for fuzzy output.

The development will allow processing a large volume of requests for loans and their administration.

The work was carried out as part of the research work «Mathematical modeling of socio-economic processes and systems», the registration number DB05038, at the Department of System Analysis and Computational Mathematics of "Zaporizhzhia Polytechnic" National University.

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