Is Robotic Process Automation Becoming Intelligent? Early Evidence of Influences of Artificial Intelligence on Robotic Process Automation

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Abstract. Advances in Artificial Intelligence (AI) are changing the nature of work and enable the increasing automation of tasks. The trend around AI technologies has also reached Robotic Process Automation (RPA). To date, RPA is known as a software solution that performs simple and routine tasks based on clearly defined rules. However, past research indicates that through the application of AI and Machine Learning technologies, RPA is starting to get "smart" by including intelligent features. Since little is known about the capabilities of intelligent RPA in academia, this paper examines how AI impacts the capabilities and applicability of RPA. Based on case studies with global RPA software providers and RPA integrators, evidence for cognitive capabilities within RPA is examined within the boundaries of a definition of cognitive intelligence. The paper also discusses the general necessity for cognitive intelligence within RPA software.

Keywords: Robotic Process Automation · Artificial Intelligence · Cognitive intelligence · Machine Learning · Intelligent Process Automation

1 Introduction

Artificial Intelligence (AI) is entirely changing the nature of work. Even complex tasks, which were previously performed exclusively by human knowledge workers, are increasingly being automated by machines [1]. The increasing automation is made possible by recent advances in AI technologies, the increasing processing power of computers, and the availability of vast amounts of data [2,3]. The trend around AI has also reached Robotic Process Automation (RPA). Various researchers indicate that sophisticated RPA solutions are starting to get "smart" and include AI and Machine Learning (ML) capabilities to recognize and process unstructured data or to learn in cooperation with human users [e.g., 4–6].

However, research on RPA mainly focuses on simple RPA. Per definition, RPA is an umbrella term for computer programs that mimic and replicate human

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activities by imitating manual, screen-based manipulations [7–9]. Simple RPA is limited to the execution of well-structured routine tasks based on explicit and predefined rules and substitutes for the "arms" and "legs" of human workers [5,6]. Little is known about RPA with intelligent capabilities, even though it appears to be a major trend in industry. Agostinelli et al. (2019) focus on intelligent RPA by analyzing different RPA software and identify limited self-learning abilities within the examined RPA solutions [10]. Other authors address intelligent RPA only marginally as an idea or early indication but do not provide in-depth analyses [5,8,11].

Given the increasing importance of and attention on RPA and AI in industry as well as the lack of research in academia, this paper raises the question of how intelligent RPA is and thus asks: *How does AI impact the capabilities of RPA as well as its applicability, with focus on suitable task characteristics?* Due to the limited theoretical understanding and present dynamics in the field of intelligent RPA, a multiple case study approach is applied to assess the level of intelligence of current RPA solutions [12]. Specifically, rich field and archival data from nine global RPA software providers and six RPA integrators are used.

This research comes with several contributions. First, based on an operationalized definition of cognitive intelligence as a subdomain of AI, the level of intelligence of RPA is assessed. It becomes clear that RPA has only very limited cognitive capabilities and, as per its nature, remains a rule-based execution engine. Only intelligence that enables RPA to work more efficiently and expand its applicability without affecting the predictability and accuracy of outcomes is built into RPA engines. Second, a platform approach to combine RPA with external cognitive capabilities is introduced and discussed. All examined RPA providers offer platforms to add intelligent capabilities from external solutions to RPA. Finally, the impact on process and task suitability is examined. The findings reveal that increasing intelligence expands the potential fields of application of RPA, since the necessity for structured data input, standardization, and process stability becomes less important.

The paper is organized as follows: Sect. 2 provides an overview of fundamental knowledge about RPA and AI, followed by the introduction of the research method in Sect. 3. The analysis of RPA robots and platforms and their level of cognitive intelligence as well as implications on the applicability are presented in Sect. 4. Finally, key findings, limitations, and future research opportunities are summarized in Sects. 5 and 6.

2 Background

2.1 Definition and Introduction to Simple RPA

RPA is part of the Business Process Management domain and aims to automate existing processes based on available IT infrastructure by applying robots to digitally perform tasks [7,8]. RPA is used as an umbrella term for a computer program or software based on scripted language that mimics and replicates human activities by imitating manual, screen-based manipulations and reacting to events on the screen [7–9]. The software can be configured by humans to capture and interpret existing applications, process transactions, manipulate data, trigger responses, or communicate with other systems. RPA robots can either be traditionally programmed, configured by using a graphical user interface, or trained based on recorded process steps [6]. The software operates on graphical user interfaces or computer systems in the way a human would and can, therefore, interact with a wide range of software systems without requiring changes to existing applications [4–6]. This definition of RPA is mainly valid for simple RPA solutions without any kind of cognitive intelligence, which was the primary focus of past research.

2.2 Artificial Intelligence in the Context of RPA

In order to decide whether a system or software is intelligent, one first needs to define the term "intelligence". For computer scientists, the term "intelligence" refers to AI, machine intelligence, or computational intelligence as a subset of human cognitive behavior [13]. It is common in research to apply the concept of human intelligence to approach the definition of AI as machines that exhibit aspects of human intelligence [13,14]. Intelligence is regarded as the ability to learn from experience and adapt to the environment [15]. This research refers to the definition of AI by Kaplan and Haenlein (2019), who define AI as "the ability [of a system] to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption" [16]. This definition is particularly suitable in the context of RPA, since it builds on management literature and specifically targets application in business environments. The authors introduce three types of intelligence: cognitive intelligence, such as pattern recognition or systematic thinking, emotional intelligence, such as adaptability or self-awareness, and social intelligence, such as empathy or teamwork. Since most of the AI systems used in the context of RPA aim to emulate cognitive intelligence by generating a cognitive representation of the environment as well as by learning from past experience to inform future decisions, it is sufficient to focus on cognitive intelligence to assess the degree of "intelligence" of RPA [5,8]. Humanized AI with emotional and social intelligence is not included in the analysis, since it is not available yet [16]. Moreover, intelligence can also be classified into weak and strong AI. The hypothesis of weak AI constitutes that machines act as if they were intelligent, apply AI only to specific areas, and are not able to solve problems autonomously [16,17]. In contrast, strong or general AI assumes that machines actually think and do not just imitate human intelligence [16,17]. In the context of intelligent RPA, cognitive intelligence is considered a form of weak AI [14].

2.3 Classification Framework for Cognitive Intelligence

To analyze cognitive capabilities of RPA, cognitive intelligence is operationalized by cognitive computing. The technology is inspired by the human mind and aims to interact with external sources, process and understand contextual meaning, learn from past experiences, and draw conclusions based on large volumes of data [3,18]. Cognitive computing includes technologies, such as Natural Language Processing (NLP), ML, Neural Networks, or Automated Reasoning [19].

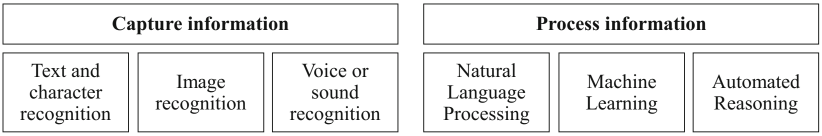

Fig. 1. Classification framework for cognitive intelligence

Cognitive computing comprises two core capabilities: information capturing and information processing [3,19]. For this research, they are applied as a framework to discuss and identify intelligent capabilities of current RPA software solutions in the context of implemented use cases (cf. Fig. 1). The first dimension, capturing information, includes the collection of data and information as well as the perception and observation of the environment. Data collection includes information from text, vision, sound, or voice. The second dimension, processing information, includes capabilities to analyze and interpret contextual meaning via NLP, to learn via ML capabilities, and to reason and take decisions via Automated Reasoning. NLP uses computational techniques to understand natural language and produce human language content. It thereby serves as a basis for human-machine or machine-machine communication [20]. ML solutions provide the ability to recognize patterns, to learn, to develop solutions, and to adapt to new circumstances based on the applied learning algorithm. In the context of RPA and this paper, ML refers to supervised learning methods that learn based on the mapping of a given set of input variables to a given set of predefined output variables [16]. Automated Reasoning allows computers to autonomously reason about knowledge they have gained completely, or almost completely, answer questions, and draw conclusions [21].

3 Research Method

Given the limited theoretical understanding and present dynamics in the field of intelligent RPA, this paper applies a multiple case study approach as described in [12] to assess the impact of AI on the capabilities and applicability of RPA. The multiple case study approach is broadly used in Information Systems research and is particularly suitable for research on newly emerging technologies in organizations, such as RPA in combination with cognitive intelligence [22,23].

As shown in Table 1, several data sources are included: semi-structured interviews with top management as well as technology and innovation managers from RPA software providers and RPA integrators, informal follow-up interviews, and archival data such as product specifications or case documentations. The sample

Table 1. Interview panel

Company	Origin	Interview and archival data			
		Position	Interview type	Duration (IV/FU)	Archival data
RPA provider A	North America	Director Partnerships	Phone call	75/15 min	6 PS, 1 PR, 2 CD
RPA provider B	North America	IT Solution Manager	Phone call	80/15 min	4 PS, 2 PR, 1 CD
RPA provider C	Europe	IT Solution Manager	Phone call	60/10 min	6 PS, 2 CD
RPA provider D	Europe	Business Development Manager	Phone call	75/20 min	2 PS, 2 CD
RPA provider E	Europe	IT Solution Manager	Phone call	60 min	2 PS, 2 CD
RPA provider F	Europe	Director RPA	Phone call	55 min	4 PS
RPA provider G	North America	Director RPA and AI	Phone call	70/15 min	1 PS, 1 PR, 5 CD
RPA provider H	Europe	Global Head IoT	Phone call	80/30 min	4 PS, 2 CD
RPA provider I	Europe	Account Manager	Phone call	50/10 min	3 PS, 1 PR
RPA integrator A	Europe	Managing Director	Phone call	50 min	2 PS
RPA integrator B	North America	Managing Director	Phone call	50 min	1 PS, 1 CD
RPA integrator C	Europe	R&D Manager	Phone call	55 min	1 PS, 1 CD
RPA integrator D	Middle East	Managing Director	Phone call	55 min	1 PS
RPA integrator E	Europe	Innovation Manager	Phone call	90 min	2 PS
RPA integrator F	Asia	Managing Director	Phone call	45 min	1 PS

Legend: IV = Semi-structured interview, FU = Follow-up interview, PS = Product specification, CD = Case documentation, PR = Press release

consists of nine RPA software providers, including three global market leaders, who provide a technology-driven perspective. For a bottom-up validation, six RPA integrators, who worked with the examined RPA software, are included. They provide an application-driven perspective and verify the technology view of the software providers.

The interview process consisted of three waves, starting with the three globally leading RPA providers, followed by six interviews with second and third tier RPA providers, and six interviews with RPA integrators. Follow-up interviews were used to clarify information. As proposed by Eisenhardt and Graebner (2007), the data analysis consisted of a within-case and a cross-case analysis of the transcribed interview and archival data from all RPA providers to detect patterns and to develop constructs [12]. Data from software integrators were used to refine, confirm, or reject the findings and emerging hypotheses.

To ensure data validity, a broad panel of RPA software providers was included. The technical capabilities were critically challenged and only accepted if use cases prove their successful application. Also, the interview transcripts were sent out and reviewed by the experts to ensure accuracy. To overcome a potential elite bias, interviewees from various functional areas and hierarchical levels were included. Finally, a detailed overview of the research project was given beforehand and anonymity was granted to overcome a potential lack of trust.

4 Classification and Analysis of RPA Software

The analysis of the conducted interviews and case studies based on a framework for cognitive intelligence, as introduced in Sect. 2.3, reveals two different approaches with regard to RPA and cognitive capabilities. The approaches are in line with past research [5,6,8]. On the one hand, RPA is defined as standalone software and any kind of cognitive intelligence is incorporated into the RPA software itself. This further development of RPA can be referred to as intelligent RPA and is detailed in Sect. 4.1. For the purpose of this research, all software that is defined as RPA without external solutions that are not incorporated into the software engine is regarded as intelligent RPA. On the other hand, features from cognitive intelligence can be combined with RPA using a platform approach. This means that the concept of simple RPA, as rule-based software, is not touched upon. The intelligence is added by external software, which is integrated into an RPA platform. The platform approach is detailed in Sect. 4.2 below. Academia and industry introduced Intelligent Process Automation or Intelligent Automation to specify this approach [4,24].

4.1 Examination of Cognitive Intelligence Within RPA Solutions

Based on the operationalized definition of cognitive intelligence from Sect. 2.3, Table 2 provides an overview of identified elements of cognitive intelligence that are incorporated into intelligent RPA solutions. They are derived from the analyses of the conducted case studies. The RPA robots A to I correspond to the solutions of the software providers A to I, as introduced in Table 1.

Capturing Information. Capturing information from digital text files with structured electronic text in the form of character recognition is regarded as a standard feature of RPA and included in all examined RPA solutions. The extraction of data from text files constitutes rule-based processing of information. It can be triggered either based on predefined rules within a process flow or based on events that are initiated by activities or keywords. The robots, for example, copy text strings and transfer them into other systems, classify documents based on specific keywords, or use keywords to extract text information.

Optical Character Recognition (OCR) enables the extraction of text from images, ranging from scanned printed documents to pictures with text elements such as traffic signs. Five of the examined robots are able to process images, i.e., robots A, B, C, E, and F. However, most of them are limited to basic OCR capabilities. Basic OCR provides the ability to process scanned, printed documents with a structured nature of text and printed fonts and convert the content into a digital text string. Only solution C contains advanced OCR capabilities. Advanced OCR technology enables texts within images or tables, texts that are randomly located, or texts that are hand-written to be processed and transformed into structured output with a high level of quality. All other vendors do not include OCR in their RPA, as software provider D described:

Table 2. Overview of incorporated cognitive capabilities within RPA solutions

Robot	Capture information			Process information		
	Text and character recognition	Image recognition	Voice or sound recognition	Natural Language Processing	Machine Learning	Automated Reasoning
RPA robot A	CR, KS	Basic OCR, CV	—	—	DC, TC, CV	—
RPA robot B	CR, KS	Basic OCR, CV	—	—	CV	—
RPA robot C	CR, KS	OCR, CV	—	—	DC, TC, CV, SH	—
RPA robot D	CR, KS	CV	—	—	CV	—
RPA robot E	CR, KS	Basic OCR, CV	—	—	CV	—
RPA robot F	CR, KS	Basic OCR	—	—	SH, RE	—
RPA robot G	CR, KS	CV	—	—	CV	—
RPA robot H	CR, KS	CV	—	—	CV	—
RPA robot I	CR, KS	—	—	—	—	—

Legend: CR = Character recognition, KS= Keyword search, OCR = Optical Character Recognition, CV = Computer Vision, DC = Document classification, TC = Text classification, RE = Recommendation engine, SH = ML-based scheduling

We do not include OCR in our RPA solution, because we want to keep our solution flexible and the results predictable. For us, RPA is the execution engine that performs rule-based tasks. If a client wants to extract unstructured data, they need to apply external software.

To verify the basic OCR capabilities, a use case with robot B from the banking industry is analyzed. After a new e-mail with scanned mortgage contracts arrives, the robot saves the files on a local drive and converts them into a digital text string by applying OCR. After identifying the corresponding contract number based on a predefined keyword search, the robot uploads the text into a data management system and completes the process.

Seven out of nine examined RPA solutions utilize Computer Vision technologies to identify, understand, and classify digital elements and objects on user interfaces, i.e., robots A, B, C, D, E, G, and H. The technology is based on similarity analysis and reacts to visual conformance. Computer windows and on-screen elements can be identified and used as a trigger for process activities. Computer Vision is regarded as an integral part of RPA and is used for applying RPA when underlying data cannot be accessed, as explained by provider E:

Computer Vision is a core feature of RPA. Our strategy is to make the RPA engine just as intelligent as necessary to detect and process elements on the screen. The purpose is really RPA, which is why it is embedded.

Computer Vision provides several advantages. First, the technology eliminates the reliance on selectors and underlying data, since it workswith visible screen elements. It is even possible to use screen elements as anchors and access User Interface (UI) elements that are located within a certain distance. This enables a broader integration of elements and applicability. Second, the flexibility of RPA processes increases. Elements can be accessed even after modifications of software or changes in homepage designs. Third, Computer Vision enables remote automation on a virtual screen based on graphical data. This serves as a fallback solution if other automation methods do not work.

None of the examined RPA solutions can process rich media, such as voice or sound. The technology is not regarded as an essential part of process automation with RPA. RPA provider F commented:

> *Processing of rich media is complex and a different technology than RPA. It is not part of our solution, since we see enough demand on the text side. In addition, some of the tools and technologies in the market are not as robust as required yet. If you want to achieve a sufficient accuracy level, it starts to get expensive. If required by a client, voice processing can be combined with RPA as third-party software.*

Processing Information. None of the examined RPA solutions contain incorporated NLP capabilities. Only basic NLP features in the form of keyword search are included. However, the keyword search is strictly rule-based and does not require any cognitive intelligence. In general, most RPA software providers do not regard NLP as a critical or core capability of RPA. NLP is utilized as separate technology and integrated into RPA processes as a distinct component.

Two of the examined RPA robots provide built-in ML capabilities for document and text classification (robots A and C). Document classification enables the assignment of labels of a document type based on a predefined selection of options. The technology is based on supervised ML and combines different document properties, such as document type, author, subject, or content data [25]. After the document type is identified, specific text classification modules are applied. This enables critical information to be extracted and converted into structured output. The text classification is also based on supervised ML and trained by human employees. The integration of document and text classification capabilities correlates with the integration of basic or advanced OCR capabilities. However, there are only two RPA solutions with inherent basic and advanced OCR capabilities that include classification mechanisms.

Computer Vision also contains ML features. Based on the shape and type of objects, ML is applied to determine the purpose and usage of objects. The algorithms are fed with a large amount of images and corresponding categories. Also, error reporting in interaction with human users is used to further develop the ML algorithm.

In addition, supervised ML is applied by RPA vendor F for exception management in the form of an ML-based recommendation engine (cf. "RE" in Table 2). The ML algorithm monitors exception handling activities of RPA users and learns based on their decisions. Thereby, changes on a code level or within workflows become superfluous, since RPA can automatically recommend configurations based on prior learnings and even perform them routinely. In the examined case, the characters "O" and "Q" cannot be assigned by the robot, which leads to an error. The algorithm monitors the human exception handling. If it detects a similar exception multiple times, it makes a recommendation to the human user, and, after approval, routinely performs the exception. Since it improves the performance of RPA, it is regarded as useful for RPA and included in the software as an intelligent component.

Scheduling is a critical part of RPA, especially if multiple robots are applied or if one robot performs multiple tasks. Most RPA solutions use a scheduler based on predefined rules about the priority of tasks, the timing, or the duration of the execution. Two RPA providers offer built-in ML-based scheduling modules (robots C and F). They enable the dynamic scheduling of robots and tasks based on multiple parameters, such as scope and time requirements of tasks, defined service levels, concurrent processes, and the performance of underlying applications. The ML algorithm takes into account the defined parameters, the former performance of the robot, and the relation between latency times of applications and the resulting robot performance and dynamically schedules multiple robots to meet the agreed service levels. This enables flexible application and reassignment as well as increased service level fulfillment and utilization.

None of the examined RPA solutions provide any kind of Automated Reasoning capabilities. The interview partners agreed that intelligence in the form of independent decision making should not be part of RPA. It weakens the ability of RPA to deliver accurate and predictable results based on explicit rules. RPA provider A distinguished between built-in intelligence in RPA solutions and intelligence outside the robot:

> *Automated Reasoning is not the kind of intelligence that we want to build into RPA. It is an external intelligence that can be leveraged to answer questions or to carry out decisions. What RPA can do is the subsequent execution.*

4.2 Enhancement of RPA with External Cognitive Intelligence

Introduction of Platform Approach. All nine examined RPA providers pursue the strategy of incorporating cognitive intelligence via a platform. This means that RPA, as a rule-based execution engine, is combined with selected external solutions. The external technologies are incorporated into the RPA platforms and can be easily integrated into the workflows as modules. RPA steers the cognitive components and executes the structured output. If needed, further external technologies can be added via application programming interfaces (APIs).

The platform approach facilitates the integration of external technologies. This allows faster and more robust automation with little time required and no need for coding. The integration without coding is important in that it enables the application of RPA at a business level. By introducing a technology partner ecosystem and modular integration, RPA can be extended with best-in-class cognitive capabilities without the requirement for in-house solutions. This means that solutions from RPA providers, clients, or third parties can be leveraged and flexibility is increased.

Table 3. Overview of cognitive capabilities integrated into RPA platforms

RPA platform	Capture information			Process information		
	Text and character recognition	Image recognition	Voice or sound recognition	Natural Language Processing	Machine Learning	Automated Reasoning
Platform A	—	OCR	—	—	DC, TC	—
Platform B	—	OCR	—	—	DC, TC	—
Platform C	—	OCR	—	—	DC, TC	—
Platform D	—	OCR	—	NLP	DC, TC	—
Platform E	—	OCR	—	NLP	DC, TC	—
Platform F	—	OCR	—	—	DC, TC	—
Platform G	—	OCR	—	NLP	DC, TC	—
Platform H	—	OCR	—	NLP	DC, TC	—
Platform I	—	OCR	—	—	DC, TC	—

Legend: OCR = Optical Character Recognition, NLP = Natural Language Processing, DC = Document classification, TC = Text classification

Cognitive Intelligence Within Platforms. Table 3 provides an overview of external cognitive capabilities integrated into the RPA platforms. Platform A corresponds to robot A, as introduced in Table 2. The digitization of input by processing images via advanced OCR is identified as a standard feature of all nine RPA platforms, which can be integrated via drag-and-drop. The providers include prepackaged leading external software solutions from suppliers, such as Abbyy or Kofax. In doing so, the RPA software providers can utilize best-in-class solutions to address specific digitization problems and keep their RPA solution simple. In addition, some of the RPA platforms also provide interfaces to integrate open-source solutions on demand.

Four of the examined RPA platforms offer a built-in preselection of NLP solutions, which can be integrated via drag-and-drop (robots D, E, G, and H). The cases reveal that NLP is mainly used for contextual and sentiment analysis to understand the intent and body of texts. These platforms mainly originate from technology companies with competence in NLP and not from specialized RPA providers. The NLP software offered is either an internal solution or based on external software and, in any case, is not part of the license model. Even though it is regarded as a critical component, the majority of RPA platforms within the sample do not contain NLP capabilities as part of their platforms, as RPA software provider E emphasizes:

> *Within RPA itself, there are no NLP capabilities yet and it is not a core functionality of our RPA platform. Nonetheless, some RPA processes*

include external NLP technologies based on license models or as open-source solutions to fulfill specific demands.

As described in Sect. 4.1, RPA engines themselves partially provide supervised ML capabilities. With the platform approach, all examined solutions provide ML capabilities in the form of text and document classification. They are added through the integration of external OCR solutions. Moreover, all platforms enable the integration of additional ML solutions via standardized interfaces. For example, the programming language Python can be applied to code ML capabilities or to use pre-trained Python models. Thus, the RPA robot or platform itself does not include ML capabilities other than those described in Sect. 4.1, but it enables the integration of external solutions. Automated Reasoning has not been part of any of the RPA platforms and examined cases.

4.3 Impact of Increasing Intelligence on Process and Task Suitability

The increasing level of cognitive intelligence within RPA software solutions or as integrated solutions within RPA platforms impacts the applicability of RPA. According to the experts, the process requirement that is affected most is the need for structured data input. Intelligent RPA can work with unstructured or fast changing data. RPA integrator E explains:

Unstructured data can be structured and made accessible based on intelligent RPA. The importance of standardization of data decreases as the level of cognitive capabilities increases.

The data first needs to be transformed and structured. RPA subsequently receives the structured data and processes it based on predefined rules. The requirement for structured data input decreases, although RPA still needs structured data to process tasks. Second, the requirement for a high degree of process standardization and clearly defined rules decreases. Intelligent RPA can perform processes with changing process steps or rules. However, rules remain critical and an important prerequisite for RPA. Intelligent RPA can, so far, only perform changes or exceptions with low complexity. Third, the requirement for process stability becomes less important. Exception management based on a supervised ML algorithm enables the handling of errors and exceptions during the process or within unstructured data input. Nevertheless, the software solution still requires human employees for decision making as well as for processing of critical tasks. Even though this impact has been confirmed by most experts, only one examined RPA robot provides ML-based exception handling capabilities.

Regardless of the increasing cognitive capabilities that impact decision criteria for RPA, basic process requirements remain unaffected. A process that is structured, simple, and mature is still more eligible than a process with less structure and with exceptions. Cognitive capabilities broaden the field of application of RPA at the cost of complexity and implementation effort.

5 Discussion

5.1 RPA and Built-In Cognitive Intelligence

This research reveals that RPA has only very limited cognitive capabilities, despite the contrary being argued by software providers and indicated by research. Almost all experts emphasize that RPA is not intelligent and does not need intelligent capabilities. It is, as per definition, a software for the rule-based processing of click sequences with predictable and stable outcomes. This has been confirmed by the interviews conducted and the analyses of nine RPA software solutions along a framework of cognitive intelligence. None of the RPA engines fulfill the prerequisites for cognitive intelligence and this therefore disproves the hypothesis of RPA being intelligent. Nevertheless, the findings show that all RPA solutions can process structured digital text and perform keyword search based on predefined rules. In addition, four of the examined RPA solutions have built-in basic OCR capabilities and one solution even provides advanced OCR. The findings are partially in line with prior research, which indicates that RPA is starting to get "smart" features, such as image recognition [4,5]. However, the results reveal that the extent to which OCR is part of RPA is very limited and the majority of RPA software providers do not regard OCR as an essential part of RPA. Additionally, none of the solutions are able to capture complex, unstructured data input from sources such as voice or sound. On the processing side, none of the RPA engines provide NLP or Automated Reasoning capabilities. They are regarded as complex and non-core technologies. According to the definition of cognitive intelligence, those components, however, would be critical to contribute machine intelligence to understand contextual meaning, reason, or draw conclusions [3,18]. Only the added value of ML is regarded as suitable to RPA. Therefore, ML in the form of supervised learning methods is incorporated in most of the examined RPA solutions, mainly through Computer Vision, document and text classification, and partially through scheduling and exception management. The findings are in line with existing research, which point out that learning capabilities should be incorporated into RPA solutions [6,8]. However, the extent to which ML is used for RPA is limited. The cases emphasize that only ML capabilities enabling RPA to work more efficiently and expand its applicability without affecting the predictability and accuracy of outcomes are built into RPA engines.

The separation of RPA and cognitive capabilities as well as the consequential lack of intelligence of RPA relies on a broadly accepted rationale. First, the definition of RPA as a rule-based execution engine sets limits, which would be undermined by an unpredictable operation. Second, RPA provides the mechanical foundation for process automation, which is a key advantage. RPA should remain with exactly these capabilities, since the demand for rule-based automation is likely to continue to exist. Besides, it is the same with RPA as with employees: building on basic requirements, companies recruit employees or train them to work on specific tasks. This flexibility can only be guaranteed with RPA if it remains an execution engine to which cognitive intelligence can be added flexibly. Third, most companies in the RPA market are RPA-only companies and have limited AI, OCR, or NLP capabilities. Since those technologies require a high degree of specialization, it is reasonable to integrate best-in-class external technologies instead of developing proprietary solutions. The integration of non-RPA technologies also drives the complexity with regard to integration, usability, and maintenance with varying update cycles and technical requirements. Fourth, commercial restrictions hinder the incorporation of cognitive capabilities within RPA. The concept of modular RPA platforms enables the flexible tailoring of solutions to customer demands and reduces the costs for simple RPA.

5.2 Development Towards Platform-Based Automation

All nine RPA providers offer RPA platforms to add cognitive intelligence to RPA as external elements. This indicates that the evolution of RPA towards more intelligent capabilities does not take place built into RPA but rather with external capabilities that can be bolted on to RPA in a modular fashion. The RPA software itself acts as an execution engine within the platform, which steers external components and processes structured outputs. The case studies reveal that mainly OCR and NLP are added via the platform. As such, the key contribution comes with the ability to process information in the form of content understanding and supervised learning. Four RPA platforms provide preselected NLP solutions and all platforms enable the simple integration of external NLP technologies. However, RPA platforms still lack key cognitive capabilities, mainly in the field of Automated Reasoning. The experts cited a lack of transparency and reliability, the level of development of AI solutions, and the reluctance of users as the main reasons against the deployment of Automated Reasoning.

In general, the development towards RPA platforms is driven by the dynamic nature of most processes, which calls for flexible and non-static solutions. The modular platforms provide interfaces and an open architecture to external solutions. Since cognitive technologies are highly sophisticated and are developing rapidly, built-in capabilities would not be reasonable. Integrating intelligence via programming interfaces makes the platforms more robust and improves the operational efficiency and stability. The modular integration also ensures simple usability. This is vital, since RPA is applied on an operational business level and needs to be set up and operated by non-IT employees.

6 Limitations and Future Research

By following the principles for data validity as stated in the methodology section, this paper aimed to prevent structural errors. Nevertheless, the research is not without limitations. First, the definition of RPA potentially differs across software providers. Even though this has been explicitly clarified, a divergent understanding of RPA could have led to missing or exaggerated capabilities, which may reduce comparability. Second, the selection of RPA software providers is not exhaustive and is limited to the globally leading providers plus a selection of additional RPA companies. Third, the experts could have potentially overstated the actual capabilities of their RPA software and platforms. To overcome this problem, a bottom-up perspective from RPA integrators is introduced and case documentations are used to confirm the capabilities. Fourth, the framework could potentially bias the results. However, core elements are included and no other features were mentioned during the interviews.

RPA and cognitive intelligence constitute interesting research opportunities. A general discussion about the definition and designation of RPA and cognitive intelligence would be needed to clarify the terminology used, since RPA is predefined and per definition rules out any kind of dynamic or intelligence. Since this research provides indications of influences on process suitability, future research could address the question of how decision support criteria are affected by intelligent RPA. Another interesting research opportunity is the question of which cognitive capabilities complement RPA best and should be integrated. Moreover, research could address the implications of RPA with cognitive intelligence on its applicability as well as the resulting effects on performance. Finally, the question of how AI could be used to understand and process exceptions and assist with coding without human intervention is of interest.

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