# Cognitive Automation of Real Property Management Processes

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## Abstract

The article discusses the possibility of using Automated Valuation Models (AVM), enhanced with technologies such as machine learning algorithms and artificial neural networks, for cognitive processing in the field of Facility Management. Experiments verifying the behaviour of a cognitive inference machine in the processes of operational real property management were described. The focus was to assess the functioning of decision service algorithms induced by automated inference engines which operated in the context of general information about real property. The research results confirm that the cognitive perspective, combined with advanced technologies, brings significant benefits. AVMs supplemented with cognitive technologies are able to dynamically react to varying market conditions and real property characteristics. The key aspect of the cognitive approach is that it eliminates the constraints related to different input states and lack of information, which increases the flexibility and efficiency of the processes of operational real property management. This means that real property managers can make more informed decisions while also saving time and resources. The conclusions drawn from the research confirm the importance of using modern technologies in Facility Management and open up new perspectives for the automation of management processes.

## Key words

automated valuation models, facility management, real estate, machine learning, neural networks, cognitive systems, cognitive computing, decision-making process.

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## Introduction

Normatively, the processes of real property management are built upon the foundation of the concept of Facility Management (FM) as a comprehensive, customer-oriented service, the subject of which are comprehensive decision-making principles for optimal planning, use, and adaptation of buildings, their equipment, and services. Many authors describe the IT tools used for operational real property management. However, there exist few studies describing systems based on algorithmic inference methods used in this field. The fact that algorithmic information processing and automation operating in the data, communication, and application layers increase the productivity of the processes is an axiom. Such an approach can also be applied to real property management processes (Cheng et al., 2016; Kofi et al., 2017; Xu et al., 2019). One of the aspects of real property management is its valuation. Traditional valuation methods are increasingly often being replaced by methods employing IT systems to automate valuation processes. Automated Valuation Models (AVM) are a service allowing for real property valuation with the use of mathematical modelling (Kara et al., 2018; Bilgilioğlu & Yılmaz, 2021; Carranza et al., 2022). The subject of the experiments described in the article was the verification of the possibility of applying AVM in FM processes. They verified whether cognitive inference engines correctly perform AVM procedures in the scope of processes related to planning and budgeting the costs of forecasted future repair works.

## 1. Literature review

### *1.1 Real property management and administration*

The International Organisation for Standardisation (ISO) defines Facility Management as an organizational function which integrates people, place and processes within an environment built with the purpose of improving the quality of life of people and the productivity of the core business (ISO 41011:2017, 2017). The idea behind this standard is not only mechanisms for controlling and reducing the costs of real property management. The standard introduces a new approach to the ways of organising and managing the numerous and diverse operations which constitute the domain of FM. Controlling the costs is no longer sufficient. People now seek the potential and opportunities for processes that emphasise the value added (Pala & Melzi, 2009; Jensen, 2010; Xu et al., 2019). Emphasis is placed on taking a long-term approach by adopting maintenance and utilisation standards, which take into account benefits beyond those whose value for business decisions is purely economic (Opoku & Lee, 2022).

In accordance with the guidelines of the International Facility Management Association (IFMA), the concept of FM focuses on the processes of adding value as well as improving and maintaining the real property in the areas of its actual condition throughout the entire period of its exploitation. These processes put emphasis on examining the actual state of the real property in terms of: (i) efficient management, defined as the assessment of the rationality and effectiveness of the decisions being taken; and (ii) purposefulness, which consists in eliminating activities which are adverse and unnecessary in terms of the organisation's interests (Thomas, 2014; Cheng et al., 2016). The expenses are deemed to include both the costs related to the current operation of the real property; as well as the costs of renovation and modernisation work, including the investment costs of the planned work, resulting from the wear and tear of the real property. In this context, it is important to optimize the technological operation of the facility and its components throughout its entire life cycle as well as the renovation and investment policy. When perceived in this way, FM becomes a management function that focuses on how to develop, maintain and improve the physical resources needed to support and add value to an organisation's business processes (Pruszkowski, 2012; Xu et al., 2019).

Real property management can be analysed in financial (level of income from the real property), technical (technical condition, infrastructure and equipment), legal (leasing conditions, legal status) or utility terms (day-to-day operation and exploitation, provision of ancillary services). The value of the real property can therefore be shaped by operations from various fields of management. This also applies to the operational management related to the day-to-day operation and maintenance of the real property. These fields can be supported by ICT technologies based on the identification of individual factors of a specific real property et al., 2010).

The processes of information exchange between Building Information Modelling (BIM) systems and FM systems are not trivial processes. Various sources of data containing information on the components and equipment of the facility, sources of data on management, maintenance, repair processes or jobs related to occupational health and safety do not ensure interoperability (Matarneha et al., 2019). Ongoing attempts to standardise ontologies describing real property as well as services and operational management standards provided in the FM domain can be observed. Their aim is to improve the quality, cohesion and interoperability of facility management services (Office of Government Property, 2021, 2022b, 2022a).

*1.2 Automated valuation models*

Automated Valuation Models (AVM) are perceived as a fast and convenient service of computer real property valuation. In order to analyse the relationship between the value of the real property and its utility features, they employ the statistical approach (Mayer et al., 2019; Renigier-Biłozor et al., 2021; Steurer et al., 2021; Lorenz et al., 2022). Two formal definitions of AVM have been established in literature: (i) the definition contained in European Valuation Standards EVIP 6: "Automated Valuation Models can be defined as statistics-based computer programmes, which use real property information (e.g. comparable sales and real property characteristics etc.) to generate real property-related values or suggested values" (TEGoVA, 2017); (ii) the definition contained in the specification of the standard on AVMs developed by the International Association of Assessing Officers, IAAO: "A mathematically based computer software program that market analysts use to produce an estimate of market value based on market analysis of location, market conditions, and real property characteristics from information that was previously and separately collected" (I.A.A.O., 2018).

It can be concluded that AVM are a computer program used to estimate the market value of a real property based on the analysis of its location, characteristics, and market conditions. AVM is based on three components of the valuation process: (i) an information database containing data on real property characteristics and transaction prices, (ii) analysis of the collected information, (iii) valuation values. The operation of valuation is carried out by software, operating in a deterministic manner and in accordance with built-in workflow mechanisms, searching for the market features of the real property and the conditions for concluding the transaction which have been pre-defined in the query (O.M.G.WfMC Specification, 2000). Real property features, as rules of conduct, are defined by legislation and professional standards on the principles of real property valuation (Gallin et al., 2018; Valier, 2020).

The widespread emergence of advanced technologies based on artificial intelligence (AI) and the increase in the availability of data, both in terms of frequency and level of observation, allow the development of AVM for the real property sector. AVM software can be converted into stand-alone software bots. A bot is an automated program designed to perform a specific task. By expanding it with artificial neural networks using multiple layers of algorithms, it is possible to allow bots to learn and adapt to new scenarios. As a result, they allow for increasing the flexibility and ability of the software to solve complex tasks. Including tasks going beyond deterministically defined scenario steps (Es Soufi et al., 2016; Tetzlaff & Szepannek, 2022). If an AVM uses information about real property transaction prices, whether it takes into account the change in these prices over time and information entered by users - concerning the building or the number of rooms, for example - it is now technically possible to extend the scope of the information analysed at will (Kok et al., 2017; Bergadano et al., 2019; Manko, 2022; Vathana et al., 2022). The potential costs of future and expected repair works can be analysed as a result of predictive analyses of similar real property and assessing the technical condition of a specific real property (Dimopoulos & Bakas, 2019; Rousopoulou et al., 2022). The determination of the value is based on the basis of a cost estimate, which determines the estimated value of the works based on the market prices of the same or similar component or using the available price indices for construction and assembly production. On this basis, renovation budgets can be planned.

The use of cognitive technology and the application of artificial Neural Networks, (NN) and Machine Learning, (ML) algorithms creates the conditions for exploring the possibility of making decisions only in an automated way without human intervention, using technical solutions, in the real property sector. Whereby the automated manner denotes operation: (i) without waiting for human instructions, (ii) learning through feedback, and (iii) autonomously using data mining mechanisms.

*1.3 Cognitive inference*

Cognitive Computing (CC) systems based on Artificial Intelligence (AI), and using Machine Learning (ML), for Machine Reasoning (MR), play an increasingly important role in the functioning of organizations. They are widely used in various sectors of the economy, being responsible for data analysis and improving business decision-making processes. Importantly, the essence of CC is to teach computers to solve problems on their own without receiving specific instructions on how to do it. They are supposed to be able to solve problems without requiring human assistance (Gathani et al., 2021; Geng & Varshney, 2023; Malibari et al., 2023).

Machine Learning is an artificial intelligence technique using mathematical algorithms to create predictive models. ML is based on the analysis of data in terms of the of the patterns occurring in it. ML algorithms are capable of processing large amounts of data and "find" hidden patterns used to build predictive models for the proposed result. Predictive models are used to make informed predictions or decisions about new data. Validation of the correctness of models is conducted based on known data. Performance indicators for specific business scenarios are measured. The process of validation and modification is called "learning". Models are modified and improved, as necessary. However, ML algorithms, being based on statistical and deterministic methods, do not provide a method for explaining the causes of the outcome. The argumentation explaining the decision selection criteria, the validity of the criteria, or the ranking of preferences in relation to different choice options is unknown (Nene, 2017; Adamskiy et al., 2019). MR technology is used to identify the causes. Machine reasoning is a technology that extends the results obtained by ML with a synthesis based not only on information sources but also on contexts and conclusions. MR systems use various inference algorithms to manipulate available knowledge in order to solve problems. They process not only logically successive facts but also data characterized by ambiguity and uncertainty. They independently create semantic models which provide the best mapping of logical reasoning. MR generates not only answers to numerical problems but also creates hypotheses and recommendations, eliminating subjectivity and increasing accuracy. This highly organised way of processing information, involving the instantaneous manipulation of representations relating to the external world, can be termed an intelligent one (Nowak-Nova, 2018; Garcez et al., 2019; Ray et al., 2023). The technologically mapped cognitive mechanisms driving MR, rather than repeatedly performing a specific task with little or no change, provide the models with intelligence owing to which they can adapt to the changing environment to achieve the desired goal. They can be used for decision-making processes such as: (i) perceiving information, (ii) understanding the results of observations using existing knowledge, and (iii) making a reasonable change in the environment. Systems implementing such processes are called Cognitive Systems, (CS), because the calculations they perform can simulate human thought processes in a computer model (Sathish & Venkataram, 2009; Lemaignan et al., 2017; Engel et al., 2022). CS have sufficient potential for holistic data interpretation in a dynamic business environment. Research showing gaps in traditional decision-making systems indicates that CS systems, through access to unlimited information, enable organizations to increase efficiency (Kaur et al., 2019; Welck et al., 2020).

*1.4. Summary of sources and indication of the scope of research*

The results of the literature review demonstrated that advanced technologies have the potential to improve operational efficiency and enable organizations to implement comprehensive and autonomous decision-making processes. Particularly with regard to the specificity of real estate management. However, there is a lack of coherent and comprehensive studies combining Facility Management (FM), Automated Valuation Models (AVM) and Cognitive Computing (CC). The study of the application of CC technology, using statistical AVM models, for the FM area will be interesting for decision-makers, practitioners and researchers who want to have a better understanding of the processes taking place in the real estate sector.

Three potential areas of issues that may be merged and compiled during the study emerge from the literature review.

Real estate management denotes activities whose main objective is the effective coordination of many processes related to real estate management. Analysing the financial aspect, it can be seen how important it is to minimize operating costs while efficiently generating income from real estate. By delving into the technical area, it can be noticed how crucial it is to maintain the infrastructure and adapt to modern technological solutions. In legal aspects, real estate provisions and the rental agreements formed on their basis are crucial. In the operational area, the importance of efficient service, maintenance and sustainable use of real estate is emphasized.

Constantly developing technologies, especially in the field of real estate valuation, are bringing about a revolution owing to Automated Valuation Models. These modern computer tools, based on statistical analysis, offer an instant assessment of the value of real estate. They can use advanced technologies such as artificial intelligence, artificial neural networks and machine learning algorithms, which opens up new possibilities for automating decision-making processes in the real estate sector. This reflects an evolution towards technology offering tools for advanced, adaptive systems that will take into account a variety of market data.

Cognitive computing systems based on artificial intelligence and using machine learning play a key role in the evolution of the functioning of an organization. These advanced technologies bring about the capability of solving problems autonomously, removing the necessity for detailed instructions from humans. Using mathematical algorithms and analysing patterns in the data, CC creates predictive models to improve decision-making processes.

The fusion of these three areas of issues allows for formulating a hypothesis that the introduction of modern technologies will revolutionize the manner in which operational processes proceed in organizations. The hypothesis assumes that AI and ML possess the potential to improve operational efficiency and increase the precision of decision-making processes in the area of real estate management. The following research questions were formulated in the text:

RQ1: Are cognitive decision-making algorithms employing neural networks and machine learning suitable as inference engines in AVMs?

RQ2: Does the extension of AVMs with cognitive decision-making services, allow automatic assessment of a building's technical condition, prediction of future malfunctions, planning of repair work or necessary upgrades?

The text is structured as follows. The first part reviews the literature on real estate management and administration, models of automatic valuation and cognitive inference. The second part describes the methodology and experiments carried out related to the cognitive inference machine and the application of the AVM in the management of operations and building maintenance. The third part presents the results of the research, and finally, the fourth part contains conclusions and directions for further research.

## 2. Methodology

The experiments simulated AVM applicability to operational aspects of real property management. The subjects of the study were process models constituting an FM component and algorithm-driven decision-making machines. The logical correctness of the performance of cognitive algorithms as inference engines for assessing the technical condition of buildings and predicting future breakdowns or necessary repairs, as well as estimating the costs of such works, was studied. IBM Rational Software Architect version 9.7 was used as the research environment. The TIBCO Business Studio BPM Edition software version 5.4.0 was employed to test the effectiveness of the processes. In the study, the following were modelled: (i) the processes for identifying renovation needs resulting from the assessment of the technical condition of the real property; and (ii) the processes of budgeting based on the current maintenance costs and estimating work costs for renovation works.

Information concerning real property under the administration of an organization responsible for the management of a total of 446 residential buildings, 180 residential and office buildings, and 372 office buildings was adopted as input data for experiments. These buildings contain 14 009 residential units and 1235 office units. The number of 1201 renovated residential units, 545 empty units, and 174 renovated office units were used as data for the renovation work carried out. The number of 48 construction repairs, 20 repairs of infrastructure installations, 3 finishing repairs, 28 design works, 16 technical opinions, expert opinions, and 102 173 repair works performed as a result of breakdowns were assumed as the works carried out over the years 2019-2021. The data was provided in the form of flat files, extracted from systems used for current facility management, semantic PDF and DOCX files, and spreadsheets. For the purposes of research, they were converted into a text form of TXT files.

### *2.1 Experiment 1: Cognitive inference machine*

The RQ1 study verified the logical correctness of execution and the runtime efficiency of cognitive algorithms using neural networks and machine learning as inference engines in AVM. The decision model of a cognitive inference machine consisted of modules responsible for the functions performed. Collectively, these modules formed a feedback process cycle, enabling continuous improvement of the modules forming the cycle. The employed modules were the following: (i) <Planning> as a module responsible for the design of goals and specification of criteria. (ii) <Analysis> as a module using indicators and variables for the assessment of the solution proposed by the decision-making subprocesses. (iii) <Control Policies> supervising compliance with normative constraints and introducing corrections to the process behaviour. (iv) <Decision State> being a module presenting the best decisions resulting from the decision-making process.

The following steps were adopted for the study:

1. <Planning> defines goals and performance criteria, defining the target limits (SLA). The indices (Y) represent efficiency which is customer satisfaction (S) and the quality of the developed plan (Q). The indices (Y) depend on the performance parameters: Y = (S,Q). The parameters (X) are represented by decision state variables and include cost (C), timeliness (T), and completeness (R). The parameters (X) are presented by the formula: X = (C,T,R). At the stage of launching the process, their values are determined based on the parameters contained in the databases forming <Decision-making

Services>. The measures are functions ($\digamma$) used to map the decision state variable coefficients (X) onto the performance indicators (Y) according to the equation $\digamma$: X → Y. The module <Planning> provides information about $C_o$ and $R_o$ (which represent <Planning Cost> and <Completeness of Requirements>).

2. <Analysis> concerns the calculation and evaluation of the indicators for the correctness of the analysed information. This stage maps indicators C, T, and R onto performance indicators S and Q. The task is carried out by a subprocess <Decision-making Service> which selects the appropriate process classification <Cognitive Decision-making Process>. It is also executed by a subprocess which calculates indices for S and Q based on real costs ($C_A$) and information on the completeness of requirements ($R_A$) which are sampled over time ($T_o$). <Sampling> ($T_o$) is associated with the collection of qualitative and quantitative information about variables (X). Vector X contains C, T and R, which represents the period of collecting new information about X. In the study, $T_o$ is defined as equal to the planning period, therefore information on the actual cost ($C_A$) and actual completeness of requirements ($R_A$) is generated at the end of the process. In the study, it was assumed that the real time ($T_A$) is equal to the sampling time ($T_O$), therefore it is not included as a variable for computing.

3. <Control Policies> govern the behaviour of the process. They take into account the laws, norms, standards, and internal regulations of the organization implemented in the workflow rules based on <ontology> and controlling the process flow, ensuring that the decision (d) generated by <Cognitive Decision-making Process> using <Supervised Machine Learning> decision (d) will be consistent with the assumed (SLA).

4. <Decision State> an interface presenting a conscious, non-random selection of one of the recognized and considered to be feasible options for action.

The model of the decision-making process by the cognitive inference machine is shown in the figure below.

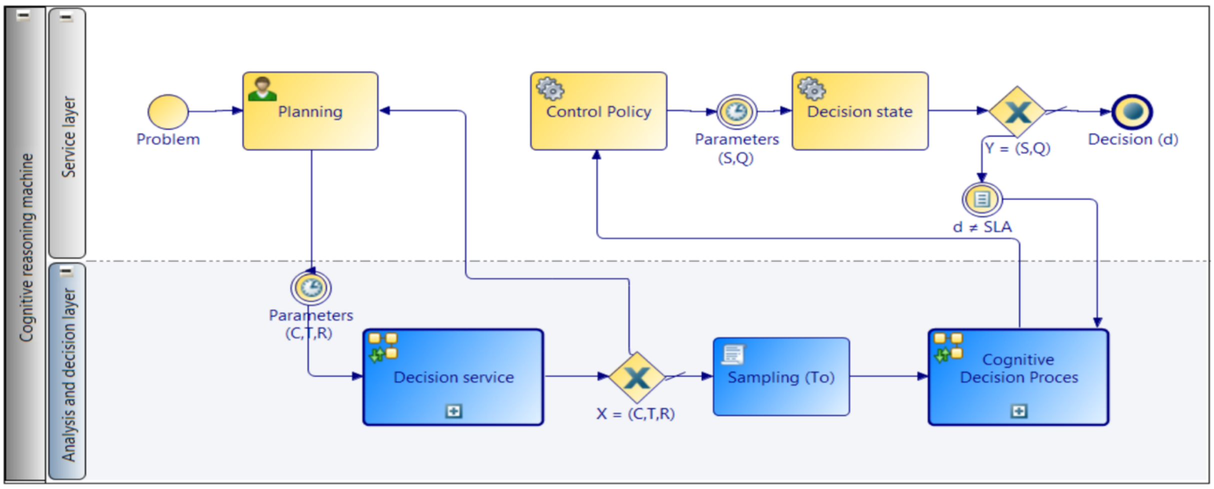


**Figure 1.** The decision model of a cognitive inference machine in BPMN notation

Source: the author's own compilation based on research.

The <Cognitive Decision-making Service> pattern was designed in accordance with the decision-making model in DMN notation (O.M.G.DMN Guide, 2019). This ensured a uniform decision-making model which guaranteed repeatable applications for each <Decision-making Service> used.

According to it, prior decisions enriched the <Decision Repository> by providing <Business knowledge> which is the basis for activating quality criteria, thus expanding the analysed sets. The <Cognitive decision-making process> consisted of individual <Decision-making Services> for the FM domain areas: <Accommodation Resource Services>, <Record Services>, <Rental Services>, <Operation Services>. It operated in the <Service Bus> environment and was performed by the <Agent Algorithm>. <Accommodation Resource Service>, <Record Service>, <Rental Service>, <Operation Service> as "packages" of tasks were launched by successively narrowing the area of the dependencies discovered between the O classification, their A attributes and R associations. Each <Decision-making Service> could carry out its tasks asynchronously after receiving a specific event, at the most suitable moment. The role of the orchestration was fulfilled by the <Agent Workflow> which supervised the process. The orchestration was responsible for sending commands to initiate events and the correctness of their execution. The categorisation, clustering and creation of associations were performed by ontology, which provided recognisable and understandable <concepts> subject to semantic analysis when searching for criteria for useful decision-making strategies (C) and alternative solutions (W). The Quantitative determination of C and W was supervised by the qualitative assessment (Qc and Qw). The choice of the preferred decision was made on the basis of the most closely matching fulfilment of the conditions of accuracy d = ƒ(C,W). A narrowing scale was adopted as standard deviation for individual services: from 0.4 in the former case to 0.1 in the latter case. The aim of the study was to verify the effectiveness of performed tasks. Varied duration of working times of each service, lack of preliminary tasks and the expected maximum effectiveness of using the working time at the level of 99% were assumed. The occurrence of new tasks was generated through uniform distribution, during which tasks have an equal probability of starting in a given range determined by the minimum and maximum, and in accordance with the task completion time.

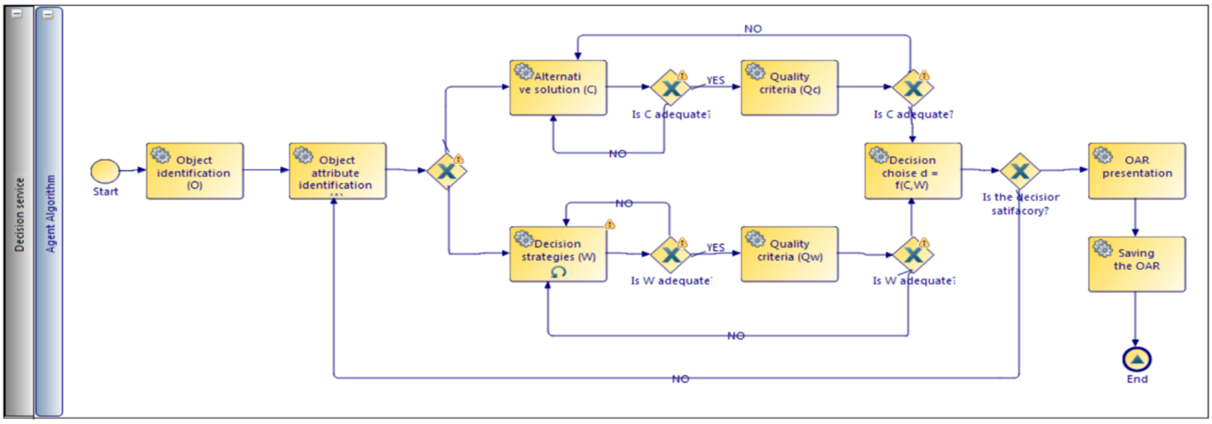


**Figure 2.** The <Cognitive Decision-making Service> model for a single decision implemented by the <Agent Algorithm> presented in BPMN notation

Source: the author's own compilation based on research.

The <Cognitive Inference Machine> processed the value-oriented processes that served as components of the Facility Management domain as well as decision-making machines controlled by algorithms. Everything was performed under the supervision of machine learning. The subject of the analysis was a case of creating a process capable of identifying and reporting potential renovation needs caused by the condition and wear-and-tear of the real property (damage communication). The study consisted in the execution of the Supervised Learning task on data sets containing text documents and their <Labels> (metainformation). The time it took to perform computational operations and the completeness of information were subject to analysis. In the study, the data pipeline coming from statistical sources (databases in the form of flat files) was divided into increasingly smaller parts for three different scopes of information regarding the recording, rental and exploitation of real property resources. The efficiency of performing all assumed operations was subject to investigation, with the assumption of their completeness.

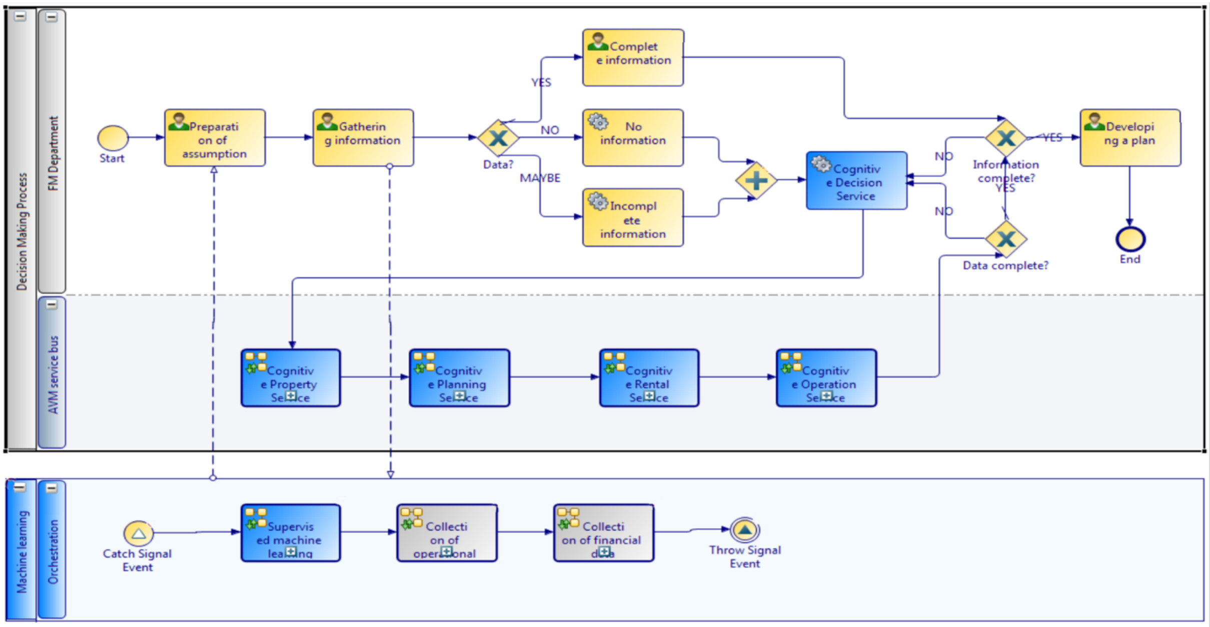


**Figure 3.** The <Cognitive Inference Machine> model presented in BPMN notation
Source: the author's own compilation based on research.

*2.2 Experiment 2: The use of AVM to manage the operations and maintenance of a building*

The RQ2 study, with the assumption that AVM are used to estimate the market value of a real property based on the analysis of its location, features and market conditions, verified whether the use of AVM to automatically assess the technical condition of buildings and predict future breakdowns or necessary repairs of the real property resulting from predictive analyses of similar properties benefits the real property manager. For this purpose, an AVM process based on induced automated decision-making services, which used cognitive technology algorithms to determine the values, was created.  AVM employ statistical evaluation techniques. In the first step, data is collected and analysed to develop an assessment model that can be applied to equivalent properties in the same or similar area. The data subsequently undergoes stratification in order to organise it into homogeneous groups characterised by similar properties <Vectors> of the layers. In later steps, these layers are subject to adjustments, which assess the population of the properties; and then calibration to determine the coefficient associated with each variable. Calibration using neural network algorithms allows for the calibration of models which consist of data analysed both in both a linear and non-linear manner.

In the study, classification tasks were triggered by independently performed flows of complete tasks. Subtasks were closed as a series of steps created from the following components:

1. <Data Collection>, which is the definition of the problem and leads to the determination of the scope of business data.
2. <Data Transformation> responsible for data cleaning processes and determining function engineering, i.e., values that the model uses during learning and for production purposes.
3. <Input Data> that the supervised learning model uses for learning so that the model is able to learn and predict the required <Problem Class> in order to solve the pre-defined business problem.
4. <Feature Vector> containing information describing the properties of <Input Data>.
5. <Labels>, are categories of <ontological classes> predefined in the <ontology>, taken into consideration by the model.
6. <Algorithm> used in the study.
7. The <Predictive Model> presenting results based on the <Input Data> set and predicting new <Labels>.

The structure of the model together with functional blocks is demonstrated in Figure 4.

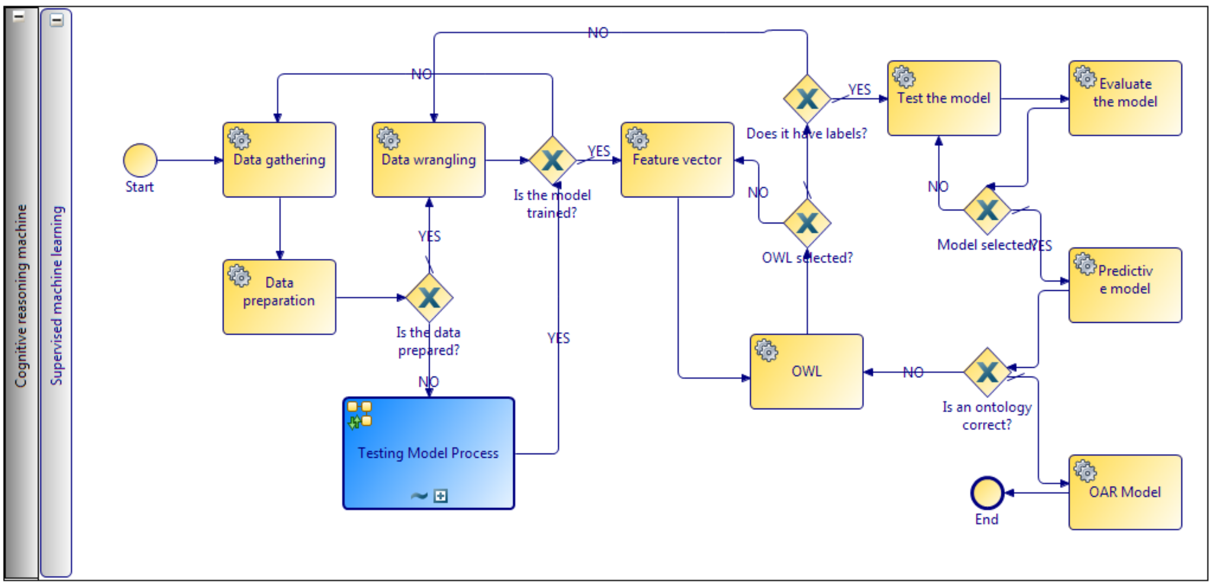


**Figure 4.** The course of the cognitive inference process using neural networks and machine learning in AVM

Source: the author's own compilation based on research.

Subsequently, in the <Cognitive Inference Machine>, after entering the variable with the assigned weights, the software component defined as the <Agent Algorithm> explored and ordered the <Input Data> by finding its best matches. Matching was performed using a neural network. The matching process used mechanisms contained in a hidden layer in which the weights were corrected (calibrated) in a way that reduced the root square error. Because the neural network learns on an ongoing basis as new information is received and processed to recognise and match unclear or incomplete data patterns, the process was conducted in an iterative manner. The measurement in the <Services> made available in the <Service Bus> met a set of the following criteria:

1. The <Agent Workflow> identifies the type of request and a <Business Model Specification> follows, consistent with the <Cognitive Service> category that forms the <Business Rule>.

2. <Model calibration> uses business process specifications by transforming them into data mining rules, according to a dictionary of <ontology>. The <Agent Algorithm> executing a task may notify of an exception or several exception types. Exceptions are intercepted by the <Workflow Agent> exception handler. The exception is handled by calling the <Feature vector> value which decides whether the <Business Rule> requires retrospective information, contained in <Internal data>, or a request for information or data in <External data>. Once the data has been compiled, the new value is checked and either returned to <Model Calibration> or is passed directly to <Testing>. Exceptions are recorded in the repository in order to handle them correctly in the future.
3. <Testing> is responsible for examining the validity of generalizations in other circumstances. <Agent Workflow> acting within the constraints specified by the established <Quality Criteria>, examines whether the selection corresponds to the level of satisfaction. The process is repeated iteratively until the model's quality assurance tests are successfully completed.
4. <Modification of Specification> occurs when <Model Calibration> requires the application of new or modifications to existing <Business Rules>. In this case, <Agent Workflow> handles the <send info()> command to <Model calibration> starting a renewed assessment. If a new <Business Rule> is created, its <New model> is moved into the repository.
5. After the process is completed correctly, the control sends the command <answer service()> outside the process.

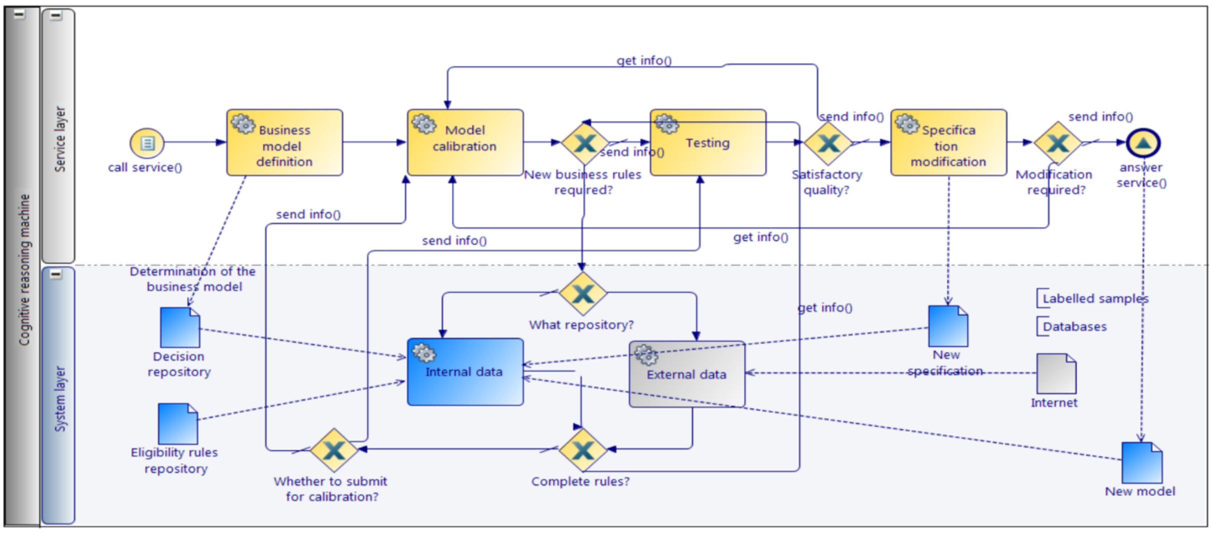


**Figure 5.** Diagram of the measurement model in the <Cognitive decision-making service> made available by the enterprise service bus in BPMN notation

Source: the author's own compilation based on research.

## 3. Research results

*3.1 RQ1: Are cognitive decision-making algorithms using neural networks and machine learning suitable as inference engines in AVM?*

Single decision-making processes associated with individual FM domains were examined, and the aggregate behaviour of all cognitive services operating in the <Enterprise service bus> was also investigated. The visualised effects of each service are illustrated in the Figure 6–9 and Table 1–4.

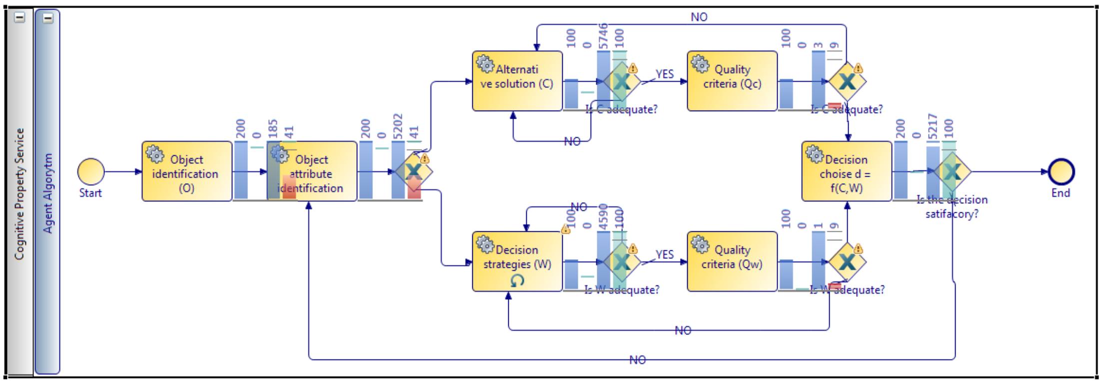


**Figure 6.** Values of actions for Cognitive Property Service in BPMN notation

Source: the author's own compilation based on research.

**Table 1.** Effectiveness parameters of the cognitive decision-making process for the Cognitive Property Service

| Step name | Number of cases | Cases not implemented | Sum of adjustments | Efficiency of working time |
|---|---|---|---|---|
| Object identification (O) | 200 | 0 | 185 | 41 |
| Identification of an attribute of the object (A) | 200 | 0 | 5202 | 41 |
| Alternative solution (C) | 100 | 0 | 5746 | 100 |
| Quality criteria (Qc) | 100 | 0 | 3 | 9 |
| Decision-making strategies (W) | 100 | 0 | 4590 | 100 |
| Quality criteria (Qw) | 100 | 0 | 1 | 9 |
| Choice of decision (d) | 200 | 0 | 5217 | 100 |

Source: the author's own compilation based on research.

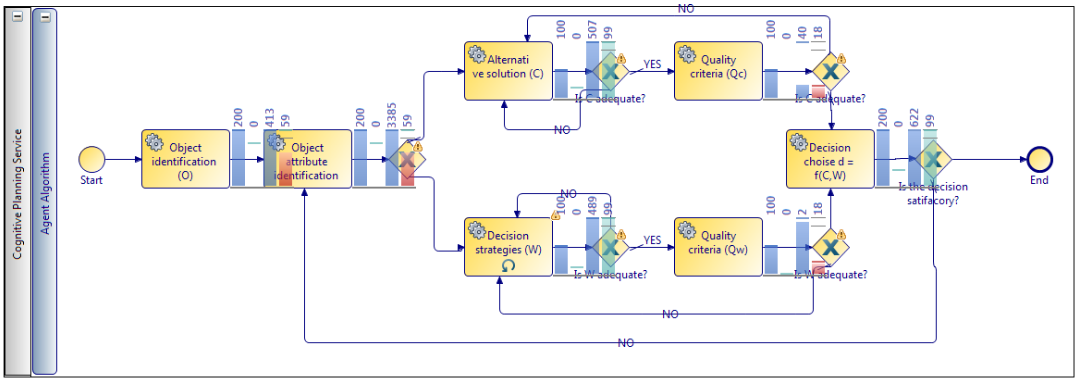


**Figure 7.** Values of activities for the Cognitive Planning Service in BPMN notation

Source: the author's own compilation based on research.

**Table 2.** Performance parameters of the cognitive decision-making process for the Cognitive Planning Service

| Step name | Number of cases | Cases not implemented | Sum of adjustments | Efficiency of working time |
|---|---|---|---|---|
| Object identification (O) | 200 | 0 | 413 | 59 |
| Identification of an attribute of the object (A) | 200 | 0 | 3385 | 59 |
| Alternative solution (C) | 100 | 0 | 507 | 99 |
| Quality criteria (Qc) | 100 | 0 | 40 | 18 |
| Decision-making strategies (W) | 100 | 0 | 489 | 99 |
| Quality criteria (Qw) | 100 | 0 | 2 | 18 |
| Choice of decision (d) | 200 | 0 | 622 | 99 |

Source: the author's own compilation based on research.

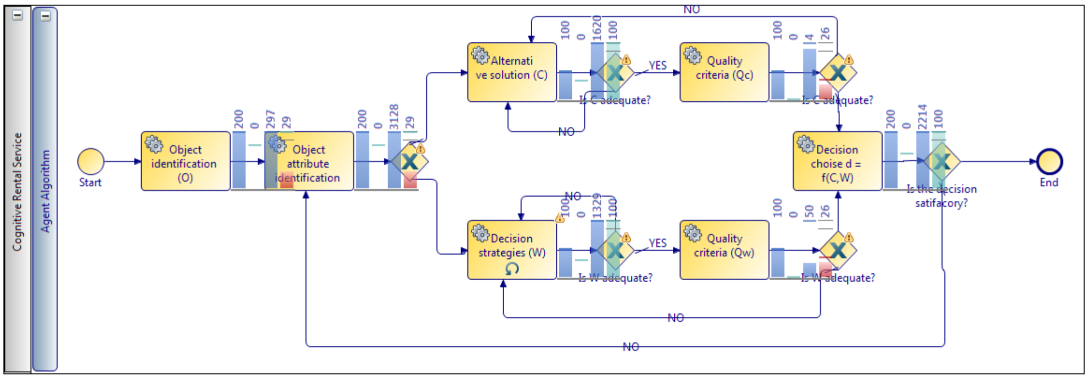


**Figure 8.** Values of actions for the Cognitive Planning Service in BPMN notation

Source: the author's own compilation based on research.

**Table 3.** Performance parameters of the cognitive decision-making process for the Cognitive Rental Service

| Step name | Number of cases | Cases not implemented | Sum of adjustments | Efficiency of working time |
|---|---|---|---|---|
| Object identification (O) | 200 | 0 | 297 | 29 |
| Identification of an attribute of the object (A) | 200 | 0 | 3128 | 29 |
| Alternative solution (C) | 100 | 0 | 1620 | 100 |
| Quality criteria (Qc) | 100 | 0 | 4 | 26 |
| Decision-making strategies (W) | 100 | 0 | 1329 | 100 |
| Quality criteria (Qw) | 100 | 0 | 50 | 26 |
| Choice of decision (d) | 200 | 0 | 2214 | 100 |

Source: the author's own compilation based on research.

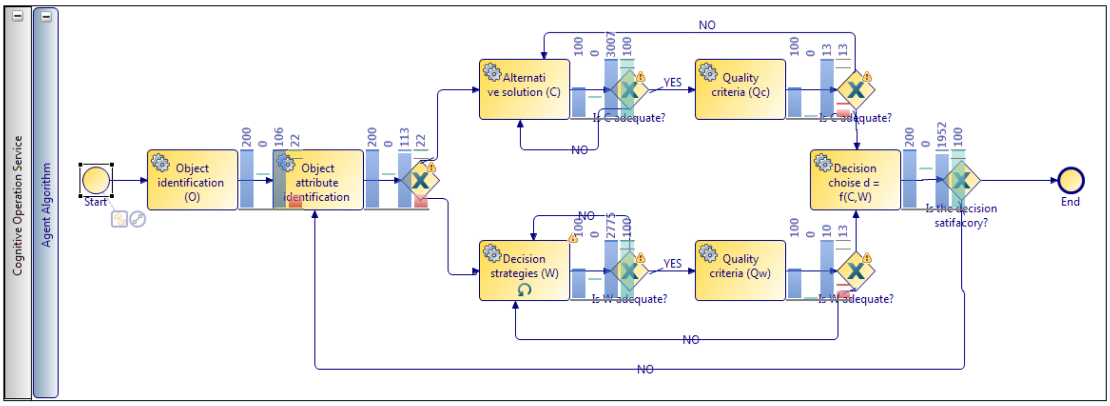


**Figure 9.** Values of actions for the Cognitive Operation Service in BPMN notation

Source: the author's own compilation based on research.

**Table 4.** Performance parameters of the cognitive decision-making process for the Cognitive Operation Service

| Step name | Number of cases | Cases not implemented | Sum of adjustments | Efficiency of working time |
|---|---|---|---|---|
| Object identification (O) | 200 | 0 | 106 | 22 |
| Identification of an attribute of the object (A) | 200 | 0 | 113 | 22 |
| Alternative solution (C) | 100 | 0 | 3007 | 100 |
| Quality criteria (Qc) | 100 | 0 | 13 | 13 |
| Decision-making strategies (W) | 100 | 0 | 2775 | 100 |
| Quality criteria (Qw) | 100 | 0 | 10 | 13 |
| Choice of decision (d) | 200 | 0 | 1952 | 100 |

Source: the author's own compilation based on research.

The simulation results for the entire planning process using algorithms and automated decision services which is launched in the <Enterprise service bus> are presented in Figure 9. The summary parameters of cognitive services are based on the values for individual transactions executed by the system during the process simulation. A single transaction is assigned to a one-off action of the participant in the process, and then the program calculates the cost of the action (the duration of the action multiplied by the participant's unit cost). The bars presented in the diagram denote: (i) the number of analysed cases, (ii) the size of the queue of uncompleted cases, (iii) the sum of adjustments in the implementation of actions resulting from delays in previous actions, (iv) effectively used working time.

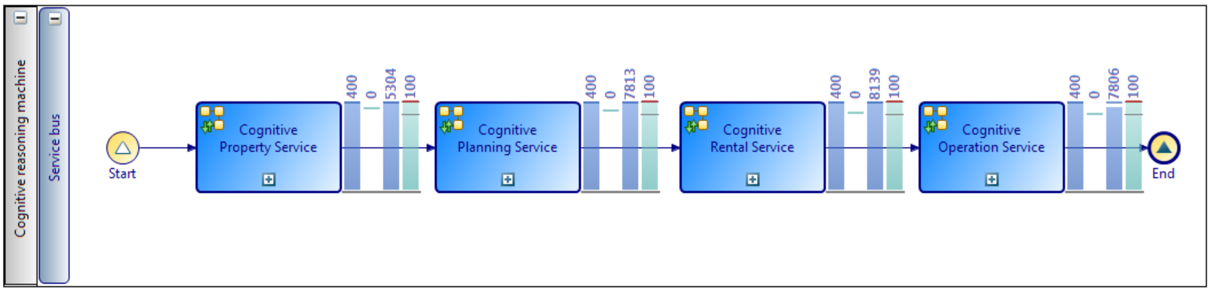


**Figure 10.** Values of individual <Cognitive services> operating in the <Service bus> in BPMN notation

Source: the author's own compilation based on research.

*3.2 RQ2: Does the extension of the AVM to include cognitive decision-making services allow the automated assessment of the technical condition of a building, the prediction of future breakdowns, the planning of repair work, or necessary upgrades?*

In the study, based on the pre-defined parameters, the model specification process identified features (variables) that influenced the model structure, and then selected the appropriate (most favourable) <Business process> model for calibration. The calibration of the model consisted in deriving new parameters for previously defined variables. New variables were created through transformations. The basic steps followed the pattern proposed as a standard for using AVM: (i) defining the scope, (ii) data identification, (iii) exploratory data analysis, (iv) stratification, (v) determining data representativeness, (vi) model specification, (vii) model calibration, (viii) quality assurance, (ix) model application and value review. Steps (ii-ix) were carried out by cognitive services running sequentially in the <Service bus>. The model provided an interface where all the required information about the real property was presented. Access to the range of data was individualised according to roles and their assigned authorisation levels.

1. The operator indicates the range of data being of interest to them, including limiting and hypothetical conditions triggering a process of sequentially triggered cognitive decision-making services running implicitly in the <Service bus>.
2. The first service is the <Cognitive Property Service> sending the request <get info()> to the <Cognitive Planning Service>. The request is supervised semantically by the respective <ontological classes>. The request is executed sequentially until the exhaustive scope of the request is reached.
3. In the next step, the <Cognitive Planning Service> responsible for providing information related to the registration data of the real property is launched. In the case of lack of data, the sub-process

of the <Cognitive Inference Machine> responsible for providing the decision (d) in accordance with the assumed (SLA) is started. The request is executed sequentially until the exhaustive scope of the request is reached.

4. Next in line to be launched is the <Cognitive Rental Service> responsible for up-to-date data on rental agreements, their terms, conditions, methods, and manners of calculating the cost of using the real property. Also in this case, before the result of the request is delivered, the data is updated and reworked by the <Cognitive Inference Machine> according to the rules of <ontology>.
5. Last to be launched is the <Cognitive Operation Service> providing the entire set of data on operational issues for the real property. In the case of missing or obsolete data, the <Technical Data Collection> subprocess supervised by the <Cognitive Inference Machine> is launched. The operation of the service is carried out sequentially until the end result is exhaustive in the scope of the request.

A flow diagram of the process is shown in Figure 11. The bars presented in the diagram denote: (i) the number of analysed cases, (ii) the number of cases not completed, (iii) the sum of adjustments in the implementation of actions resulting from delays in prior actions, (iv) effectively used working time.

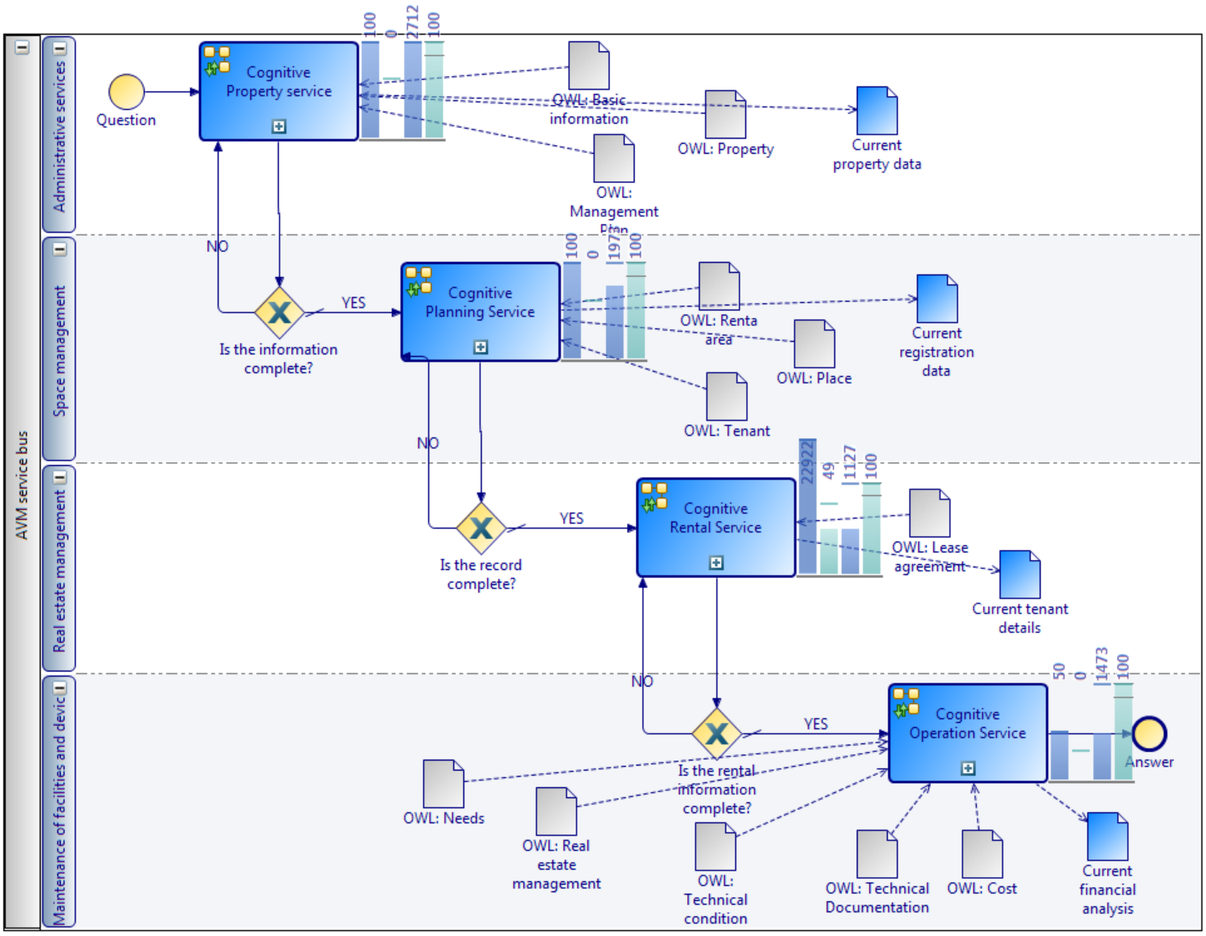


**Figure 11.** Process of sequentially triggered cognitive AVM services in <Service Bus> in BPMN notation

Source: the author's own compilation based on research.

**Table 5.** Values of individual <Cognitive Services> in the planning process using algorithms and automated decision-making services

| Step name | Number of cases | Cases not implemented | Sum of adjustments | Efficiency of working time |
|---|---|---|---|---|
| Cognitive Property Service | 100 | 0 | 1076 | 100 |
| Cognitive Planning Service | 100 | 0 | 2629 | 100 |
| Cognitive Rental Service | 3676 | 49 | 1173 | 100 |
| Cognitive Operation Service | 50 | 0 | 1466 | 100 |

Source: the author's own compilation based on research.

## 4. Discussion

### *4.1 RQ1 study conclusions*

The study analysed whether cognitive decision-making algorithms using neural networks and machine learning are suitable as inference engines in AVM. The <Cognitive Inference Machine> applied in the study used decision-making machines controlled by algorithms and processed processes which are part of the Facility Management domain. The entire process took place under the supervision of machine learning. Each cognitive service was tested autonomously, then the entire sequential process running in the <Service Bus> was evaluated. For each service, the effectiveness of decision making was calculated at the level of 100%. The input state related to the number of analysed attributes or alternative solutions did not affect the effectiveness. Similarly, the initial <Lack of Information> and <Partial Information> status did not have any significance for the flow and time of the information completion process. This means that in the case of using algorithms and automated decision-making services as inference engines in AVM, the input state is irrelevant or of minimal importance for the effect of the entire process. The processes execute themselves correctly and at the same time display high efficiency.

### *4.2 RQ2 study conclusions*

The study analysed whether the use of AVM for automated real property valuation brings benefits to the real property manager. The conducted simulation showed that the <Value Measurement Models> running independently for each of the cognitive services work properly and perform calculations without disturbing the entire sequential process carried out by the <Service Bus>. For each cognitive service, the efficiency of its performance was 100%. <Cognitive Rental Service> (3676) was responsible for the most repeated iterations, looking for appropriate associations in the provided data sequences. This is due to the large, natural dynamics associated with the formation of rental agreements. This affected the <Cognitive Planning Service>, in which an increased number of re-analyses on vacant units were observed (2669). Importantly, this did not disturb the <Cognitive Operation Service>, which was responsible for providing the most appropriate decision presenting the value sought. For the 50 analysed reference cases, 1466 probable and expected minor repair works resulting from breakdowns were observed. The process was carried out entirely by software. It involved <Agent Algorithm>, <Agent Workflow>, <Agent Software> and <Agent System>. The study confirmed that AVM can be used to assess the characteristics of the real property in an automated manner, thus creating an advantage (in the form of cost and time devoted to the implementation of tasks) for the real property manager.

### *4.3 Future research direction*

Cognitive automation of real estate management processes is a novel approach using machine learning algorithms to analyse real estate data, combining artificial intelligence technology with automation. It makes possible autonomous decision-making by software bots (AI agents) without the need for human intervention. Operating on the principle of cognitive data processing, such systems are able to not only interpret information items occurring in logical succession one after another but also deal with ambiguous data, which makes them intelligent. The research described in the article concerned the cognitive automation of real estate management processes in the field of optimizing renovation budgets and forecasting changes in real estate value. It seems that this technology may improve not only the operational processes related to the maintenance of facilities but also, thanks to holistic data analysis, it may contribute to more effective and flexible management of other processes in the real estate sector. Research into Automated Valuation Models in the context of Facility Management opens up the prospect of improving the efficiency and precision of processes involved in the widely understood management of real estate. One key area of research could be the integration of cognitive technologies, such as machine learning and machine reasoning, in order to improve models of other FM processes. Research should focus on understanding how these technologies could improve the ability of models to analyse data from different sources and generate more precise valuations.

Exploring the potential for the development of autonomous software bots (AI agents) within Automated Valuation Models is another fascinating area of research. The use of artificial neural networks for learning and adaptation may increase the flexibility and ability of models to solve more complex problems in the context of real estate valuation.

As autonomous software bots can take greater responsibility for end-to-end processes, minimizing or even completely eliminating the required human intervention, this can affect the efficiency of other "manual" processes currently functioning in organizations. If all information and data are delivered through digital channels, bots can work faster, throughout the whole process from start to finish. Viewed in this way, "smart" digital automation will provide a greater return on investment and the final comprehensive solutions will be more efficient than the sum of digitized individual processes. An important area of research is data standardisation in the context of Facility Management and Automated Valuation Models. Exploring opportunities to standardize real estate information may improve data exchange between different facility management systems and AVMs. This can also be achieved by running a single cognitive adapter working with any older system and as a result, digitize new areas of business processes. Research into analysing the impact of external factors, such as market changes, economic trends or regulation, on real estate values may lead to improvements in AVM models, enabling them to improve prediction of changes in value. In addition, research into the optimization of decision-making processes within Facility Management may lead to more effective planning of investment, renovation or budget. The analysis of the impact of cognitive technologies on valuation processes and assessing how these modern approaches can change traditional real estate appraisal methods are further areas of research that may contribute to the further development of advanced and flexible AVM models. Cognitive computing systems and machine reasoning technology have the potential to change traditional decision-making methods, enabling organizations to solve problems faster through more comprehensive data analysis. The combination of digital technology with cognitive robotics may lead to improved operational efficiency, increased precision of data analysis and the creation of more autonomous decision-making processes in various sectors of the economy.

## Conclusions

The article focuses on the perspectives of using Automated Valuation Models, which have been enriched with advanced technologies of machine learning algorithms and artificial neural networks, in the area of Facility Management. A series of experiments simulating AVM activities in the context of operational management of the real property was carried out. The study focused on assessing the effectiveness of decision-making service algorithms, activated by automated inference engines, in terms of general information about real property and the process of planning with the use of algorithms. The conclusions of the study indicate that adopting a cognitive perspective in relation to AVM, as well as the use of advanced algorithm technologies and artificial neural networks in operational real property management, may significantly increase the productivity of processes. This in turn results in benefits for real property managers. In addition, the experiments demonstrated that AVM combined with advanced cognitive technologies excels at adapting to changing market conditions and the specifics of various real properties. Machine learning algorithms allow for the rapid analysis of huge quantities of data, which allows continuous monitoring and assessment of the technical condition of buildings. Meanwhile, artificial neural networks enable advanced inference and forecasting of future breakdowns or maintenance costs.

Noteworthy is the fact that the cognitive approach to AVM eliminates barriers related to various input states and lack of information, which translates into greater flexibility and efficiency in operational real property management. As a result, real property managers are able to make decisions with better justification while saving time and resources. The conclusions indicate a great potential for the use of modern technologies in Facility Management and open up new perspectives for the automation of management processes.

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