USING AI TO AUGMENT RPA: A CONCEPTUAL FRAMEWORK

Research Paper

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Abstract

Robotic Process Automation (RPA) has seen significant uptake in practice over the last years due to its ability to cut costs and rapidly connect legacy applications. However, organizations struggle to apply RPA to tasks with higher complexity. The use of Artificial Intelligence (AI) capabilities to augment RPA promises to overcome this limitation. Nevertheless, little detail is available on how these technologies can complement each other. Drawing on the theoretical links of the Task-Technology Fit model, we propose a set of AI capabilities that fit specific RPA tasks. Based on these fits, we propose a typology of use cases that AI enable in RPA. These results are derived from a literature study, nine case studies, and 15 expert interviews and validated through a case simulation and expert evaluation.

Keywords: Robotic Process Automation, Artificial intelligence, Intelligent automation, Task-technology fit.

1 Introduction

Robotic Process Automation (RPA) is an automation tool that operates on a computer system's user interface like a human would (Aalst *et al.*, 2018). A user of RPA can configure one or more scripts, enabling RPA bots to mimic or emulate certain structured and repetitive tasks (Stoudt-Hansen *et al.*, 2019). It functions on top of existing applications, which means there is no need to develop or replace legacy systems (Lacity and Willcocks, 2015). Moreover, RPA can be configured without the need for advanced programming skills (Lacity and Willcocks, 2015).

RPA has seen significant uptake in practice over the last years due to its ability to cut costs and rapidly connect legacy applications (Aalst *et al.*, 2018). Even though RPA has shown to bring various benefits, many organizations struggle to apply RPA to more complex processes. Currently, RPA can only follow simple, logical rule-based processes and cannot handle unstructured data. However, both academia and industry see more potential in RPA by enhancing it with Artificial Intelligence (AI). Van der Aalst et al. (2018), for example, posit that for "more widespread adoption, RPA needs to become smarter", and the use of AI and machine learning might make RPA suitable for "more complex and less defined tasks". Also, in industry we see a broad interest in augmenting RPA with AI (e.g. Ray *et al.*, 2019).

While multiple studies suggest that augmenting RPA with AI is the next step to allow RPA to support a wide variety of tasks (Anagnoste, 2017; Aalst *et al.*, 2018; Ivančić, Suša Vugec and Bosilj Vukšić, 2019), little detail is available on how these technologies can complement each other. Therefore, multiple authors call for future research in this area (Hofmann, Samp and Urbach, 2019; Santos *et al.*, 2019; Enríquez *et al.*, 2020; Syed *et al.*, 2020). Also, industry calls for clarity. Gartner states that “there is a lack of guidance helping organizations to assemble RPA with other tools, causing these organizations to miss out on strategic business values” (Ray *et al.*, 2019). Moreover, a survey from Deloitte showed that executives consider the identification of appropriate use cases as the most significant barrier for successful RPA and AI implementations (Watson *et al.*, 2019).

The goal of this study is to capture the potential of RPA augmented by AI and provide guidance in applying these technologies in an organizational context. To support this goal, we will draw upon the Task-Technology Fit (TTF) model from Goodhue and Thompson (1995), which enables us to match the functional capabilities of AI to characteristics of organizational tasks that can be automated by RPA. Based on literature, case studies, and expert interviews, we propose a conceptual framework that contains set of AI capabilities linked to specific tasks that might be automated with RPA.

In the following section, we will first outline our research method. In Section 3, we present the theoretical background (including the results of our systematic literature review). This section results in the proposal of a conceptual framework for augmenting RPA with AI. Section 4 presents five task-technology fits that we could identify from our analysis of the literature, cases and expert interviews. In Section 5, we present the results of a focus group in which we evaluated these fits. Finally, in Section 6, we present our conclusion and discussion.

2 Research method

In this study, we follow the Design Science approach as described by Peffers *et al.* (2012). Our study was carried out from November 2019 to July 2020 and the data collection took place from February 2020 to May 2020. The details of the study are documented in Nieuwenhuijs (2020).

In phase 1, we studied the literature and talked to RPA and AI experts to *identify the problem and motivate our research*. The result of this phase is presented in the introduction. Then, in phase 2, we conducted a systematic literature review to *design objectives of a solution*. Specifically, this meant we identified and defined relevant characteristics of tasks that might be automated with RPA, as well as AI capabilities. Subsequently, in phase 3, we *designed and developed* our conceptual framework. We carried out case studies of existing RPA and AI projects and interviewed experts. Phases 4 and 5 comprise the *demonstration and evaluation* of the framework. We conducted a case simulation and expert evaluation in two focus groups. The goal was to evaluate whether the framework can help users in recognizing opportunities for RPA and AI. Finally, in the *communication* phase, the results have been presented to professionals and will be published for a scientific audience.

2.1 Defining objectives for a solution

In phase 2 of our study, we conducted a systematic literature review following Okoli (2015). With this review we aimed to answer several questions, such as ‘What AI capabilities used within RPA?’ and ‘What tasks are being automated by RPA and AI?’ Figure 1 shows the process we followed and the choices that were made. We selected 51 sources from which we identified and defined relevant task characteristics (for RPA) and AI capabilities. Based on this, we established a first version of our solution: a conceptual framework that links tasks characteristics and AI capabilities.

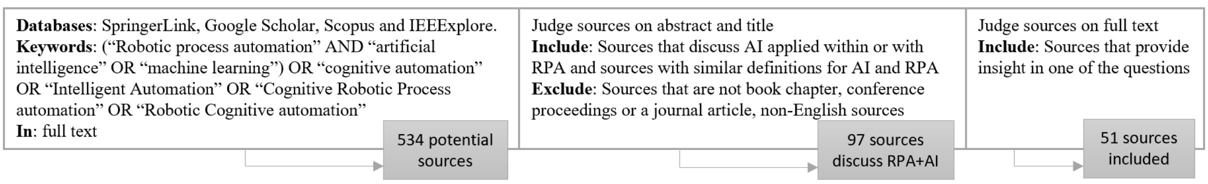

Figure 1. Systematic literature review process

2.2 Developing the conceptual framework

In the third phase, we developed the framework using *methodological triangulation* (Kaplan and Maxwell, 2005). This approach allowed us to study RPA and AI in a realistic setting by performing a *multiple-case study* (Yin, 2017) on deployments of RPA augmented by AI. However, considering the combination of RPA and AI is a new phenomenon, it cannot be assumed that observing all scenarios is possible. Therefore, as a second research method, we use *expert interviews* (Bogner and Menz, 2009). The main advantage of this type of interview is that it is possible to formulate conceptualization on the studied phenomenon without the need to observe them all. In the following sections, we will outline how we carried out the case studies and expert interviews.

2.2.1 Multiple-case study

The case study is characterized as a multiple embedded case design (Yin, 2017). Multiple cases increase generalizability and produce more insight (Runeson and Höst, 2008). Moreover, the embedded design allows us to compare the cases using the TTF constructs consistently. As part of the sampling approach, we aimed for *maximum variation sampling* by including different industries and AI applications. As *criterion sampling,* all AI technologies need to conform to the definition of this research, and RPA needs to be applied to (parts) of tasks. To recruit potential study participants, we used the network of a large consultancy firm. Evidence in the cases is collected by performing *systematizing expert interviews* in which we acquire process knowledge (Bogner and Menz, 2009) and *documentation* (e.g., presentation slides). Table 1 provides an overview of the context information on the type of business process, sector, location, and the operational RPA bots on a local level[1]. The size of the organizations ranges from 50.000 to 500.000 fte. For each case, we interviewed one informant and studied documentation such as process descriptions. We recorded and transcribed the interviews. Based on the documentation and interviews, we drew process models for each case that was reviewed by the case informant.

#	Business process	Sector	Location	RPA bots	Informant
1	Insurance claim	Insurance	Italy	10-20	External consultant
2	Reporting	Retail	Netherlands	80-90	External consultant
3	Know your customer	Banking	France	70-80	Internal consultant
4	Document extraction	Audit	Netherlands	10-20	Internal manager
5	Password reset	Government	Netherlands	30-40	External project leader
6	Invoice processing	Logistics	UK	50-60	External consultant
7	Invoice processing	Government	Netherlands	30-40	External consultant
8	Invoice processing	Consumer goods	Netherlands	0-10	External project leader
9	Procurement	Construction	USA	0-10	Software vendor founder

Table 1. Case overview

2.2.2 Expert interviews

In addition to the multiple-case study, we carried out 16 expert interviews. We interviewed three categories of experts: (1) *service providers* that implement RPA and AI solution, (2) *vendors* that develop RPA solutions that include AI capabilities, (3) *end-users* of RPA within the industry. As *criterion sampling,* the interviewees had at least one year experience with RPA, experience with augmenting RPA with AI, and were involved in the delivery of RPA and AI deployments. Table 2 provides an overview of the interviewees, their role, and primary industry. The interviews took place as

[1] The number of operational RPA bots is presented on the local level. For example, if the company is active worldwide but the case is a deployment in Italy, we only present the number of RPA bots in Italy

semi-structured interviews and focused on obtaining interpretative knowledge (e.g., orientations, rules, points of view, and interpretations) (Bogner and Menz, 2009). The topics covered in the interviews included the tasks that were automated as well as their characteristics (e.g., diversity of input and variability of output), the type of automation (RPA and/or AI), the automation level, and the perceived performance impact.

#	Type	Role	Industry	#	Type	Role	Industry
1	Service provider	Sr. consultant	Public	9	Service provider	Manager	Financial services
2	Service provider	Sr. manager	Consumer goods	10	End user	Head robotics	Asset management
3	Service provider	Manager Tax	Tax	11	Service provider	Manager	Public sector
4	Vendor	CTO EMEA	Software	12	End user	Robotics technical lead	Banking
5	Service provider	Director Tax	Tax	13	Vendor	Global VP automation	Software
6	Vendor	Technical consultant	Software	14	Vendor	Digital workforce evangelist	Software
7	Service provider	Freelancer	Software	15	End user	Information manager IT	Government
8	Invoice processing	Director	Financial services	16	End user	Innovation manager automation	Insurance

Table 2. Overview of interviewees

2.2.3 Analysing the data

The goal of our data analysis was to identify AI technology capabilities and task characteristics related to RPA and the fit between these. We coded the transcripts of the case interviews, the documentation, and the transcripts of the expert interviews in NVivo. The first level of our coding scheme was based on the main constructs TTF model, e.g. technology capabilities, Task-Technology Fit, and task characteristics. The second level consisted of technology capabilities and task characteristics that resulted from our literature review (see Section 3). For example, in case 1 we found that the RPA bot had to extract signatures from documents with a high variety in structure. In this deployment, the AI component had to classify whether there is a signature on some of the documents. This was coded as a fit between the AI technology capability 'Search' (can extract structured data from unstructured documents) and the task characteristic 'Variety' (of input documents). This task characteristic is expressed in a complexity dimension (in this case 'Variety') related to an input component ('Input'). An elaborate overview of our coding scheme can be found in Nieuwenhuijs (2020).

2.3 Demonstrating and evaluating the framework

Evaluation of artifacts in Design Science is a central and critical part of Design Science research (Hevner, March and Park, 2004). We conducted two *confirmatory focus groups* (Tremblay, Hevner and Berndt, 2010), consisting of RPA experts; practitioners that all had experience with RPA projects.

In the first phase of the, participants applied the framework on a case simulation (Sonnenberg and vom Brocke, 2012) in order to find out whether the framework helps users in detecting automation opportunities for RPA and AI. The participants applied the framework on a loan application process that was published by Dumas *et al.* (2013). The first two authors of this paper also identified automation opportunities and compared our results with the results of the participants. Secondly, the participants performed an *expert evaluation* on the framework to find out how the experts perceive the framework.

The expert evaluation took place as an interactive questionnaire, in which participants first voted on a statement after which they saw the results from the other participants. Considering that participants voted without seeing other answers, the effect of social pressure or differences within the group was limited (van Zolingen and Klaassen, 2003). We considered the four evaluation criteria for models from March and Smith (1995): completeness, fidelity with real-world phenomena, internal consistency, and level of detail. Since practitioners would be using the framework, we added understandability – practitioners need to be able to understand it before they can use it, and usability – practitioners need to able to use the model in their profession. Based on these criteria, we constructed a questionnaire containing two statements per criterion.

Both case simulation and expert evaluation are considered artificial forms of evaluation. However, since the evaluation was carried out by *real users* who also validated the realism of the case, we strengthened the *real task* (Sun and Kantor, 2006).

3 Theoretical background

In this section, we explain the theoretical foundations of our conceptual framework for RPA and AI. We elaborate on the existing work on RPA and AI, explain the Task-Technology Fit model of Goodhue and Thompson (1995) that forms the foundation of our framework, and we identify the task complexity dimensions and AI capabilities that we use as ingredients for the framework. The task complexity dimensions and AI capabilities are results of our systematic literature review mentioned in Section 2.1.

3.1 Robotic process automation and Artificial Intelligence

Artificial Intelligence (AI) is, broadly speaking, concerned with making artificial systems behave intelligently. One way to define an AI system is according to what it can do: perceiving and acting rationally in complex environments or, as Burgess (2018) puts it, *capturing information* and using it to *find out what is happening* and *why*. Another way to define AI is according to the specific techniques used. Currently, data-driven (deep) *machine learning* is most often mentioned, although there are many other AI techniques (e.g., knowledge graphs, search algorithms etc.). For our definition of AI, we focus on 'what it can do', adopting the AI capabilities from Burgess (2018) (see Section 3.4). We further limit our definition of AI to machine learning techniques. This allows us to clearly delineate AI (machine learning) and RPA (rule-based techniques) and is in line with the currently popular view of AI, which many of the case study informants and experts we interviewed subscribe to.

Augmenting RPA with AI is still in its early development, with only 18% of organizations having experimented with it (Jędrzejka, 2019). Authors emphasize the lack of understanding of how AI can add value to RPA (Gotthardt *et al.*, 2019; Kirchmer and Franz, 2019) and stress that this should be studied from an implementation perspective (Gotthardt *et al.*, 2019; Syed *et al.*, 2020).

According to literature, the predominant use of AI to augment RPA is converting unstructured or semi-structured data into structured data (Burgess, 2018; Flechsig, Lohmer and Lasch, 2019; Kirchmer and Franz, 2019; Scheer, 2019). Moreover, task complexity increases as data and rules become less structured or defined, the number of steps increases, and the amount and variety of data increases (Lacity and Willcocks, 2018). AI can enable RPA to perform such more complex, less clearly defined and changing tasks (Ansari *et al.*, 2019; Teli and Prasad, 2019; Kirchmer and Franz, 2019). Finally, many authors propose a combination with chatbots to bridge the gap between RPA (i.e., back-end automation) and customer service (i.e., front-end) (Taulli, 2019b; Syed *et al.*, 2020).

3.2 Task-Technology Fit

An exploration of the applicability of specific technologies on specific tasks should be based on comprehensive insights into the overarching conditions that affect the performance impact of a technology. In this study, we draw on the Task-Technology Fit (TTF) model (Goodhue and Thompson, 1995). The TTF model focuses on matching the functionality of a technology to the requirements of a task (Dishaw and Strong, 1999). As such, it perfectly fits our goal of matching the capabilities of AI with the characteristics tasks that might be automated with RPA. We use the *fit-as-deviation approach* (Junglas, Abraham and Watson, 2008), which means that we measure the TTF indirectly by measuring the *task characteristics* and *technology characteristics* separately (Teo and Men, 2008).

In order to be able to measure the fit between RPA and AI, we first need to establish the sets of task characteristics (related to RPA tasks) and technology characteristics (related to AI capabilities). We will do so in the next two sub sections. Two other constructs proposed by Goodhue and Thompson are *utilization* and *performance impact*. Utilization refers to the behaviour of employing the technology in completing tasks (Goodhue and Thompson, 1995; Davis et al., 1989) and usually measured by constructs such as frequency of use. We particularly look at the level of automation that a reached by a certain fit, so we call this construct *automation level*. We use two levels to indicate how much assistance is provided by an RPA bot: *human in the loop*, where humans validate all data points resulting from the AI augmented task and *human for exceptions*, where humans are only involved when the AI augmented task results in an exception. Finally, we define performance impact as a mix of improved efficiency, improved effectiveness, higher quality, etc.

3.3 Task complexity

Goodhue and Thompson (1995) do not prescribe specific task characteristics that should be used to measure TTF. Instead, they emphasize that this depends on the study at hand. The literature reported in the previous section anticipated that augmenting RPA with AI will allow for the support of more complex tasks. However, since task complexity is an umbrella term, we need to define it. Several highly cited studies are published on task complexity—e.g., Campbell (Campbell, 1988) and Wood (1987). Liu and Li (2012) reviewed and summarized this work and proposed a comprehensive framework on task complexity which we use as basis for our task characteristics.

Liu and Li (2012) distinguish multiple elements that make tasks complex: 1) *task components* are inherent parts of a task: input, process, output, and user interface; 2) *complexity contributory factors (CCF)* are factors or indicators that externally reflect the task complexity level; and 3) *complexity dimensions* describe "the interior structure of task complexity" and are "composed of several related CCFs" (Liu and Li, 2012). To clarify the difference between a complexity contributory factor and a complexity dimension, we provide an example. Consider, for example, the complexity dimension 'size'. This dimension could be measured by several complexity contributory factors, such as 'number of steps used in the process, and 'quantity of output results'.

Table 3 shows eight complexity dimensions Liu and Li (2012) distinguish. We drop two dimensions from the original framework: Incongruity, which relates to visualization that is a mismatch to a task (e.g., text when tabular is desired), and Action complexity, which focuses on inherent cognitive (e.g., IQ and memory) and physical requirements (e.g., strength). Both are irrelevant for automation.

Dimension	**Explanation**
Ambiguity	Degree of clarity, structure, or ambiguity.
Size	The number of inputs, steps, and output.
Variety	Number of dissimilar task components.
Variability	Unstable characteristics of task components.
Novelty	Non-routine, random or irregular events.
Relationship	Non-routine, random or irregular events.
Temporal demand	Complexity factors caused by time.
Unreliability	Inaccurate or misleading information.

Table 3. The eight adopted task complexity dimensions from Liu and Li (2012).

3.4 AI capabilities

We adopt the framework on AI capabilities from Burgess (2018), as explained in Section 3.1. This framework takes a holistic perspective, compared to a functional perspective (e.g., Strohmeier and Piazza, 2015), is very detailed, and makes connections to other concepts in AI. Burgess (2018) defines two current main objectives of AI: 1) *capturing information*, and 2) finding out *what is happening*.

The objective *capturing information* contains the following AI capabilities (Burgess, 2018):

1. *Speech Recognition:* encoding speech (live or recorded) into words or sentences.
2. *Image Recognition:* processing and interpreting images (i.e., unstructured data).
3. *Search*: extracting structured data from unstructured or semi-structured text.
4. *Data Analysis/clustering:* identifying patterns or clusters in structured data.

The objective finding out *what is happening* contains the following AI capabilities (Burgess, 2018):

1. *Natural Language Understanding*: extracting meaning from text in order to act as a translator between humans and machines.
2. *Optimization*: reaching a desired goal with a set of possible actions to get there. Characteristics are that a goal needs to be achieved, a problem needs to be solved, or a plan needs to be made.
3. *Prediction*: using historical data to match new data to an identified group.

3.5 Conceptual framework

Figure 2 presents our conceptual framework for augmenting RPA with AI, based on the TTF model of Goodhue and Thompson (1995). It combines the task components and complexity dimensions of Liu and Li (2012) with the AI capabilities of Burgess (2018) to enable us to determine the fit between an AI capability and the characteristics of a task that might be automated with RPA. The model is complemented with the Automation level, where humans are either in the loop, or only used in exceptions.

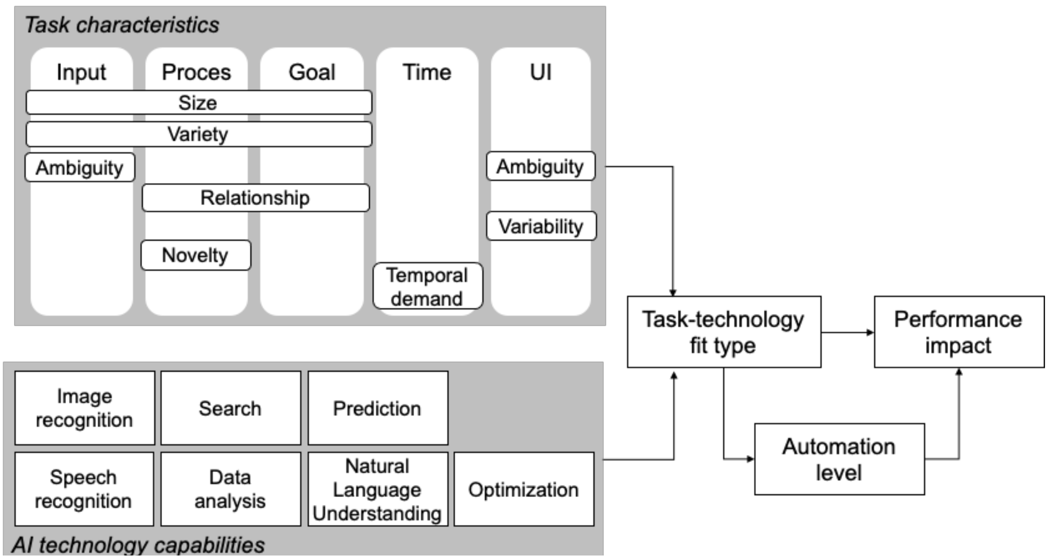

Figure 2. The intelligent RPA framework: a conceptual framework for augmenting RPA with AI

4 Intelligent RPA framework

Based on our data analysis, we grouped the data in the constructs of the conceptual model developed in the previous phase. First, we established the fits between an RPA task requirement and the AI technology capability. *Table 4* presents the list of fits, including the supporting literature, cases, and interviews.

Fit	AI technology capability	RPA task characteristic	Supporting literature	Supporting cases	Supporting interviews
Input component					
1	Speech recognition	Variety	Burgess (2018a); Lacity and Willcocks (2015); Schmitz et al. (2019)	5	-
2	Speech recognition	Ambiguity	Burgess (2018a)	5	-
3	Search	Variety	Burgess (2018b); Lacity and Willcocks (2018a); Mohanty and Vyas (2018); Schmitz et al. (2019)	1-4, 6-8	-
4	Natural language understanding	Variety	Burgess (2018a); Lacity and Willcocks (2015); Schmitz et al. (2019)	9	1, 2, 5-7, 9, 11-13, 15
5	Natural language understanding	Ambiguity	Burgess (2018b); Gollapudi (2019)	-	1, 2, 4-7, 9, 11-13, 15
6	Natural language understanding	Size	-	9	3, 12, 13
Process					
7	Data analysis & Prediction	Size	Anagnoste (2018)	2	2, 3, 6-8, 12, 13
8	Data analysis & Prediction	Relationship	-	2	2, 4, 12, 16
9	Data analysis	Novelty	-	-	5, 7, 10, 11
Goal					
10	Optimization	Size	-	-	1, 6-8, 15, 16, 18
11	Optimization	Relationship	-	-	1, 6-8, 15, 16, 18
User Interface					
12	Image recognition	Ambiguity	Beerbaum (2020); Taulli (2019)	-	1, 2, 5, 6, 12
13	Image recognition	Variability	Beerbaum (2020); Taulli (2019)	-	1, 4, 5, 6, 12

Table 4. List of identified fits, accompanied by the supporting literature, cases, and interviews

After establishing the fits, we developed a typology in which we aggregated the fits into categories. These categories are based on the specific task components (e.g., input or process). In the following sections, we will discuss each category.

4.1 AI structuring for RPA (fit 1-6)

This use case resembles all types of deployments where AI structures input for RPA, such as extracting data from documents or identifying damage on an image of a car. Figure 3 shows the following fits:

- *Speech Recognition – Variety of input:* Words are can be pronounced in different ways. In case 5 a voice bot was implemented to help users resetting their password. This bot asked several security questions to identify the user. AI was used to recognize the answers given by the users.
- *Speech Recognition – Ambiguity of input:* In spoken language, the same pronunciation can have multiple spellings, e.g., ‘I went to the sea to see my friend’. This means that the context is essential to determine the spelling. The voice bot in case 5 had to deal with spoken language.

- *Search – Variety of input:* The search capability can extract structured data from unstructured documents when the variety in document format is too high for RPA to handle. Our informant of case 3 explains: "… while the OCR engine scans the documents and extracts the data, machine learning models have been designed to read this data, to retain this data, and to reapply it [in the] right [way] for the next set of documents (…) this is where the learning part of the machine comes into picture.
- *Natural Language Understanding – Variety of input:* there are many ways of phrasing and wording the same meaning. This was for example mentioned by interviewee 4: "there is a big problem space... there are many ways of phrasing and wording the same thing".
- *Natural Language Understanding – Ambiguity of input:* The meaning of text can be ambiguous and might change in another context. For example, interviewee 7 explains: "if you take a sentence ... you can give five different definitions to it" (depending on the context).
- *Natural Language Understanding – Size of input:* the size or volume of the text also affects the complexity to capture meaning from it. According to the informant of case 9: "The documents that are input for the task can be 10 to 15 pages. If it was a one-pager, maybe it would have been easier... But the fact that it is hidden in the 10 to 15-page document makes it that you need NLP for that".

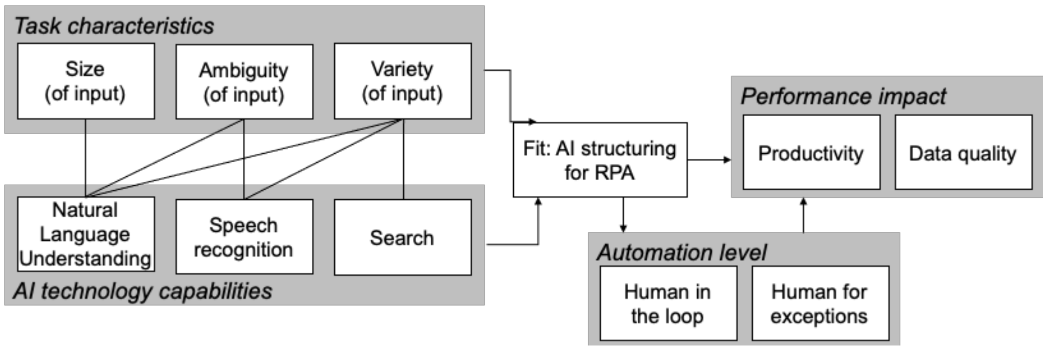

Figure 3. Use case AI structuring for RPA.

In this type of use case, there are two possible automation levels: either a human is entirely in the loop and checks all output (cases 4, 6-9), or a human is only handling exceptions (cases 1-3, 5). The distinguishing factor here is trust in AI within the organization, but also the business critically of the process. In performance impact, we see that the performance impact of these types of use cases is increased productivity (case 1, 2, 3, 5-7, 9) and data quality (case 6, 8).

4.2 AI capturing complex patterns for RPA (fit 7-8)

RPA often falls short, capturing complex patterns. Whereas RPA can only handle a pre-configured list of scenarios with business rules, AI can capture and analyse more complex patterns and predict for the future. Figure 4 visualizes the following relevant fits:

- *Data analysis & Prediction – Size*: to the number of factors that are included to capture a phenomenon. This was used in case 2, where AI was used to predict future sales. As the informant explained "it was a kind of task where you would just plug in a bunch of data that may or may not be relevant". AI was used to analyse this and predict future sales, which depended on a large quantity of factors in this deployment.
- *Data analysis & Prediction – Relationship*: the relationship or interdependence between the relevant factors that influence a phenomenon. Also in case 2, the sales prediction during the Christmas season had to be handled differently than in other time periods: weather was not important (in contrast to other seasons), but the price levels of other vendors were.

We identified one automation level, namely human in the loop, since a decision is never taken solely by the AI. Performance impact in this use case relates to an increase in productivity, but also an increase in ineffectiveness (case 2). Humans cannot capture complex patterns as AI can; therefore, this use case creates value that was not available before, since it involved too much data, or was too complicated.

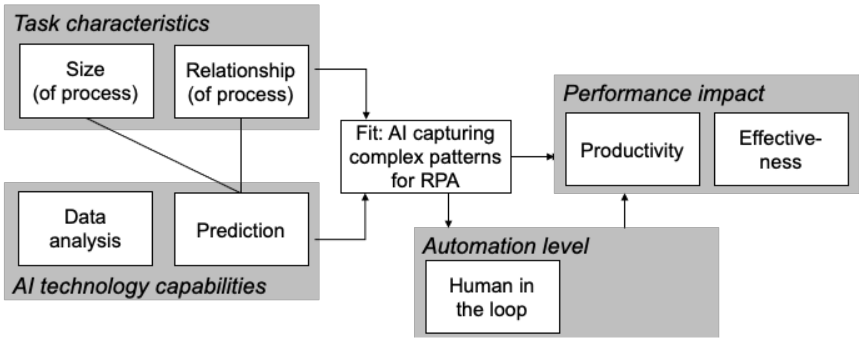

Figure 4. Use case AI capturing complex patterns for RPA.

4.3 AI increasing RPA robustness (fit 12-13)

Environments that lack an underlying technology connection that allows RPA to extract meta on UI elements have difficulty supporting RPA (Beerbaum, 2020). These environments are virtualized layers (e.g., Citrix) and most legacy applications (Beerbaum, 2020; Syed *et al.*, 2020). Deploying RPA on the server-side is often challenging due to political challenges, approval from information security, etc. Therefore, RPA tools are often deployed on the client-side. The AI increasing RPA robustness use case can be of high added value here because it makes RPA interact with these types of UI more robustly. It makes RPA less susceptible to all sorts of changes in the UI. Figure 5 visualizes the following fits:

- *Image recognition – ambiguity (of the UI)*: Ambiguity in the UI means that RPA lacks an underlying technology connection that allows RPA to analyse metadata on UI elements. As interviewee 12 points out: “we definitely need the RPA tool itself to become smarter to know how to recognize objects on screen”. Image recognition techniques can solve this.
- *Image recognition – variability (of the UI)*: problems for RPA occur when cosmetic changes happen in the UI. Interviewee 5 explains: “If a button moves from left to right, and if you programmed your bot correctly, it would solve this automatically. But in a virtual environment (…) the bot cannot always identify the right buttons. Then, you need computer vision.”

Automation levels are not relevant for this use case. Performance impact relates to safeguarding the continuity of RPA deployments.

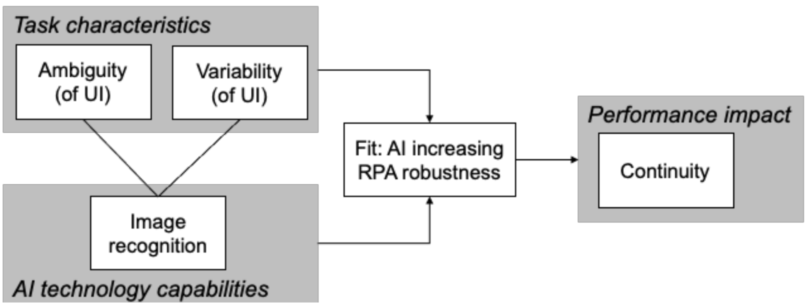

Figure 5. AI increasing RPA robustness.

4.4 AI optimizing for RPA (fit 10-11)

In this use case, AI optimizes a complex goal or problem, and RPA executes the relevant activities. This use case has the least evidence to support it, and only the expert interviews show support for this use case. Figure 6 visualizes the following relevant fits:

- *Optimization – size*: optimization applies to tasks with several goals at the same time. As interviewee 6 provides a retail example: "Every store needs to balance its stock levels: too high increases costs, too low might result in unsatisfied customers. RPA can place the actual order, and AI optimizes the right volumes to order."
- *Optimization – relationship*: there has to be some kind of trade-off between two goals. Using the previous example of interviewee 6: these two goals are in conflict: Every store needs to balance its stock levels: too high increases costs, too low might result in unsatisfied customers.

Due to a lack of data from our cases and interviews, we did not include the possible automation levels and the performance impact for this use case.

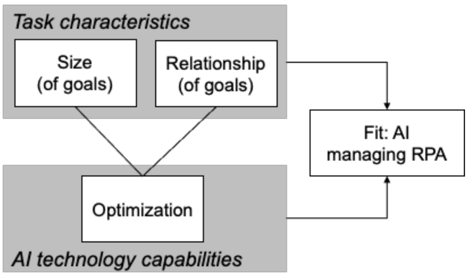

Figure 6. AI optimizing for RPA

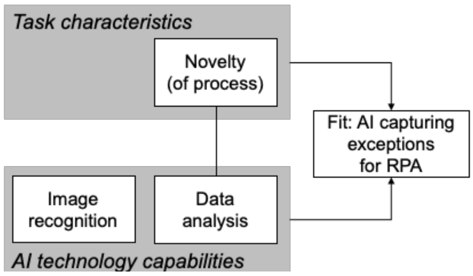

Figure 7. AI capturing exception for RPA

4.5 AI capturing exceptions for RPA (fit 9)

This use case differs from the other use cases because it is not related to an AI implementation in the process itself. Instead, in this use case, AI is used to analyse data on exceptional situations and builds an RPA bot based on this data. Although this use case is different, we chose to include it because it was mentioned as a high potential use case by many interview participants. Figure 7 shows the following fit:

- *Data analysis – Novelty*: Data analysis can be applied to resolve exceptions occurring within a business process. Data analysis constructs a process flow and builds an RPA bot based on this. A human only needs to configure the last parts. Interviewee 7 explains: "You can monitor what an employee does in certain exceptions (…) Using computer vision in combination with process mining could result in in the discovery of this process. (…) This can be added to the RPA flow."

Due to this different nature, we do not consider automation levels relevant here. We do not have data on the performance impact. However, we anticipate that it would strengthen the RPA performance impact.

5 Evaluation: focus group sessions

We performed two focus groups to evaluate the Intelligent RPA Framework. Each focus group consisted of two phases: a simulation and an expert evaluation. For the simulation, we developed a case consisting of a process model, a process description, and an input data specification. In this process model, we identified six tasks that could be automated through RPA of which three also could be augmented with AI. The process steps that could be automated through RPA and/or AI are listed in Table 5. For detailed process model, we refer to Nieuwenhuijs (2020).

During the first phase of both focus groups, we asked the participants individually to identify opportunities for RPA, which we then discussed in the groups. Then, the participants individually identified which RPA opportunities could be augmented by RPA, which we also discussed in the groups. In general, the participants were able to apply the framework consistently. All RPA and AI opportunities were identified by the groups and by the majority on an individual level (as shown in table 5).

Process step	**Opportunity**	**Rationale**	**# participants**
Check credit history	RPA & AI	Use RPA and Search to extract from various document formats	7 of 8
Assess loan risk	RPA & AI	Use AI to predict a loan default	5 of 8
Prepare acceptance pack	RPA	Let RPA prepare the acceptance pack	7 of 8
Check if insurance quote is requested	RPA	Let RPA perform check	7 of 8
Verify repayment agreement	RPA & AI	Use RPA and Search to extract scanned image from system and assess if there is a signature	6 of 8
Approve/cancel application	RPA	Use RPA to update systems and send out emails	7 of 8

Table 5. Tasks evaluated in the simulation.

In the second phase of the focus groups, we evaluated the experts' opinions of the framework, through a questionnaire. Table 6 provides the results of the scores based on a 5-point Likert scale. Each of the evaluation criteria in Table 6 was tested by asking the respondents to rate two statements. Both the criteria and the statements were based on the work of March and Smith (1995) and Aier and Fischer (2011). *Level of detail* scored lowest with a 2.9. Between the first and the second focus group, we added further examples which improved the average score from 2.6 to 3.1. Overall, the framework helps to make people understand in a structured way when to use RPA and when to integrate RPA with AI. No participant had significant issues understanding the framework.

	Completeness	**Fidelity to real-world**	**Internal consistency**	**Level of detail**	**Operationability**	**Understandability**
Session 1 average	3/5	3.3/5	3.9/5	2.6/5	3.8/5	4.1/5
Session 2 average	3/5	3.8/5	4.4/5	3.1/5	3.4/5	3.8/5
Total average	3/5	3.5/5	4.1/5	2.9/5	3.6/5	3.9/5

Table 6. Results of the expert evaluation.

6 Conclusion and Discussion

AI capabilities can augment RPA to allow for the support of tasks with a high complexity. In our study we developed the intelligent RPA framework, a conceptual framework for augmenting RPA with AI. In our empirical study, we identified 13 fits of specific AI capabilities that can be used to augment RPA. Moreover, we constructed five Task-Technology Fit types, expressed in concrete use cases, that show how AI can augment RPA.

Our study confirms the potential of AI to allow RPA to support more complex tasks (Aalst *et al.*, 2018; Gotthardt *et al.*, 2019; Scheer, 2019). Comparing the identified use cases with literature, we see that the use case *AI structuring for RPA* to convert unstructured data is reflected in other studies (e.g. Devarajan, 2018; Kobayashi *et al.*, 2019; Van Belkum *et al.*, 2018). Also, several studies indicate that AI can help RPA to go beyond rule-based pre-configured scenarios (Schmider *et al.*, 2019), or judgment decisions (Madakam, Holmukhe and Kumar Jaiswal, 2019; Met *et al.*, 2020), which corresponds to our use case *AI capturing complex patterns for RPA*. The use case *AI increasing RPA robustness* is mentioned by

Beerbaum (2020) on a conceptual level. The interviews provided important extra information on the usefulness of this use case and showed the dilemma of a server-side implementation.

Not explicitly mentioned in literature is the use case *AI optimizing for RPA*. However, some authors mention that future RPA capabilities will self-configure (e.g. Hofmann, Samp and Urbach, 2019; Jędrzejka, 2019). Furthermore, Hull and Motahari Nezhad (2016) pointed out that AI (specifically Cognitive Computing) will enable automatic learning about business processes. Also, more generally, using AI in optimization is not new (e.g., Huang *et al.*, 2011; Schallner, 2019). The use case *AI capturing exceptions* for RPA has not been reported before in literature. Although some authors point out the potential of process mining and RPA (Santos *et al.*, 2019; Syed *et al.*, 2020), or AI creating RPA bots (Hofmann, Samp and Urbach, 2019), these studies look at this problem from a process discovery perspective to identify RPA tasks, while we look into existing RPA implementations. The same technique can be used in both cases.

We picture several practical implications of this research. First, the developed framework can be used as a starting point for discussion and provide a basis of the type of use cases that AI enables in RPA. Secondly, the results of this research can help organizations automate more processes end-to-end. Organizations that tried to implement RPA but struggle with some tasks can use this model to identify what complexity they are dealing with. Subsequently, these organizations can locate the AI capabilities they need, based on the complexity they have in their process. Finally, organizations could map the use case typology on a set of their processes. As a result, a broad and structured overview of the automation potential in different departments, type of use cases, and required AI capabilities is provided. Therefore, our findings can offer guidance from a strategic management point of view.

A limitation of this research concerns the consistent understanding of the used constructs in the interviews. We tackled this threat by asking additional probing and specifying questions and by consistently comparing the examples mentioned by the interviewees with the delineated task characteristics. Also, some fit scenarios are solely based on expert interviews because they are observed in cases and not found in literature. Further research is necessary to further develop and evaluate the constructs and fit scenarios.

Further work could focus on extending the framework towards a process assessment method to enable assessing organizational processes on their exact potential of AI. Another research direction is to develop an instrument to quantitatively measure the relations between fit type, automation level, and performance impact. This would enable us to make statements about what kind of performance gains can be expected from certain AI and RPA implementations and the extent to which this should be automated. Finally, more research needs to be done to how sustainable RPA implementations are and how they affect the work needed to digitize (other) business processes.

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