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AI-DRIVEN INNOVATION IN BANKING – THE CASE OF COGNITIVE RPA

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Purpose: The aim of this article is to characterize the determinants and effects of implementing disruptive artificial intelligence (AI) innovations in banking operations, particularly regarding AI's relevance to the development of a new generation of robotic banking process automation systems (i.e., cognitive RPA).
Design/methodology/approach: Based on a comparative analysis of the literature and an empirical comparison of leading banks in the European Union, this article highlights the main areas of innovative improvement in banking activities through cognitive RPA applications and examines their potential to radically streamline future banking operations.
Findings: The analysis of AI innovation has found that cognitive RPA is dramatically transforming banking processes. In practice, cognitive RPA enables banks to achieve higher levels of efficiency across all dimensions of their operations, particularly in optimizing the management of a bank's wide range of risks.
Originality/value: Given the still nascent stage of AI innovation and its implementation in banking, this article combines the theoretical foundations of artificial intelligence with empirical examples from leading European banks, presenting a research area that has not yet been addressed in Polish literature and remains underexplored in global literature.
Keywords: Artificial Intelligence, Automation, Innovation Processes, Commercial Banks.
Category of the paper: Literature review, case study.

1. Introduction

Disruptive innovation in the form of artificial intelligence (AI) has been evolving since the 1950s. The AI systems focus on developing integrated decision-making algorithms that enable computer systems to perform tasks resembling human intelligence. These tasks involve complex processes of data acquisition, identification, and processing within defined boundary conditions. The application of AI facilitates real-time decision optimization through analysis of data interdependencies within vast databases (commonly known as Big Data).

When AI models are used to generate new content and make autonomous decisions, this set of activities is referred to as generative artificial intelligence. Examples of this type of AI include IT systems communicating with users in natural language (NLP), recognizing sounds, creating images, and designing decision-making processes. Generative AI has led to applications such as virtual assistants, which, in the form of avatars with speech recognition and generation capabilities, allow computers to interact with humans in an interpersonal manner.

A distinguishing feature of generative AI is the rapid development of practical applications, such as chat-based AI models (e.g., ChatGPT). In this context, banks see generative AI as a promising tool for achieving significant efficiency gains through the automation and personalization of customer service processes (i.e., front office), integrated with the optimization of back-office systems and data management in the middle office (Bielas, 2020, pp. 1-3).

The surge in the popularity of generative AI in banking is also due to its rapidly expanding range of applications. Generative AI systems have the capacity for self-improvement and automatic efficiency development. Using AI to create a specific ecosystem of data that then serves as training material for further AI models is crucial for cost reduction and resource optimization. Currently, banking systems still rely on partially automated data processing.

In this context, the purpose of this article is to characterize the factors influencing the application of AI in robotic process automation (RPA) within banking and to demonstrate the practical effects of this innovation, leading to the development of a new generation of RPA systems, i.e., cognitive RPA. The article aims to demonstrate the originality of cognitive RPA innovation as a complex integration of traditional RPA systems with machine learning and deep learning techniques within AI.

The structure of the paper is as follows. First, the literature on AI innovation is reviewed and the stages of development of Robotic Process Automation (RPA) are described. Next, the study delves into research methodology presenting results. The paper ends with the summarizing remarks.

2. AI innovation – main dimensions

Machine learning is the science of algorithms and systems that improve their decision-making and predictive performance as they learn and gain new experience. In practical terms, machine learning is an artificial intelligence technology focused on using data and algorithms to mimic human learning methods to incrementally improve decision-making and predictive accuracy (Milana, Ashta, 2021, pp. 189-209).

The idea behind machine learning is to use statistical and optimisation methods in the process of learning computers by a human (trainer), who creates algorithms to analyse datasets and identify patterns between the data, and watches over their development. Mahesh (2020, pp. 3811-382) points out that with extensive data sets and statistical methods, algorithms are trained to independently classify data, make predictions and infer from them.

In contrast, deep learning is an advanced type of machine learning using so-called artificial neural networks. Therefore, there are fundamental differences between machine learning and deep learning techniques. Deep learning shows an advantage over conventional machine learning algorithms. This advantage is due to the fact that deep learning is capable of generating more extensive and more accurate results. During deep learning applications, there is autonomous learning and self-improvement of decisions in subsequent rounds based on an extensive data set. This type of machine learning is more effective the greater the availability of training data.

Unlike other machine learning techniques, deep learning algorithms do not require the active intervention of a trainer during analysis, as the algorithms autonomously discover relationships between the data along the lines of human decision-making processes as experience increases. Deep learning requires very high computing power of computers. This is due to the processing of extensive data sets and more complex and multiple calculations (Wang, 2020, pp. 1726-1744). Also, the time required to obtain satisfactory results in deep learning models is considerably longer due to the huge amount of data and mathematical parameters and formulas. A simple machine learning algorithm can be trained adequately in as little as a few seconds to a few minutes or hours, while a deep learning algorithm may require a minimum of several hours to even several weeks to train (Kumar, Garg, 2018, pp. 22-25).

Standard machine learning algorithms typically analyse data in parts, which are then combined to produce a specific result or solution. Deep learning algorithms analyse the problem at the full scale of the data. This is because deep learning systems recognise relationships between data using the entire available database (up-bottom approach). In contrast, machine learning techniques search databases to identify human-defined types of data and their relationships (bottom-up approach) (Gutierrez-Garcia, Lopez-Neri, 2015). It does not imply that deep learning is always better than machine learning. The important thing is to choose the right solution for the specific problem. Complex deep learning algorithms using multi-layer neural networks are not necessary in every case. For some applications, it will be equally useful and more cost- and time-efficient to use simple machine learning algorithms.

3. Robotic process automation (RPA)

Traditional banking processes are often time-consuming and prone to human error. In addition, they generate a lot of forms that require manual processing and file verification, which absorbs human resources and generates high operational costs for the bank. As banks' interactions with their customers become increasingly digital, the efficient management of extensive data sets across intricate banking processes is becoming the most important cost optimization imperative for banks.

Robotic Process Automation (RPA) are based on the use of robots (so-called bots), i.e. computer programs that have been designed to independently carry out activities described by the rules of business processes. In practice, bots are a set of algorithms in which a sequence of strictly defined actions has been programmed into a given computer network. Bots perform repeatable processes, transaction patterns and tasks, with human involvement required only in exceptional cases (Nguyen, 2023, pp. 2959-2966). Bots can interact independently with other computer systems and autonomously carry out a specific data processing process from start to finish, once activated based on a schedule or condition that initiates the bot (so-called unattended RPA). There are, however, robotic process automation technologies in which bots collaborate with humans to provide support for activities performed by employees as part of more complex processes that cannot be fully automated (so-called attended RPA) (Dogc, 2022).

As a virtual workforce, RPA is a solution suitable for banks to increase the efficiency and reduce the costs of back-office banking systems as a result of the full automation of activities that are individually characterised by repetition and low added value. These activities require interaction with data from various sources, such as risk assessment systems, customer databases or external systems such as the National Bank of Poland (FINREP, COREP reporting) or reports from the Credit Information Bureau. RPA tasks are carried out within a defined sequence of data exchange between different banking systems, with large volumes and dispersion of data.

It is important to distinguish RPA from other forms of process automation, such as automatic data mining (screen scraping) or macros, which require a special development environment. RPA automates processes between applications at the user interface (GUI) level, i.e. in the environment in which humans work. As a result, developers do not need to create APIs to connect systems, so robotic banking applications are used in natural applications for employees (e.g. checking balances, preparing contracts, matching policies with contracts). The bots are programmed to understand what is on the screen, navigate across systems, identify and extract data to perform predefined actions (Axmann, Harmoko, 2020, pp. 559-562). Thus, RPA solves the problem of special process replication in the development environment, which is the case in the traditional IT systems integration model.

Banking operations generate a large number of tasks and processes, so there is plenty of rationale for implementing intelligent automation. The implementation of RPA in a bank includes all rule-based processing activities, within processes that do not require human intervention, such as logging into applications, reading and writing to databases, performing calculations, filling in forms, connecting systems via application programming interfaces (APIs), extracting data from documents or retrieving data from internal and external databases.

A particular challenge at the bank is related to unstructured data, which does not have a predefined data pattern and does not occur in a structured way. This data takes a variety of sizes and formats, i.e. textual, numerical, graphical and even audio. Traditional RPA systems face significant problems in recognising and processing unstructured data, which affects the quality of robotic output. Data processing is much simpler for structured data, which is organised in databases according to predetermined attributes and is processed after pre-labelling (i.e. semantically tagged), but such data is of a decided minority in practice.

Considering the artificial intelligence systems of robotic process automation (RPA), four phases of evolution can be distinguished:

- RPA 1.0 - assisted RPA,
- RPA 2.0 - unassisted RPA,
- RPA 3.0 - autonomous RPA,
- RPA 4.0 - cognitive RPA.

RPA with support (RPA 1.0) is being implemented in banks on individual staff workstations to automate processes. RPA bots require the intervention of employees or the system administrator. For this reason, they are most often used for customer service activities for standard tasks (e.g. handling documentation flows). Given that bots and employees collaborate on processes that are not fully automatic, assisted RPA 1.0 can be classified as a type of human-robot collaboration (ang. human-robot communication).

Unassisted RPA (RPA 2.0) is most commonly used in a bank to integrate activities in the bank's back-office systems, as it allows for full automation of processes in an end-to-end model. RPA bots operate independently and have high performance, performing tasks and interacting with other applications without the intervention of a bank employee. This type of automation is applicable to standard banking processes with exceptions, as the RPA system can only handle structured data. Consequently, the rules of operation must be based on processes running in a loop, where the data must first be transformed into structured data.

Autonomous RPA (RPA 3.0) is typically deployed in the cloud (cloud computing), enabling dynamic scaling of operations and flexible use across all the bank's business units. RPA 3.0 takes automation to a higher level of efficiency and implements more advanced processes that integrate different departments. Although RPA 3.0 introduces some aspects of artificial intelligence to process more complex tasks, it is still limited to handling structured data and has no self-optimisation capabilities. As such, workflows still rely on processes running in a loop to structure the data that the bots can process. Autonomous RPA uses advanced predictive analytics with a system of alerts for employees in emergency situations.

The most advanced form of robotic process automation technology is cognitive RPA (RPA 4.0), which can process any type of data (both structured and unstructured data), in any format (text, image, audio, video) on a variety of media and transfer data from internal and external databases. To manage unstructured datasets, bots first transform and organise the data using advanced artificial intelligence applications such as natural language processing (NLP).

The basis of RPA 4.0 is machine learning applied to automate complex tasks to perform extensive analytical functions with high business value for the bank (e.g. updating risk models within boundary conditions set by the regulator), and in recent years also deep learning.

4. Cognitive RPA systems

Although there is no universally accepted definition of cognitive systems, the term is used to describe a set of computer technologies that, when processing data and making decisions, mimic the way the human brain works in knowledge creation. Cognitive systems make use of robotic models of processes, but rely primarily on models of artificial intelligence (Gutierrez-Garcia, Lopez-Neri, 2015). In this aspect, machine learning models for processing huge datasets from multiple sources and deep learning models for state-independent knowledge workers to generate hypotheses and formulate conclusions by recognizing hidden interdependencies in vast datasets are applied within cognitive systems (Nowak-Nova, 2018, pp. 165-167).

The goal of cognitive systems is to develop a consistent, unified, universal inference mechanism based on comprehensive data analysis inspired by the capabilities of the human mind. Cognitive systems use algorithms that can automate increasingly complex processes, simulating both human thinking and involvement in realised actions without human assistance. They have an autonomous learning capability that allows them to work through interactions with between different applications and learn from their own conclusions, extending the knowledge in the bank.

Cognitive Robotic Process Automation (CRPA) is the result of the integration of RPA and artificial intelligence (AI) methods. In addition to automation, cognitive RPA transforms banking processes into a system of efficient decision-making systems with consideration of risk and external regulation. Cognitive automation uses sets of algorithms and technological approaches from the field of artificial intelligence, such as natural language processing (NLP), fuzzy logic technologies in data mining and deep learning neural networks to create intelligent banking interfaces (Martínez-Rojas, Barba, Enríquez, 2020, pp. 161-175).

A distinctive feature of cognitive RPA is not only the automation of tasks, but the ability to learn responses in reaction to the emergence of new data or tasks. In other dimensions of RPA, such situations lead to bot stasis. Thus, cognitive robotic process automation (RPA) technology is capable of detecting and reacting to non-standard situations where risk factors or consequences of errors are very important to the bank.

Artificial intelligence systems within cognitive RPA also allow unstructured data to be processed by pre-cleaning databases of duplicate or corrupted data and defining their meaning. For this purpose, cognitive RPA bots use tools such as optical character recognition (OCR) and natural language processing (NLP). This is followed by automatic identification of data relationships, which automatically initiates decision patterns.

Artificial intelligence techniques discover the business value of data regardless of its type with very limited human involvement. As a result, so-called cognitive RPAs can autonomously assess and make for complex decisions where there are ambiguities or a range of outcome options. The processes used are then used to optimise decisions made as a result of analysing extensive large and complex data sets that come from many different sources. Thus, cognitive RPA has a distinct advantage over traditional RPA technologies, which only process structured data in well-defined rule-based tasks.

When analysing the differences between traditional RPA and RPA supported by artificial intelligence (i.e. cognitive RPA), several dimensions of the change in metrological approach can be distinguished, such as:

- methodology,
- underlying technologies,
- data processing capabilities,
- type of data,
- scope of application.

Traditional RPA uses a process-based methodology that automates activities according to conditional (i.e. 'if-then') rules. This primarily provides workflow automation through the integration of computer systems. CRPA, on the other hand, uses a methodology based on inference and knowledge building as a result of machine learning and deep learning algorithms. Artificial intelligence cognitive technologies, on the basis of identified data dependencies, give the process automation system human-like competences for inference (including predictive models). Thus, in the CRPA, the bots not only automate actions, but also learn from the data and are able to recommend courses of action and make decisions like bank employees.

Traditional RPA does not require a programming language, as it mainly involves the configuration and implementation of a defined application structure. These include the mechanism of how RPA works and how to feed a dataset of general-purpose libraries to perform specific tasks. Against this backdrop, cognitive RPA uses artificial intelligence technologies, which require pre-programmed processes and system training.

Standard RPA can only use standardised data, so it only processes data when it is available in a specific format. Meanwhile, cognitive RPA can also handle unstructured input data thanks to the advanced recognition capabilities of artificial intelligence. This exponentially increases the scope for business process automation, including task sequences that process a dataset along a specific path (work flow). The business value for the bank as a result of the combination of RPA and artificial intelligence is that the results obtained in cognitive RPA are not final on a given slice of tasks, but are part of comprehensive solutions covering the entirety of the banking systems.

5. Research methodology

The research covers the own investigation of six banks operating in the European Union to analyze the empirical applications of cognitive RPA in their activity. Based on an analysis of sample of big commercial banks selected according to their advanced technology strategy adoption. In this paper the following dimensions of cognitive CRPA activity are analysed:

- management of the bank's liquidity position (LP),
- optimisation of liquid balances in customer accounts (LB),
- application of predictive analytics for customer service (PA),
- improvement of automated supervisory reporting (SR),
- analysis of banking operations in view of risks e.g. cyber security (RI),
- optimisation of back office systems (BO),
- automation of KYC and KYB procedures (KY).

Table 1.
Cognitive RPA in research sample of the banks

Items		COGNITIVE RPA DIMENSIONS					
	LP	**LB**	**PA**	**SR**	**RI**	**BO**	**KY**
Bank 1		x	x	x			x
Bank 2		x		x	x	x	x
Bank 3	x	x	x	x		x	x
Bank 4		x	x	x	x	x	x
Bank 5	x	x	x				x
Bank 6		x		x	x	x	x

Source: Own research on the confidential banks' reports.

6. Results

The cognitive RPAs systems used to streamline the processes of identifying bank exposures to all liquidity risk (LP) are present in two out of six banks in the research sample. These systems include compliance with internal and liquidity limits and modelling and automatic alerting of intraday liquidity and collateral changes is also exploited. The CRPA system identifies intraday changes in banks' liquidity, its cost and collateral value with rapid identification of suprathreshold transactions and automatically responds to them regardless of the source of risk (i.e. internal and external). Importantly, cognitive RPA takes into account the organisational and system specificities of the two given banks.

In all of researched banks, CRPA systems streamline and automate liquidity management systems on client accounts providing better control over processes (LB). Cognitive RPA transforms manual banking processes into digital workflows, providing automated balance optimisation and error levelling. By reducing manual handling, cognitive RPA systems allow researched banks increasingly accurate prediction of liquidity balances as the range of data processed increases. This provides a rationale for the increased effectiveness of advanced liquidity analysis systems in customer service across different generic cross-sections.

The customer data is analysed in CRPA systems (PA) in almost 70% of researched banks. These banks gain insight into current needs of their customer and the risk factors associated with these relationships (so-called contextual banking). Within CRPA the banks benefit from the predictive analytics in customer data management to automatically identify customer behavior and strengthen their Customer Management systems. This allows four researched banks to react faster and offer a more personalised service with automated decisions provided in real time, thus saving time, reducing costs, minimising errors and reducing risks. The implementation of cognitive RPA is changing the way the researched banks interact with customers. Cognitive banking creates much individualized value of banking services for customers. The automated recommendation system supports the knowledge of experts and account managers, allows for the personalisation of customer service and provides instant access to analytical and transactional systems. This enables a responsive bank-customer relationship, accelerates banking service processes, provides analysis and support for operational models, which altogether creates a new dimension of proactive banking service.

More than 80% of researched banks has taken effort to streamline with CRPA regulatory reporting (SR). Thanks to the artificial intelligence tools such as natural language processing (NLP), these banks automatically extracts data from voluminous documents, reports on key legal and financial aspects and generates periodic reports for internal and external regulator use. The bots prepare automated reports so as to provide full real-time updates with compliance risks. In practice, the researched banks save time and increase the transparency of banking processes in back office systems. Cognitive RPA shortens the waiting period for bank decisions on customer applications and leads to the elimination of manual processes during correspondence with regulators, contract preparation and customer file management.

Cognitive RPA is used in about 40% of researched banks as a solution for detecting and preventing fraud in remote channels (RI), including in particular to increase the efficiency of cyber security systems by detecting so-called vulnerabilities of the systems. In order to identify suspicious activities, algorithms check all payment transactions in real time and compare them with the transaction history within the framework of so-called early warning systems.

Thanks to cognitive technology, the process of activating services in back office systems (BO) in the half of researched bank's becomes faster and more accurate. This is especially vital in processing vast customer data where errors are identified and eliminated in real time. The back office process automation allows four researched banks to nullify the problem of erroneous forms, matching documentation (e.g. contracts with insurance policies) and reading the content of correspondence to the bank without involving bank staff. The systems will also help to generate contractual content tailored to individual customer cases and check data against legal risks, including compliance.

All researched banks use Cognitive RPA for KYC (Know Your Customer) and KYB (Know Your Business) procedures (KY) as mandatory components of money laundering and terrorist financing (AML/CT) prevention systems. Banks focus a lot of resources on verifying customers for procedures under AML policies. Due to the costly manual process, all researched banks have started to use cognitive RPAs to optimise automated processes for collecting, checking and validating customer data (e.g. identifying the beneficial owner in a large conglomerates). This ensures systemic compliance and minimizes the risks associated with money laundering, terrorist financing and other financial crimes. CRPA systems use advanced data analytics for this purpose to detect suspicious transactions in real time. AI algorithms identify inconsistencies, initiate alerts and identify areas for the bank's staff to undertake detailed KYC and KYB checks, demonstrating self-enhancing features.

7. Conclusions

The analysis of cognitive RPA applications in the researched banks indicates that artificial intelligence systems have significant potential to enhance the efficiency of process automation systems and are already finding practical applications in the banking sector. Artificial intelligence, as a disruptive innovation in the banking industry, has become an essential part of a modern bank's business structure, influencing both front-office and back-office operations.

The implementation of RPA supported by AI systems introduces a new form of assistance-cognitive RPA-which enables banks to achieve substantial strategic benefits from a holistic perspective by integrating a wide range of internal processes with diverse characteristics.

The practical cases of cognitive RPA applications presented in this paper demonstrate the capabilities of intelligent automation. They also highlight the high potential for AI development in the banking sector, particularly in the era of cloud computing and extensive database systems, where effective data management serves as the foundation for the growth and evolution of banks' operations.

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