From Symbolic RPA to Intelligent RPA: Challenges for Developing and Operating Intelligent Software Robots

Lukas-Valentin Herm[1](✉), Christian Janiesch[1,2], Hajo A. Reijers[3,4], and Franz Seubert[1]

[1] Julius-Maximilians-Universität, Würzburg, Germany
{lukas-valentin.herm,christian.janiesch, franz.seubert}@uni-wuerzburg.de
[2] HAW Landshut, Landshut, Germany
[3] Utrecht University, Utrecht, The Netherlands
h.a.reijers@uu.nl
[4] Eindhoven University of Technology, Eindhoven, The Netherlands

Abstract. Robotic process automation (RPA) is a novel technology that automates tasks by interacting with other software through their respective user interfaces. The technology has received substantial business attention because of its potential for rapid automation of process-driven tasks that would otherwise require tedious manual labor. This article explores the dichotomy between the practical reality of symbolic RPA, which requires handcrafting robots using process models and rulesets, and the promise of intelligent RPA, which relies on artificial intelligence technology to implement intelligent robots. Our research is based on a scholarly literature review as well as an interview study to derive and discuss challenges for this transition. We found that issues such as the lack of training data, human bias in data, compliance issues with transfer learning, poor explainability of robot decisions, and job-security-induced fear of AI robots all need to be addressed to enable the transition from symbolic to intelligent RPA.

Keywords: Robotic process automation · Artificial intelligence · Symbolic RPA · Intelligent RPA · Challenges

1 Introduction

Due to its heavyweight development load and the lack of application programming interfaces (APIs) of legacy software, it has become apparent that BPM software does not provide suitable automation solution for every business process [1, 2]. This has triggered the emergence of lightweight techniques for automating digital and manual tasks such as robotic process automation (RPA) [3]. In essence, RPA uses software robots that are designed to mimic human employee behavior by relying on existing user interfaces (UI) of legacy software instead of using APIs. In practice, this technology allows for the rapid automation of simple, repetitive tasks and, consequently, a fast

A. Polyvyanyy et al. (Eds.): BPM 2021, LNCS 12875, pp. 289–305, 2021.
https://doi.org/10.1007/978-3-030-85469-0_19

return on investment, since employees are no longer required to operate monotonous, non-value-added processes [1, 2].

The application of RPA, however, faces several challenges. Since not every process is predestinated for RPA-based automation, identifying suitable processes can be quite difficult [3]. Likewise, due to the symbolic character of current RPA practices, which means that it relies on handcrafted flow models and rulesets, the process of identification and development is still time-consuming and limited by the abilities of the involved designer [4]. There is a cut-off point at which RPA development becomes inefficient due to the large and complex variants and rulesets [3, 4].

A reflection on these challenges reveals similarities with early artificial intelligence (AI) research on expert systems. These systems are commonly referred to as *symbolic AI* [5]. AI is nowadays a highly successful technology by advances in machine learning (ML), leading to AI applications that outperform humans [6]. ML encompasses algorithms to build models for data-driven task solving that do not require explicit programming. Instead, data is used for autonomous learning [5]. Considering this successful transition of AI, it is only logical to explore a similar path for RPA: by infusing AI capabilities into RPA, it seems feasible to overcome the limitations of *symbolic RPA* and arrive at what we refer to as *intelligent RPA*.

There are already various proposals that point to AI as the future of RPA, which may eventually lead to the approach of hyperautomation [7, 8]. Likewise, comprehensive surveys, for example Syed et al. [1], identify the need for future research to develop innovative solutions for AI-assisted RPA. Nevertheless, they also note that it is not apparent what challenges need to be addressed to enable its productive use. Agostinelli et al. [9] and Chakraborti et al. [4] have proposed several research challenges and tool-oriented challenges, but their validity and practical relevance has not been assessed.

In this paper, we derive and investigate the relevance of challenges for the amalgamation of RPA and AI, and consequently for intelligent RPA. This results in the following research question:

RQ*: Which challenges exist for the development and operation of software robots based on intelligent RPA?*

The contribution of our paper is an overview of ten concrete and distinct challenges, which we assessed with respect to their relevance, severity, and longevity. One significant improvement over the state-of-the-art is that our work brings a specific focus and deeper layer to more abstract RPA challenges identified before. Furthermore, the challenges we describe are not just grounded in theory but firmly rooted in the industrial application of RPA. This is important since the practice of RPA is at times well ahead of rigorous theory-grounded research in academia.

This paper is structured as follows: In Sect. 2, we present the theoretical foundation for RPA and our conceptualization of intelligent RPA. Section 3 presents the research design, including details on the conducted literature review and expert interviews. In Sect. 4, we introduce existing RPA and AI challenges as well as intelligent RPA challenges, which we discuss in Sect. 5 in detail. Section 6 provide a discussion of theoretical and practical implications. Lastly, in Sect. 7 we conclude with a summary, limitation, and outlook.

2 Theoretical Background

2.1 Symbolic Robotic Process Automation

Following the idea of the long tail of processes [10], van der Aalst et al. [3] proposed a Pareto distribution for the applicability of RPA. Depending on case frequency and possible types of cases, they motivate the application of traditional backend automation with BPM, automation with RPA, and the continued manual execution of specialized manual human processes.

In this respect, RPA is an umbrella term that comprises many different automation tools, which operate on the UI layer of off-the-shelf, legacy software in an "outside-in" manner. They have in common that they enable software robots to mimic human knowledge workers and perform their digital yet manual tasks with no adjustments to existing software [1–3].

Currently, most state-of-the-art software requires users to implement their software robots in a symbolic fashion [9]. This means that processes or simple sequences of tasks need to be explicitly modeled and decisions need to be documented in handcrafted rulesets [2]. While being simpler and timelier to realize than business processes using traditional BPM software, these factors still limit the development of RPA. It entails that implementing a robot must also be carried out by business users with knowledge about variants and decisions as well as technical users with the ability to codify this knowledge. In analogy with symbolic AI, which describes the handcrafting of explicit if-then rules in early AI applications [11], we denominate this type of RPA as *symbolic RPA*, since RPA is currently constrained by the inability of humans to manually code complex and shared tacit experiences in comprehensive explicit rulesets [5].

2.2 Intelligent Robotic Process Automation

Using AI for RPA can help to mitigate the limitations of the rule-based specification of software robots and leverage the ability to apply flexible AI-based pattern recognition techniques representing human-like cognitive abilities to solve problems [12]. Hereby, we use the umbrella term AI, for the application of ML and deep learning (DL). While, ML relies on statistical algorithms to train analytical models, which can solve problems without being explicitly programmed to do so [6], DL refers to complex models using (deep) artificial neural networks whose inner workings are intransparent to human users. The latter are especially useful for high-dimensional datasets [5]. DL models tend to outperform shallow ML models and even humans for specific applications [6].

Ultimately, this entails, that robots will not only be able to complete tasks by themselves without the necessity of explicit process models or rulesets, but that they will be able to perform tasks that require cognitive abilities, such as perceiving and reasoning. Consequently, they will become more convenient to create and more versatile in their deployment since they can complete tasks so far unsuitable for robots developed through symbolic RPA. Examples include process identification, image recognition, (process) prediction, natural language processing (NLP), chatbot functionality, or automated reasoning [1, 4]. Currently, RPA vendors have begun to include AI capability into their RPA software to unearth some of these potentials [12]. Yet in academic literature, there is only little information on how to combine RPA and AI successfully and which challenges need to be addressed in the course [1].

Closely related to intelligent RPA is the term hyperautomation [8]. Gartner defines it as the joint application of advanced technologies such as ML or DL to automate processes and augment humans. While our focus is on RPA as an automation technology augmented by the use of various AI technologies, hyperautomation also refers to the sophistication of the automation process itself. Hence, we include this concept in our search for relevant work.

3 Research Design

3.1 Overview

In general, we followed an iterative, design-oriented procedure that uses theory-building elements for data collection, specifically (1) a structured literature review and (2) expert interviews [13, 14]. As shown in Fig. 1, our research can be divided into four distinct phases.

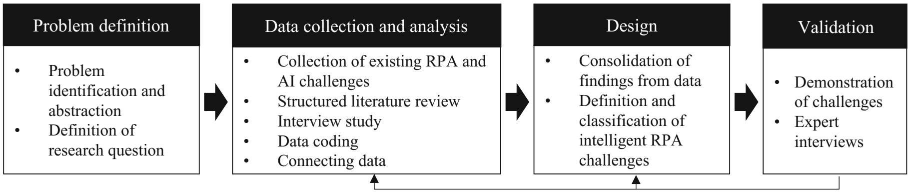

Fig. 1. Research procedure

Problem Definition. Syed et al. [1] and Gotthardt et al. [7] demonstrate the need for more clarity in how the combination of AI and RPA can successfully be applied. While Agostinelli et al. [9] discuss a lack of learning capabilities, they do not explore ML in detail. Chakraborti et al. [4] discuss only abstract and general AI challenges and opportunities. In contrast, our aim is to derive theoretical and practical challenges at the intersection of RPA and AI that must be addressed in concert.

Data Collection and Analysis. First, we aim for saturation in theoretical knowledge. We connect existing RPA, ML, and DL challenges from seminal review literature as well as with a structured literature review according to vom Brocke et al. [13], in which we focus on the combination of RPA and AI towards intelligent RPA. Second, we propose initial challenges derived from this analysis. Note that Sect. 4.3 contains an overview that has already been revised based on the feedback from the last phase. Third, since practice is at least on par if not ahead of academia, we conduct an interview study with practitioners to investigate and assess these challenges further.

Design. Through the connection of our findings, we can formulate and assess different challenges for intelligent RPA, which future research and practice must solve. Thereby, we also include a ranking, severity, and estimation from practitioners, who are facing these challenges in real life. See Sect. 5 for a detailed presentation.

Demonstration. Lastly, we demonstrate and discuss our findings. Here, the experts were able to validate or dispute our findings. Following that, we discuss implications (see Sect. 6).

3.2 Literature Review

Procedure Literature Review. To investigate the state-of-the-art of applications and challenges in the field of intelligent RPA, we conducted a structured literature review according to vom Brocke et al. [13]. In this vein, we examine the state-of-the-art in challenges associated with it. Consequently, we screened for theoretical and practical contributions that use RPA and any kind of AI for process automation.

Within our literature search, we focused on the computer science-related databases IEEE Xplore and ACM Digital Library, information systems-related databases Science Direct, AIS eLibrary, and Web of Science, as well as economics-related databases such as EBSCOhost and Emerald Insight. Due to the novelty of the topic and its practical nature, we did not restrict our search by rankings and considered industry reports as relevant. For our literature review, we used the following search string: "*(IPA | intelligent process automation | cognitive automat* | hyperautomat*) OR ((AI | artificial intelligence | deep learning | machine learning | (natural language processing) AND (RPA | robotic process automation | desktop automation))*". Hereby, we included the topics of intelligent process automation and related fields such as cognitive automation and hyperautomation. In addition, we considered contributions relevant that deal with the combination of RPA and different kinds of AI such as ML or DL, including NLP. We derived these terms iteratively from literature on intelligent RPA and intelligent automation to ensure comprehensiveness of our results.

Using the proposed search string resulted in the identification of 642 contributions. Then, we performed a reduction based on title, keywords, and abstract, followed by a full-text analysis. Lastly, we applied a forward and backward search on the remaining contributions. This resulted in 47 contributions classified as relevant for our research. A summary of the procedure is shown in Fig. 2.

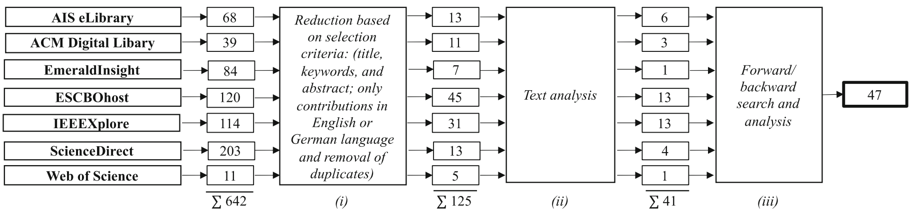

Fig. 2. Results of literature review according to vom Brocke et al. [13]

Meta-synthesis. In the following, we present a meta-synthesis of the 47 contributions. For this purpose, we grouped them based on their year of publication and their type of contribution.

For 2019 ($n = 18$) and 2020 ($n = 19$), the number of contributions on intelligent RPA rose rapidly. Before 2019, we identified only $n = 10$ contributions dealing with intelligent RPA or related topics. Considering the different types of contributions, it becomes apparent that since 2019 the number of contributions presenting a proof of concept, or an implementation project has increased markedly. Nevertheless, many contributions still provide more theoretical contributions such as design principles, interview studies, or literature reviews (2019: ≈46%; 2020: ≈65%). Related to this predominance of theoretical contributions, we identified only a few relevant practical reports (Fig. 3).

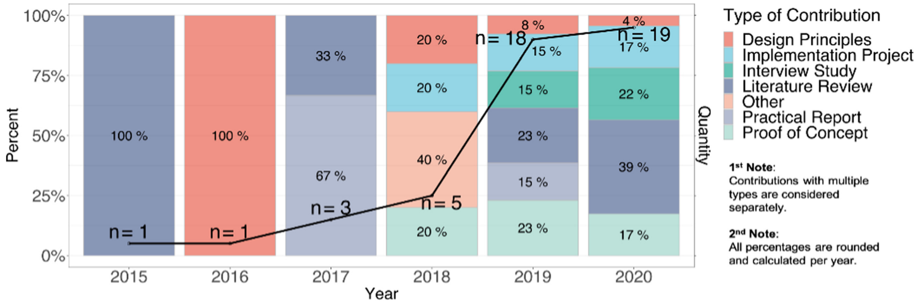

Fig. 3. Meta-synthesis of literature review

3.3 Expert Study on Intelligent RPA in Current and Future Business Practice

To gain further insights into intelligent RPA challenges, we conducted four expert interviews. These lasted between 60 and 90 min. All interviewees currently work in the field of RPA and engage with issues of intelligent RPA implementations. We spoke with experts from Germany, the Netherlands, and Belgium. Therefore, the interviews were multilingual, and the discussion of the concepts were later translated into English.

Due to the novelty of the topic, we followed a semi-structured interview guide divided into four parts. First, we asked for information about their (company) background and their confidence in the topics of RPA and AI. Second, we openly discussed our challenge proposals (see Sect. 4). Here, we asked them about their opinion and critical appraisal. Likewise, we asked them to modify and rename the challenges where appropriate. Third, we invited them to rank the challenges in order of importance, to classify the challenges in terms of severity, timing of occurrence, and implementation, to provide their opinion on whether the challenges should be solved in the short or long term, and to identify who should approach solving these challenges. Finally, we asked about any additional challenges they could think of. Thereby, through a result discussion, the experts validated or disputed our initial findings.

Following [14], the interviews were recorded and analyzed. This approach allowed us to overview and compare expert perceptions across all interviews. In total, the audio recordings of our interviews have a length of 295 min. While the small number of interviews could be considered a limitation, we noticed a saturation for most topics. See the Table 1 for an overview of the interviewees.

Table 1. Overview of interviewees

I#	Focus of company	Role	Years of experience	Confidence in RPA*	Confidence in AI*
1	Software development and IT consulting	Head of department and product manager for automation	5–10	Agree	Neutral
2	IT consulting	Lead developer	2–5	Agree	Neutral
3	Intelligent automation	Founder, director, and product manager	2–5	Strongly agree	Agree
4	Intelligent automation	Managing partner	>2	Strongly agree	Agree

*On a 5-point Likert scale: *"I'm confident in the field of […]"*, metric: *strongly disagree,…, strongly agree.*

4 Proposed Challenges for RPA, AI, and Intelligent RPA

4.1 RPA Challenges Impacting Intelligent RPA

The rapid deployment of robots in practice has left research catching up with practice to rationalize what is happening. There are several authors that have formulated challenges or opportunities for RPA development and use. We have consolidated the works of several authors [1, 7, 15–18] and systematize them along the meta themes introduced by Syed et al. [1].

RPA1: Realization of Needs and Benefits. Companies must be committed to identify and justify the need to implement RPA. The development of guidelines and best practices can ensure the consideration of RPA to realize cooperative strategies [15]. Likewise, metrics must be defined to measure benefits and ensure long-term support [2].

RPA2: Readiness. Companies must not only identify the need for applying RPA, but companies must also be prepared for new automation technologies. For example, they need frameworks for maturity and technology infrastructure assessments [1]. These frameworks can be used to support implementation projects [2].

RPA3: Capabilities. Similarly, companies need to be aware of what intelligent RPA can and cannot do [17]. Only by doing so, they can use appropriate technologies for given projects and organizational contexts. This includes building organizational and analytical capabilities to gather specialized knowledge to develop innovative and intelligent solutions [1, 2].

RPA4: Methodologies. Methodological support is necessary for a successful integration of RPA. Therefore, companies must develop such support for adoption and implementation to ensure success. This entails the definition of critical success factors [1].

Lastly, companies have to brief employees, so that they will consider RPA as an assistance rather than as a substitution as using software robots can have socio-technical implications that need to be approached [15, 17].

RPA5: Technologies. There are several technology issues to consider. First, task selection for automation is still highly subjective. Also, companies need to develop templates and guidelines for implementing and reusing technologies as well as maintaining robots [2]. This includes procedures for exception handling. Likewise, they need to define metrics to evaluate their implementations [18]. Lastly, while the initial use of robots works well on a small scale with limited resources, scaling them is highly dependent on the elasticity of resources [7].

4.2 AI Challenges Impacting Intelligent RPA

Several socio-technical challenges for ML and DL applications have been formulated [19–22]. Janiesch et al. [6] condense and highlighted several technology-related meta themes related to analytical model building and use in intelligent systems. We employ them to systematize the impact of AI on intelligent RPA engineering and use.

AI1: Model and Training Data Selection. Comparing or assessing ML and DL models for automated decision making is difficult, due to limitless options for algorithms, hyperparameter tuning, and the handling of training data [23]. Further, companies must consider economic limitations resulting in a trade-off between a models' ability to uncover all patterns within data and compute costs for training and execution [23]. Lastly, results of test system and live system can differ making it difficult to assess the suitability of implementation in real-life.

AI2: Bias in Data. ML and DL models learn from data. Biases within this data will be adopted and reinforced by the model's decision logic. This means that an AI trained on human data is not as impartial as an explicit ruleset but will mirror the subjective nature of cognitive decisions taken in the past. Thus, training data for analytical model building must be carefully reviewed and preprocessed [24].

AI3: Drift in Data. Similar to bias, drift in data can lead to insufficient or wrong decisions over time. Drift means that the historical data used for training does not correspond well to current data and trends [25]. Drift in real life is constant may be more subtle than explicit changes to business rules.

AI4: Transfer Learning. To overcome the "cold start" problem of DL models, companies either need to have gathered large datasets for their initial training or they have to resort to pre-trained models [19]. For the latter, a pre-trained general model is tuned for its new task with comparably few specific observations in a process called transfer learning [26]. However, acquiring and using third-party pre-trained models, such as NLP models for chatbots, often means using a black box, which can exhibit any kind of prejudicial behavior such as local social or geographical biases or even susceptibility to adversarial attacks or [27].

AI5: Model Explainability. The so-called black-box nature of DL models is rooted in their inherent complexity. As a result, these analytical models are intransparent to humans. However, in many cases, decision making must be traceable [22]. Thus, companies must either use inherently transparent white-box models or integrate explainable AI (XAI) augmentations to explain the decision-making process of the models [20, 22].

AI6: Effect on Employees. Fear about job security due to RPA implementations (see RPA4) goes hand in hand with the effect of AI implementation in workplaces. Arguably, this extends even further with AI as AI can solve more complex tasks and is often perceived as anthropomorphic [28].

4.3 Derivation of Challenges at the Intersection of RPA and AI

Using the 11 meta themes (*RPA1–5* and *AI1–6*) as a guideline, we reviewed the 47 articles of our literature search. This led to the formulation of 10 distinct challenges that need to be addressed for intelligent RPA to materialize successfully. In Sect. 5, we describe and discuss each challenge in more detail. See Table 2 for an overview of the

Table 2. Proposed challenges for intelligent RPA

C#	Proposed challenges	Challenge rationale		
		RPA[1]	AI[2]	Intelligent RPA[3]
1	Transfer learning causes trust and compliance concerns	–	*AI4* [26, 27]	[12]
2	Employees with knowledge at the intersection of RPA and AI are scarce	*RPA2–3* [1, 2]	*AI6* [29]	[1]
3	Intelligent RPA is not (yet) a commodity	*RPA4* [2]	–	[30, 31]
4	Insufficient training data obstructs intelligent robot development	–	*AI1* [19]	[7, 32]
5	Automated learning of task sequences is an un(der)explored issue	–	*AI1* [23]	[9, 33]
6	Intelligent robot performance is hard to assess and compare	*RPA5* [34]	*AI1* [6]	[35]
7	Intelligent robots reinforce human biases	–	*AI2* [24]	[36]
8	Businesses evolve but robot training is static	*RPA5* [16, 37]	*AI3* [25]	[4, 38]
9	Fear of AI and robots can cause job-security-induced distrust	*RPA1 & 4* [17]	*AI6* [28]	[7, 39]
10	Robot decisions need to be interpretable or explainable	–	*AI5* [20]	[4, 7, 40]

Legend: [1]Based on Sect. 4.1, [2]Based on Sect. 4.2, [3]Based on literature review (Sect. 3.2).

challenges and their rationale. In the table, we also provide the meta themes and key references that we used to derive the various challenges. The ordering of the challenges only serves the purpose of conveniently referring to each of these.

Using the 11 meta themes allowed us to identify and structure if and how pre-existing RPA and AI challenges might be relevant for intelligent RPA. Also, we aimed at exploring yet unknown challenges that may arise from the combined context of intelligent RPA yet are not apparent from the domains is isolation. While we could not identify further intelligent RPA challenges that were unrelated to pre-existing RPA and AI challenges, we found that the priority or emphasis of challenges in their combination as intelligent RPA differs from their isolated consideration in either domain. Since many challenges intersected with each other, we merged closely related challenges through a consensus of experts to obtain a manageable number of distinct challenges. We validated the results through our literature review (see Sect. 3.2) and performed a subsequent interview study (see Sect. 3.3) to assess the practical validity.

With this result, it becomes apparent that we have not merely repeated the challenges of symbolic RPA or AI. While we contextualized some AI challenges specifically for RPA, in many cases prospective solutions for existing symbolic RPA challenges can be used as a baseline to solve similar challenges for intelligent RPA. In response, we have focused only on those pre-existing RPA challenges that we deem to be at the core of intelligent RPA since they extend beyond the challenges of symbolic RPA.

5 Consolidated Challenges Impacting Intelligent RPA

5.1 Overview of Challenges

In the following, we describe and discuss the findings from our literature review and expert interviews. In doing so, we go into more detail about the challenges that we derived and provide further classifications.

To provide a structured overview of our findings, we classify the challenges into one or more of four lifecycle phases of intelligent RPA in a 2×2 matrix. These phases based on extant intelligent RPA literature [4, 7, 32]. The first phase, *organizational and socio-technical challenges during build-time*, describes all organizational and socio-technical challenges that occur when considering intelligent RPA as a potential automation technique from an organizational perspective. The *technical challenges during build-time* phase relates to all technical challenges during the implementation of intelligent robots. Similarly, all technology-related challenges during the operation of robots are summarized in *technical challenges during run-time* phase. The last phase, *organizational and socio-technical challenges during run-time*, relates to all human-robot-related challenges during the operation of intelligent RPA.

As challenges may not be attributed to only one of those phases, they can occur in multiple phases. We asked the experts about the severity of challenges and who should approach solving them. The results are shown in Fig. 4 using a median calculation. Since many challenges occur and impact over several phases, we describe them according to the time of their occurrence, which is not necessarily their root-cause.

Based on these findings, we describe our ten derived challenges in the following subsections. For each challenge, we describe supporting arguments from literature and from the experts. Likewise, we show how these challenges should be solved and whether they will occur in the short or long term in an intelligent RPA implementation project.

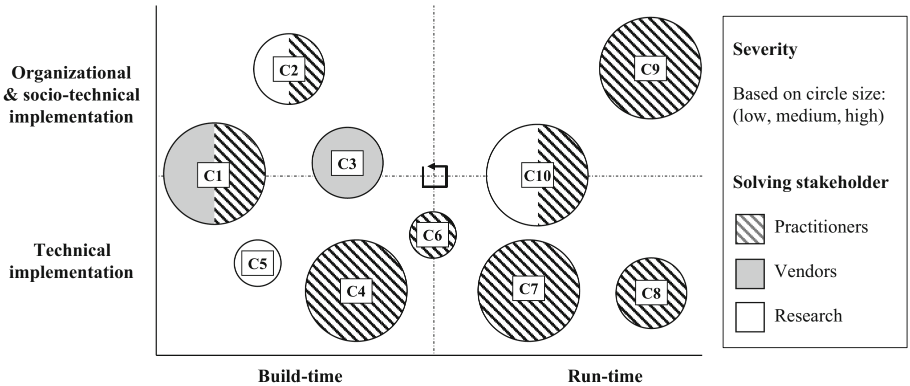

Fig. 4. Classification of challenges for intelligent RPA

5.2 Organizational and Socio-Technical Challenges During Build-Time

C1: Transfer Learning Causes Trust and Compliance Concerns. While the use of AI models acquired from transfer learning for intelligent RPA reduces development time and can also overcome a lack of training data (see C4), this process also causes trust and compliance concerns [26, 27]. In this context, companies need to build trust with vendors and developers that their AI models are unbiased and robust against adversarial attacks [12]. In our expert interviews, we found that I1 and I4 are concerned about sending customer data to AI cloud solutions for analysis mainly due to governance regulations. As a result, at this point transfer learning is not realistic (I1). As I3 noted, "*all of the time there is something about being compliant and being sure that you know where and how the model trained.*" In contrast, I2 considers this only as an issue for high-stake use cases. Further, I3 is especially concerned about dealing with personal data. Using locally trained models for transfer learning would be possible in all cases. Summarizing, I1–3 all note that this challenge must be solved by practice, may involve contracts or certifications, and constitutes a long-term challenge.

C2: Employees with Knowledge at the Intersection of RPA and AI Are Scarce. While Syed et al. [1] and Herm et al. [2] state that finding experts in the field of RPA is quite difficult, the same is true for the field of AI [29]. Our literature review revealed that finding experts experienced in both fields exacerbates this issue [1]. As an example, I1 has "*exactly one [employee] in my team […] who could do that.*" Therefore, I1 sees this challenge as the most important challenge to be solved by universities through intensified teaching in the respective areas and by practitioners through training their employees. I4 interjects that specialized knowledge in AI and RPA engineering can reside in different people and only needs to be bridged by at least one expert when applied. In contrast, I3 notes that in today's business practice, deep knowledge in AI implementations may not be necessary. Instead, a rough understanding of application and evaluation is sufficient. Consequently, I1–3 expect this challenge to impact intelligent RPA in the long term.

C3: Intelligent RPA Is Not (Yet) a Commodity. Clear cost-benefit metrics are hard to establish and their amalgamation into intelligent RPA is not available as commercial-off-the-shelf software [31]. This entails that the use of intelligent RPA, with its enhanced cognitive abilities, is not as straightforward and rapid as applying symbolic RPA and therefore may have to be managed similar to other custom development projects. However, the implications may be far-reaching. Interestingly, practitioners I1 and I4 do not think that this is an obstacle as own intelligent RPA implementation will still be worth the early adoption, resulting in a competitive advantage. Both see the use of intelligent RPA as a strategic asset. Nonetheless, I2 notes that currently the application of AI is expensive and time-consuming. Thus, he assumes that intelligent RPA will only proliferate when commercial-off-the-shelf software is widely available. Thereby, I3 adds, that companies should *"use a [low-code] platform where you basically have a way to scale it up, because you need less technical experience*" and therewith also alleviate C2. I3 predicts that this will take at least five years.

5.3 Technical Implementation Challenges During Build-Time

C4: Insufficient Training Data Obstructs Intelligent Robot Development. The development of intelligent robots faces several challenges due to a lack of data availability. Many highlight customer privacy concerns or data regulation limitations when sharing their data [7, 18]. However, as AI models are data-driven, they need to learn from data [5]. This may result in a situation where intelligent RPA is not applicable as an automation technique as not enough data is available for training robots with sufficient accuracy [7]. This is in line with our interviewees. I1–2, I4 state that generally no AI implementation is possible without sufficient data (see C1 for a possible remedy). This is most serious for new processes (I3). To generate enough data for intelligent RPA, humans must label and validate data manually, by staying in-the-loop (I3), which incurs cost. Nonetheless, I3 and I4 believe that this challenge will only affect most companies in the short-term.

C5: Automated Learning of Task Sequences Is an Un(der)Explored Issue. Although the application of AI models for single tasks within otherwise handcrafted robots is showcased in many papers [9], automated pattern learning for task sequences within processes is a difficult and not always feasible problem of cross-modal learning [23]. I1–3 all state that this challenge is far head of current business practice and not yet of their concern. Instead, the current focus is on enriching individual tasks with AI and then extending the integration to closely related tasks (I1–2) or using technologies such as process mining to detect potential processes for automation in the first place (I4). I1–4 all agree that this challenge will establish as a long-term challenge and currently is predominantly a research issue.

C6: Intelligent Robot Performance Is Hard to Assess and Compare. While most AI and RPA implementations are performed in a test environment, transferring them to a production environment can cause problems due to differences in data volume and permission management [34]. This can further lead to inappropriate models being used and insufficient results in terms of robot accuracy or latency [6]. Further, the suitability of replacing of legacy robot with new robots can only be assessed in production (I3). While I1–2 both notice a similar behavior in symbolic RPA projects, they assume that the issue will aggravate significantly in intelligent RPA projects. They suggest that AI models should be trained on data from live environments (I3) and different models must be considered (I4). I1 states that comparability is currently not a challenge at all, since RPA is not a market characterized by eliminatory competition. He adds that this may change in the future though. Therefore, we assume to be a mid- to long-term challenge.

5.4 Technical Implementation Challenges During Run-Time

C7: Intelligent Robots Reinforce Human Biases. AI models learn patterns from training data [24], which leads to intelligent robots mimicking human-biased observations in process execution. This impacts cognitive decision-making but furthermore, this can lead to non-optimized processes, workarounds, or to activities that are not relevant to the core of the process, as employees sometimes perform unnecessary tasks [36]. I1 notes that noise reduction can be achieved by monitoring data collection for ML or doing post-hoc processing (I4). Nonetheless, this data has to be investigated in detail before model training and during operation (I3). This results in a long-term challenge.

C8: Businesses Evolve But Robot Training Is Static. Robots have to be adjusted, when processes and their data are changing [37]. This drift in process execution, when businesses are evolving, also becomes apparent in intelligent robots, when current data does not correspond well to the data used for training [25]. In our literature review, we noticed that this issue is prominent for intelligent RPA [4, 38]. Further, I2 state, that they "*monitor the performance of a bot over the time*", as this is necessary for the continuous maintenance of intelligent robots in operation for longer-term use (I1–2, 4). As a result, this challenge must be handled by companies individually on a long-term basis. I2–3 both assume that companies must define an error margin for when robots should be reevaluated and retrained.

5.5 Organizational and Socio-Technical Challenges During Run-Time

C9: Fear of AI and Robots Can Cause Job-Security-Induced Distrust. The integration of intelligent robots in companies can be accompanied by many benefits. Yet the automation of processes can also cause distrust regarding the job security of employees [17]. Likewise, the use of AI can exacerbate these concerns, due to the seemingly infinite potential of AI [28]. These findings go hand in hand with the combination of both, with AI's anthropomorphic properties enabling it to perform not only monotonous, repetitive tasks, but also complex, cognitive tasks [7, 17, 39]. While this is already a critical challenge in practice, I1 notes that a work council's approval must be obtained for any current RPA implementation. Nevertheless, if the work council stalls the rollout of intelligent robots, companies may start to consider outsourcing their processes altogether. Nevertheless, I3 state that "*If a work council would block these kinds of implementations, […] we will see that this kind of work will move to other countries in the long term.*" As a result, balance is crucial (I3). Furthermore, I2 states that this distrust results from using top-down approaches in integrating intelligent robots, instead of seeing the need of automation within the departments. In today's practice AI is not (yet) capable to automate every task (I3–4) and, thus, this poses a long-term challenge.

C10: Robot Decisions Need to be Interpretable or Explainable. Although the development of intelligent robots offers many advantages [12], the use of black-box models entails drawbacks as their decision logic is not interpretable by users [20]. This results in a lack of trust and confidence that must be minimized to enable broad adoption [21], since "*trust issues will be one of the biggest challenges of intelligent RPA*" (I2). For example, Lamberton et al. [40] describes an implementation where AI classifications have to be verified by a human at the end of each day. In our literature review, we noticed two different approaches to overcome this issue. On the one hand, more interpretable, white-box ML models such as decision trees can be used (even though a DL model may perform better) (I4). On the other hand, XAI can be used to explain the decision logic and prediction to users [4, 7]. Currently, per-se interpretable ML models are common as practitioners such as I3 "*would always start with a white-box model*". However, the use of DL with XAI is also a highly targetable option. In the end, decisions have to be explainable at all times (I2–4), due to continuous model performance assessment or legal regulations such as general data protection regulation (GDPR) especially in areas such as finance (I3–4). However, implementations in practice are hampered by the novelty of the issue (I1). Lastly, I1 and I3 note that the main goal is to gain the customers' trust and provide a well-performing solution.

6 Discussion

Through our interview study, we found that the primary challenges of intelligent RPA today are the lack of training data, human bias in data, compliance issues with transfer learning, poor explainability of robot decisions, and job-security-induced fear of AI robots – all of which stem primarily from the AI domain. They all need to be addressed to enable the successful transition from symbolic RPA to intelligent RPA.

Theoretical Implications. With our research, we create awareness for the specificities of RPA as well as of AI research so that researchers from each domain can better attune to the issues of the other. Specifically, RPA and BPM researchers must understand that ML and DL do not provide a silver bullet for cognitive problem-solving and remove the need for handcrafting models in any context. While the application of AI technology comes with many benefits to solve issues that seemed unsolvable before, it comes with new challenges. Particularly, joint efforts are necessary to address the automated learning of task sequences across applications, as well as making process-based cognitive decisions explainable to business users. The latter needs to be supported with suitable and, possibly, novel metrics and visualizations, which are not only relevant for intelligent RPA but also for predictive process monitoring.

Practical Implications. Our challenges paint a clear picture that process automation and AI skills are relevant but also scarce. University teaching and professional training must pick up on these opportunities to equip the (future) workforce with appropriate abilities to automate tasks using intelligent RPA by introducing novel modules and degree courses. Furthermore, companies must introduce means to capture manual yet digital activities in a non-invasive, privacy-preserving manner to generate enough data for intelligent RPA. While the availability of such data is a practical problem, the means to collect it may require further research as well. In addition, vendors must approach the issue of trust and compliance for transfer learning to ensure that intelligent RPA products will eventually become a useful commodity. Lastly, the socio-technical issue of employee distrust in intelligent robots must be addressed openly and proactively.

Limitations. Our research is not without limitations. While we consolidated our challenges through an interview study and thereby assessed the comprehensiveness of our results, we did not test their usefulness. Implementing multiple use cases could close this gap and serve to reassess their completeness. As consequence, for future research, we plan to evaluate validity and reliability in more detail. Subsequently, we aim to provide guidelines for the successful implementation of intelligent RPA to create a foundation for future research on the constituent properties of hyperautomation.

7 Conclusion

While the amalgamation of RPA and AI will enable companies to automate more complex, cognitive tasks overcoming the limited, handcrafted behavior of symbolic RPA, intelligent RPA faces several challenges. We reviewed related challenges from the fields of symbolic RPA and AI (represented by ML and DL) and performed a literature review as well as an expert interview study to devise challenges that have the potential to shape the future discussion of intelligent RPA. In doing so, we determined the severity and the longevity of the challenges and pointed to possible solutions.

In total, we compiled ten challenges that illustrate how practice was ahead realizing symbolic RPA but has so far not completely grasped the implications that intelligent robots will entail. Currently, this results in applications that do not yet take full advantage of the affordances of AI technology. However, we observed that practice has already developed solutions and workarounds for some challenges, for example to deal with biases and drift in process execution, and mistrust and fear of job security.

Much of our research has been evaluated in the interview study with a focus on contemporary challenges of intelligent RPA. Future challenges of any type of RPA will eventually materialize when long-term effects and side-effects of replacing or augmenting manual processes with software robots become apparent.

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