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Towards Intelligent Automation (IA): literature review on the evolution of Robotic Process Automation (RPA), its challenges, and future trends

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A B S T R A C T

Robotic Process Automation (RPA) and Artificial Intelligence (AI) integration offer great potential for the future of corporate automation and increased productivity. RPA rapidly evolves into Intelligent Process Automation (IPA) by incorporating advanced technologies and capabilities beyond simple task automation. The paper aims to identify the organisational, technological, and human-centred challenges that companies face in transitioning from RPA to IPA. The research process involved conducting the scientific literature search using the ResearchRabbit AI tool, which provided a set of reference papers relevant to the formulated research questions. As a result of the conducted literature review, the authors identified key challenges and possible countermeasures for companies transitioning from RPA to IPA. The resulting collection of reference scientific articles formed the basis for this study's content and substantive analysis. Furthermore, this study contributes by identifying artificial intelligence techniques and algorithms, such as Natural Language Processing (NLP), Machine Learning (ML), Deep Learning (DL), predictive analytics, and others, that can be integrated with RPA to facilitate the transition to IPA. The paper also offers insights into potential future research areas.

K E Y W O R D S

Robotic Process Automation, RPA, Intelligent Process Automation, IPA, AI, Intelligent Automation, challenges

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Introduction

Artificial intelligence has witnessed rapid expansion in recent years, and its applications are gaining widespread popularity (Wach et al., 2023). There is a growing interest across all sectors in AI-driven automation software, driven by the near-complete automation of administrative operations and significant operational efficiency gains enabled by these technologies. Nowadays, organisations are leveraging cutting-edge automation solutions to optimise their

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informational operations, with Robotic Process Automation technology emerging as particularly important and useful (Götzen et al., 2022). This technology combines software, artificial intelligence, and machine learning to automate manual operations traditionally performed by humans. It involves programming autonomous software robots to replicate fundamental administrative procedures. With its cognitive capabilities, AI can simulate human behaviour and handle unstructured data through machine learning, natural language processing, and image processing. RPA enables intelligent agents to eliminate operational errors and replicate routine manual decisions, including rule-based, well-structured, and repetitive decisions that involve substantial amounts of data within a digital system (Ng et al., 2021). RPA should be considered one of the digital transformation technologies that assist businesses in automating repetitive and regular processes (Kudlak, 2019; Siderska, 2020). In addition to these advantages, the complementary application of artificial intelligence methods and methodologies enhances RPA process accuracy and execution in information extraction, recognition, classification, forecasting, and process optimisation (Ribeiro et al., 2021).

Robotic Process Automation and AI integration hold significant promise for the future of corporate automation and increased productivity. RPA is growing into Intelligent Process Automation (IPA) by incorporating advanced technologies and capabilities beyond simple task automation. The transition towards IPA is fuelled by the synergy of AI technologies and automation tools. IPA seamlessly integrates automation, machine learning, and artificial intelligence to enhance and streamline corporate processes.

RPA can harness AI's decision-making capabilities to enhance technical proficiency, readiness for new technologies, and process automation potential across various application domains, ultimately leading to Intelligent Automation. According to the authors, enterprises can undergo digital transformation through hyper-automation and potentially overcome some challenges associated with RPA deployment by leveraging artificial intelligence (Moreira et al., 2023). Pairing RPA with AI skills enhances their capabilities, offering an effective solution for addressing complex issues and providing the means to overcome obstacles that RPA alone faces. RPA tools extend AI's capabilities, aiding organisations in enhancing their operational and business processes. By leveraging artificial neural network algorithms, text mining techniques, and natural language processing for information extraction, optimisation, and scenario forecasting, RPA tools extend AI's capabilities, ultimately helping organisations improve their operational and business processes (Lievano-Martínez et al., 2022).

The existing literature offers limited sources on the drivers and prerequisites, challenges in implementation, and future research directions for intelligent automation (Ng et al., 2021; Siderska et al., 2023). Therefore, this article aims to identify and understand the key organisational, technological, and human-centred challenges and propose possible countermeasures for companies transitioning from RPA to IPA. Considering this background, the following three research questions were formulated to build upon existing research advances:

RQ1. What are the key advantages of integrating AI with RPA?

RQ2. What are the common AI technologies used for IPA transitioning?

RQ3. What are the key challenges of organisations transitioning from RPA to IPA?

1. Research method

As previously mentioned, there is a growing demand to investigate the research and development of intelligent automation. Therefore, this review article outlines the challenges in IPA implementation and research directions. Based on a literature review, the study aims to provide and discuss the challenges companies face when transitioning from RPA to IPA. Three main approaches were considered to achieve this: organisational, technological, and individual human-centred levels, following the socio-technical framework proposed by Goetzen et al. (2023). The authors elaborated and followed the research methodology presented in Fig. 1 to achieve the planned goals and address the research questions.

The research began with identifying key concepts and definitions within the scope of the review, including Robotic Process Automation, Intelligent Process Automation, artificial intelligence technologies, cognitive automation, etc. The adopted perspective considered RPA and IPA from both business and human-centred viewpoints.

The next step in the research process involved conducting literature screening and searches using the ResearchRabbit AI tool. ResearchRabbit is an innovative, freely accessible online tool for citation-

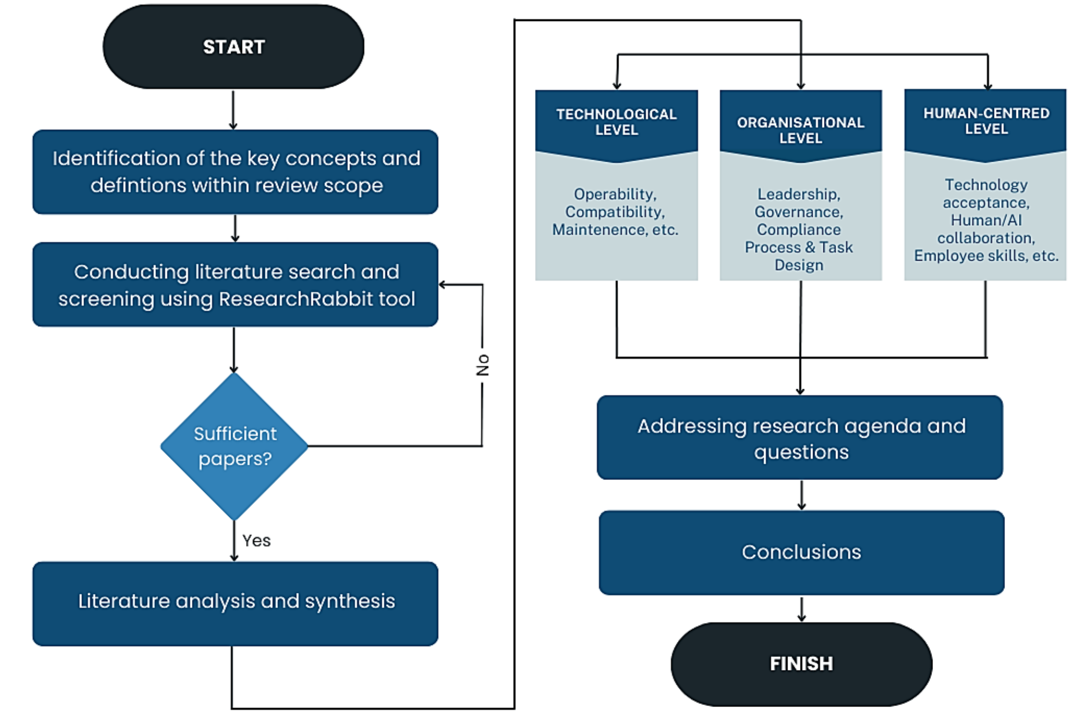

Fig. 1 Research methodology
Source: elaborated by the authors based on Goetzen et al. (2023).

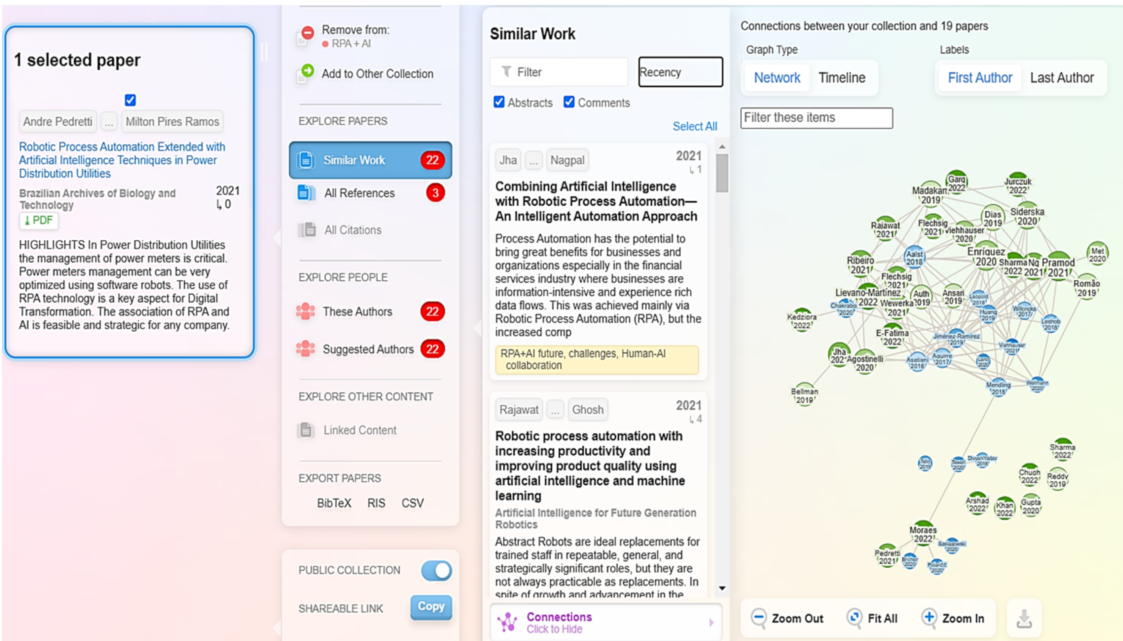

Fig. 2. Example of using the ResearchRabbit AI tool

based literature mapping. This program scours the Internet for publicly available sources and selects scientific publications based on similarities. This web-based platform offers interactive conceptual maps and streamlines the research process. The platform provides a user-friendly interface that simplifies mapping out a literature review. Its interactive visualisation allows researchers to connect their interests with related articles and authors. Users can easily link their research interests to relevant papers and authors, and

ResearchRabbit also includes features like note-taking and highlighting, making it convenient to summarise and extract essential information.

The initial step of using the ResearchRabbit tool involved providing reference papers relevant to the formulated research questions. After adding key papers to the collection, the software used AI algorithms to select 150 scientific publications based on similarities. An example of finding similar articles to the indicated work and related connections is shown in Fig. 2.

ResearchRabbit utilises natural language processing, machine learning, and semantic understanding to offer highly accurate and contextually meaningful results. It serves as compelling evidence of how artificial intelligence has the power to revolutionise information access. Key features of the tool include personalised recommendations, where it learns from users' search history and preferences; semantic understanding, which enables it to grasp the semantic context of queries, enhancing the depth and accuracy of search results; trend analysis, by which it can identify emerging trends and topics within specific research fields by analysing patterns in research publications, enabling researchers to anticipate breakthroughs or pivot their research directions; and visual summarisation, where ResearchRabbit AI utilises data visualisation techniques to condense complex information into easily digestible visual summaries.

The next step in the research process involved conducting a literature review, content analysis, and synthesis. The primary goal was to describe the theoretical or empirical nature of publications chosen by AI algorithms, highlighting major directions for future research in these fields and revealing the foundational knowledge pillars. Challenges and potential countermeasures were considered at the organisational, technological, and human-centred levels.

2. Theory development within RPA, AI, and IPA

Throughout history, innovative efforts have never ceased influencing, improving, and revolutionising human life. Recent technological advancements have proven to provide an array of solutions and opportunities for various complex problems. More specifically, the increasingly dominant role of technologies like AI has overhauled the common activities related to business processes and functions. This trend can only be expected to grow rapidly, as Furman and Seamans (2019) highlighted how AI-related activity in the workforce significantly impacted multiple industries, the labour market, and the general economy.

It is important to note that the definitions of AI prove to be contingent on its boundaries and limits, which have mostly become prevalent recently as technological developments have made it more difficult to define AI's scope (Wang, 2019) specifically. Nevertheless, AI is generally viewed as a conglomerate of different techniques, including subjects like natural language processing (NLP), machine learning (ML), neural networks, and computer vision (Sarker, 2022). Regarding the subjects of this paper, some studies show that the relevant AI techniques can be segmented into two (2) categories: classical AI and constructed AI (Richardson, 2020). Where classical AI refers to the application of pre-defined instructions towards the machine's decision-making, the latter is defined as the machine's advanced use of ML algorithms to discover patterns from data.

This notion feeds into the topic of RPA, a software solution ostensibly designed to limit the repetitive, non-value-added tasks humans perform (Baranauskas, 2018; Costa et al., 2022). Low-complexity business tasks are overtaken and concurrently pave the way for human workers to embark on more meaningful work. Furthermore, powered by low-code and clearly defined definitions, companies began to leverage RPA solutions to achieve increased productivity with ease and employee satisfaction (Kortesalmi et al., 2023). The future of RPA highlights how it serves as a powerful gateway technology towards advanced AI applications (Siderska, 2020). Eventually, as intelligent solutions rapidly evolve, industries are beginning to make headway towards an even smarter and more advanced model of RPA, coined Intelligent Process Automation (IPA). Richardson (2020) describes that the distinction between RPA and IPA lies in integrating intelligent features and algorithms (AI) that can exceed human capabilities. IPA is generally recognised as more advanced. Essentially, incorporating cognitive functions allows IPA to recognise patterns in decision-making, adapt to new data, and self-improve through experience (Berruti et al., 2017). Concerning the categorisation of AI, as RPA performs under logic-based rules for repetitive processes, it fundamentally fits within the definitions of classical AI, while IPA falls under constructed AI since it includes ML and AI technologies. Ultimately, a company's desire to meet its business challenges and increase competitiveness can be achieved through RPA and IPA integration. Despite the developmental differences between the two technologies, both can be utilised to support different business departments.

As mentioned, advanced AI technologies can be used to facilitate essential business management tasks. The features of RPA and IPAs are capable of equipping businesses with strategic opportunities and consequently aiding different stakeholders involved through their applications. More specifically, this can ostensibly be achieved through the evolution and application of IPA, with its functions overshadowing RPA's relatively limited capabilities. Advanced IPA integration can uplift processes' strategic (business) and human-centred aspects, enforcing strategic plans and business improvement. On the one hand, since IPAs can improve themselves through reinforcement learning, these machines can outperform humans in various business tasks.

Asadov (2023) highlights that streamlining IPA into the workforce effectively enables end-to-end automation that shortens lead time and eliminates process bottlenecks. Furthermore, on top of efficient resource allocation, deep learning algorithms and cognitive capabilities promise companies real-time monitoring and performance analytics (Berrutti et al., 2017). In effect, data-driven insights develop decision-making to enhance process performance and overcome organisational shortcomings, which will guide industry leaders towards green practices and subsequently create spillover effects towards achieving sustainability. On the other hand, IPA deployment reaps many beneficial impacts on the human stakeholders involved in the business. According to Berruti et al. (2017), human workers can be granted improved internal work opportunities and roles that exceed their preceding job scope. The additional responsibilities can cover more meaningful and innovative tasks, increasing their agency and allowing employees to forge their career paths. Touching on another human-centred perspective, technologically simplifying interactions through IPA can positively enhance the customer journey. Additionally, possessing comprehensive target clientele information leads companies to accurate decision-making, further enhancing customer relationships. Thus, advanced AI inclusion in IPA can unlock significant values, drive productivity gains for a business and achieve strong customer experience and retention.

With more companies transitioning towards automation, solutions like IPA emerged to meet the flourishing demands of outperforming technology. Studies show that incorporating technological resources and systems into business administration will benefit the sectors' operational and industrial growth (Ahmad et al., 2022). In the prospects of achieving increased productivity and performance, implementing advanced robotic AI solutions has impacted various business activities related to different departments and stakeholders. Incorporating automation of relevant processes through IPA is primarily needed to progress towards innovative movements like the Industrial Revolution 5.0 (IR5.0). However, even though businesses know their need to implement digital innovation and automation, they may face challenges in including such advanced technologies.

3. Challenges for organisations with IPA transitions

The relentless pursuit of operational excellence and efficiency has driven the evolving landscape of business automation. With increasing technological opportunities in AI, digital pioneers grow increasingly aware of the potential benefits IPA offers. Compared to the rudimentary predecessor RPA, which focused primarily on rule-based, repetitive tasks, IPA leverages the capabilities of AI, machine learning, and data analytics to automate routine tasks and complex cognitive functions. As a result, IPA has great potential to empower organisations to realise multifaceted advantages that resonate throughout their operations.

However, implementing IPA or transitioning from RPA to IPA presents significant challenges for companies. These challenges go beyond technical considerations and are primarily associated with organisational adjustments and the changing role of the human workforce. Organisations are challenged with redefining job roles, addressing data security concerns, and providing training and upskilling opportunities for employees. Following the socio-technical framework proposed by Goetzen et al. (2023), these challenges are classified into three distinct categories: organisational, technical, and human-centred, as shown in Table 1. A comprehen-

Tab. 1. Challenges for organisations transitioning from RPA to IPA

Challenge category/ perspective	Key challenges	Possible countermeasures	References
organisational	• leadership-related challenges, e.g., missing alignment across business areas, workforce management, and change management; • governance-related challenges, e.g., allocation of roles and responsibilities, missing rule-based frameworks and implementation guidelines; • process and task design-related challenges, e.g., routine organisation and task aspects and deficiencies; • compliance and IT security, e.g., missing policies, guidelines, and audit processes	• transparent communication protocols and knowledge transfer need to be considered within the organisational design; • clear allocation of responsibilities and incentives; • collaborative task design considering human aspects and AI limitations; • definition of clear IT security guidelines detailing access rights and data use restrictions for humans and IPA bots	Brás et al. (2023); Lievano-Martínez et al. (2022); Feio & dos Santos (2022); Chakraborti et al. (2020); Flechsig (2021); Agostinelli et al. (2020); Kedziora & Hyrynsalmi (2023); Brás et al. (2023)
technological	• lack of good quality data for ML; • wrong ML model chosen for a task; • challenges in software integration	• data curation; • trained ML engineers and better documentation of the algorithms with practical use cases and open-source reference implementations; • better standardisation and compliance with standards;	Kedziora & Hyrynsalmi (2023)
human-centred	• transformation of job roles; • novel skills and competence demands; • fear of job loss, identify void & less-abled; • mutual learning between heterogeneous actors	• clarification and implementation of new job roles; • identification of required skills and competence; • AI-related learning at the workplace with support from new HR practices	Moulaï et al. (2022); Schulte et al. (2022); Süße et al. (2023)

sive analysis of these challenges is provided in subchapters 3.1–3.3, as presented in Table 1.

3.1. Organisational challenges

Various organisational tasks arise in the transformation from RPA to IPA. The organisational tasks can be classified into four main categories: Leadership, Governance, Process and Task Design, and Compliance (Goetzen et al., 2023). The most important aspects of each category are discussed in more detail below. Afterwards, the question is addressed of whether and to what extent the emerging challenges depend on the technological maturity of IPA and the maturity levels suggested for the transformation to be classified. However, further research is needed on which challenge can be assigned to which maturity level.

Leaders are at the forefront of guiding their organisations through the complexities of IPA implementation. Their ability to provide strategic direction, promote alignment, nurture the workforce, and effectively manage change and communication is fundamental to the success of IPA initiatives. Within the literature, several leadership challenges have been identified, encompassing strategic planning and flexibility, alignment across business areas, workforce management, change management, and communication, explained in the following paragraph.

A paramount challenge in leadership involves the formulation of a roadmap and strategy for IPA implementation, which necessitates careful planning to ensure the successful integration of IPA into organisational processes (Feio & dos Santos, 2022; Kedziora & Hyrynsalmi, 2023). Notably, the strategy must be adaptable, given the dynamic nature of processes that are in constant flux (Brás et al., 2023). Organisations must adopt a comprehensive approach to harness the full advantages of automation and effectively mitigate risks, failures, or potential threats. It should involve ensuring alignment between the business and IT, business continuity, and the implementation of new controls specifically tailored to address the unique risks associated with IPA (Brás et al., 2023). Brás et al. (2023) and Lievano-Martínez et al. (2022) recommended a holistic approach to addressing this challenge. Organising and managing the workforce effectively is a multifaceted challenge. Ensuring the organisation possesses the requisite human resource capabilities is imperative for successful IPA implementation (Feio & dos Santos, 2022). Thus, employees must receive training to develop new skills related to

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IPA. Additionally, it is essential to prevent deskilling, whereby employees do not lose their creative and judgmental abilities during the automation process (Flechsig, 2021; Kholiya et al., 2021; Zeltyn et al., 2022; Feio & dos Santos, 2022). Furthermore, a challenge arises from the scarcity of qualified experts in this field (Flechsig, 2021; Kholiya et al., 2021). Change management is an integral part of IPA implementation. It involves orchestrating the transformation and ensuring the changes are seamlessly integrated into the organisational culture and practices. Effective communication is paramount in achieving internal organisational synergies, managing expectations, and mitigating user resistance (Flechsig, 2021; Mohanty & Vyas, 2018; Kedziora & Hyrynsalmi, 2023), also encompassing the readiness of the organisational culture and technology (Feio & dos Santos, 2022).

Governance is the guiding framework that ensures IPA initiatives are executed precisely and in alignment with the organisation's strategic objectives. It establishes the rules of engagement, resolves conflicts, defines the scope and provides the necessary support to make IPA adoption a success. The literature review identified three major governance-related challenge areas: allocation of responsibilities, rule-based framework, and adoption and implementation guidelines. Responsibilities and rules must be clearly defined during implementation (Flechsig, 2021). Lievano-Martínez et al. (2022) stated that responsibilities must be separated, and a review of mechanisms must ensure that conflicts are resolved quickly, e.g., via a decision matrix framework, programmed meetings, and reporting rules. According to Chakraborti et al. (2020), new frameworks and approaches are required to enable the composition and collaboration of multiple IPA-bots. In addition, the scope of autonomy and decision-making of the bot needs to be determined (Flechsig, 2021). Herm et al. (2021) claimed that critical success factors need to be identified so that methodological support for adoption and implementation can be developed. Brás et al. (2023) supported this by stating that adopting new processes entails evaluating and understanding the impact on business continuity.

The imperative for process and task (re-)design emerges as a requisite for restructuring operations, with the primary objective of optimising the synergistic collaboration between IPA bots and the human workforce. This restructuring aims to enhance operational efficiency and effectiveness by harmonising the capabilities of IPA bots with human skills and expertise. Challenges within the process and task design could be assigned to the following categories: data challenges, process and routine organisation and task aspects and deficiencies. The crucial data issue lies at the heart of process and task design. Initially, it is imperative to identify, clean, and transform the pertinent data to make it amenable to automation (Chakraborti et al., 2020). However, within the context of IPA, a heightened demand for data quality arises, accompanied by the risk of potential data gaps essential for model building (Kaarnijoki, 2019). Kaarnijoki (2019) further highlighted the data dimension by underscoring the challenge of avoiding or accounting for data bias within training data. This bias may stem from certain features present in the dataset. When an automated model is trained on biased data, it consequently inherits the same biases, potentially impacting its accuracy and fairness. A parallel challenge emerges in managing the processes and routines vital to the success of an IPA implementation. In this context, adopting new procedures unfolds rapidly, often potentially disrupting existing workflows (Brás et al., 2023). The effectiveness of automation hinges on the identification of suitable routines and processes that can be automated (Agostinelli et al., 2020, p. 4). As Godbolde et al. (2022) articulated, determining the utility of automating specific IPA opportunities requires comprehensively assessing the process complexity level and the necessary intelligence degree.

The final identified challenge category pertains to deficiencies in various task-related aspects. These include the potential absence of standardised and up-to-date process documentation, which could impede the smooth automation of processes (Kedziora & Hyrynsalmi, 2023). Additionally, challenges may arise concerning task selection and scalability management techniques. If effective strategies in these areas are missing, this could pose significant obstacles to the automation journey (Feio & dos Santos, 2022). Furthermore, robust testing and penetration testing are of paramount importance. The absence of such measures may expose vulnerabilities within the automation system, potentially rendering it susceptible to security breaches (Al-Slais & Ali, 2023).

The final major challenge category covers organisational challenges related to compliance. These challenges mainly relate to IT security concerns (Kedziora & Hyrynsalmi, 2023) and the integration with legacy systems (Feio & dos Santos, 2022). Regarding IT security, it should be added that robust cybersecurity is required to ensure safe IPA implementation and scaling (Kholiya et al., 2021). In addition, policies and guidelines must be updated to reflect audit capabilities for secure monitoring of changes (Brás et al., 2023).

3.2. Technological challenges

The evolution of intelligent automation software has been affected by technical limitations. The type of technical challenge the organisation faces depends on the intelligent automation technology in question. Therefore, the software was classified into six categories reflecting the most common types of intelligent automation. The classes were created based on the review papers on IPA by Ng et al. (2021) and Devarajan (2019) and on the literature review described in this paper. The classes, their explanations, and some use cases are given in Table 2.

The technical challenges related to conversational AI are often related to hallucinations, which refer to unreliable information generated by large language models (Ji et al., 2023) and a bias and lack of data for training. Security and compliance are also common technical challenges in many IPA types, including conversational AI (Herm et al., 2021). Overall, according to Herm et al. (2021), the four latter technical challenges are very common in IPA. All ML-based techniques may suffer from the lack of good-quality data, which is a very stringent challenge, as most IPA techniques rely on ML techniques.

Business process mining suffers from the inherent challenge of relying on past data, and thus, it is unable to account for changes in the business processes or the environment. The same applies to all ML techniques except those employing the human-in-the-loop approach, such as reinforcement learning (Sutton & Barto, 2018). De la Oliva (2020) pointed out the integratory elements of cognitive automation related to embedding automation toolsets at enterprise platforms. This challenge has also been addressed by Ng et al. (2021). Another challenge indicated by Pramod (2021) was the manual or human-driven identification of automation potential, favourably substituted by technical solutions of the

Tab. 2. Common AI techniques used in IPA

AI technique	Short explanation	Common use cases
Conversational AI, including generative AI	Techniques for the automated generation and interpretation of natural language and for keeping up a conversation. They may address several modalities, such as text, speech, sign language and gestures	Build conversational interfaces that enable communication between a computer and a human, such as an interface for filling in forms and other structured data. The agent may work, e.g., as a customer service agent or a bot, helping the expert use financial software (Moiseva, 2020; Shidaganti et al., 2023; Zeltyn et al., 2022)
Business Process or Task Mining	Using data mining and ML techniques to extract business rules from data	Automate the manual work of writing executable RPA scripts. Rules may be mined from user interface log data or history data annotated by humans (Agostinelli et al., 2020)
Intelligent OCR	Intelligent OCR is an advancement to the traditional OCR as it uses extratextual and textual information to scrape business information from scanned documents. It may contain such features as key information extraction (IE) and ML-based adaptive decision-making in unclear OCR cases. Multimodal IE incorporates extratextual information, such as layout or other visual information	Scanning damaged or unclear hand-written documents. Extracting structured data directly from physical documents, such as paper bills. (Cho et al., 2023; Kedziora & Hyrynsalmi, 2023; Hong et al., 2023)
Information extraction (IE)	Extract relevant information from natural language input, such as text documents and speech, thus creating structured data from unstructured data	Extracting software requirements from business documentation, extracting patient information from a medical doctor's speech and saving it to a database
Machine Learning (ML)	Using ML techniques, including deep learning and reinforcement learning, to create classifiers and clusters from data. Also, human-in-the-loop approaches are included	Create a classifier using ML and history data on customers and their loan payments to automate bank loan decision-making. Create an anomaly detector for monitoring fraudulent transactions using ML techniques
Data Science (incl. Predictive Analytics)	Based on past data, create a model that predicts the future	Predictive maintenance for elevators and other machines, planning of transaction volumes (Vajgel et al., 2021)

task of process mining origin (Geyer-Klingeberg, 2018), where the software controls and analyses the flow of processes based on specific rules (Huang [MOU5] & Vasarhelyi 2019). Stople et al. (2017) pointed out that challenges with infrastructural scalability negatively impact the entire ecosystem and need to be systematically updated (Lacity et al., 2015). From the perspective of the strategy for data storage and acquisition, Bhatnagar (2020) identified issues with multi-source inputs with no standardisation. Aspects of regulatory challenges for technical setups and security handling have been discussed by Priya et al. (2019). Regulatory challenges are prevalent when ML models are built using personal data, as regulations, such as GDPR, restrict the collection and use of data often required to build the models. The upcoming AI Act (Veale & Borgesius, 2021) will classify software employing AI into categories with different risk levels and limit AI application in high- or medium-risk sectors, such as healthcare or education.

IPA that relies on ML may suffer from poorly trained or immature models that might lead to unsupported or even wrong decisions and an increase in errors (Wojciechowska-Filipek, 2019). Poorly trained models may result from a lack of expertise of the ML engineers if they do not know which model to select for the task at hand. Poor-quality data is another common source of poor models (Geiger et al., 2020).

3.3. Human-centred challenges

From a human-centred perspective, AI implementation and extended use, particularly IPA, create novel employee challenges. Herm et al. (2021) pointed out a 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-based robots. In addition, implementing AI robots in professional work contexts can lead to a human perception of an identity void and a feeling of being less able (Moulaï et al., 2022). Kassekert et al. (2022) argued that the rather human-centred process of finding and having appropriate training data for ML models is rather challenging while the demands for harmonised regulatory guidance, e.g., for providing orientation for human decision-making processes, increase.

Based on several interviews and empirical analysis, Lamberti et al. (2019) emphasised that the most significant challenges during AI implementation include the skills of staff (55 %), data structure (52 %), and budgets (49 %). In addition, the authors showed that 60 % of their respondents during interviews referred to a planned increase in staff within the next 1–2 years. This increase is required to support AI use or implementation within the organisation. These results are in line with other field research results that show how the implementation of AI into the value-creation process contributes to the emergence of new job roles and profiles in the industry. While these developments also create new opportunities for the workforce, there are challenges as well, like additional time and effort human actors have to spend on learning and training initiatives (Schulte et al., 2022). Another study (Süße et al., 2023) investigated a shift in human behavioural patterns of technology interaction during the implementation and product use of an AI robot within a remanufacturing company. The authors emphasised a new set of cognitive, social and emotional competencies required for human actors to interact more collaboratively and cooperatively with AI robots.

However, while the above-mentioned literature focused rather on the human side of these newly emerging IPA-related human-AI systems, Chakraborti et al. (2020) highlighted a technological perspective with a human-centred standpoint in mind, i.e., that novel conversational systems may be required for a productive and sustainable collaboration among IPAs and users (p. 220 ff.). As such, the emergence of a mutual and rather iterative learning process between human actors and AI robots has to be enabled and supported to implement IPA-related human-AI systems successfully. It is related to another key challenge from the human-centred perspective discussed by Martínez-Rojas et al. (2021), who pointed out that a success critical factor for the implementation of AI robots and IPA is the involvement of heterogeneous experts and professionals from different disciplines with diverse skills, competences and backgrounds as the added value of transdisciplinary solutions will be required to make IPA work appropriately in organisations.

In their literature review, Jha et al. (2021) concluded that the shift in human tasks is another key challenge of IPA implementation in organisations. They argued that middle-skilled employees might migrate to high-skilled jobs with the help of extensive learning and development initiatives. Furthermore, they highlight the emergence of a new management position, which they call Chief Data Supply Chain Officer. One key component of this role is the capabilities and responsibility of creating end-to-end data supply chains across all levels of the organisation and within a value network of organisations, which could help fully leverage the extensive benefits of available data in AI (p. 261).

In summary, the authors argue that research so far points out four key IPA challenges from a human-centred perspective. First, the transformation of traditional job roles has to be addressed adequately at all hierarchical levels within the organisation. Second, employees and management require novel skill sets and competencies as both groups will interact with the new technology more collaboratively in a human-AI system. Third, trust and explainability of AI and regulatory guidance play a critical role in reducing job-security-induced fear of AI-based robots, which also relates to identity void and feeling less able among employees. Fourth, mutual and iterative learning processes between heterogeneous experts and managers from different disciplines and backgrounds and between humans and AI must be enabled and supported to contribute to the emergence of highly collaborative and sustainable IPA-related human-AI systems.

4. Future research trends

Empirical-based field research is scarce on specific skills and competence demands and more context-related specifications of job role changes. Furthermore, the human-centred perspective so far focused more on the psychological perspective of humans, e.g., the collaborative concept human actors have in mind when interacting with AI robots (Süße et al., 2023). Furthermore, research should more explicitly focus on the human–AI system as a whole and not address the human or AI, which is very often the case in most research approaches (Waefler et al., 2021).

Future research aims to address the organisational challenges arising from adopting IPA or the transition from RPA to IPA, prioritising specific essential areas, including exploring task designs and routine definitions that enable effective collaboration between humans and IPA bots. Further research efforts should also focus on comprehensive change management and communication strategies, allowing for a smoother transition to IPA (Flechsig, 2021). Ethical and legal concerns are relevant in considering the data-driven nature of IPA and potential biases in AI algorithms. Furthermore, IT security and risk management are critical areas where further investigation can help develop robust strategies to safeguard information when using IPA. As a descriptive framework, IPA maturity models could offer organisations valuable orientation for assessing their readiness and progress on their automation journey. Finally, exploring scientific approaches to seamlessly integrate IPA with legacy systems, ensure regulatory compliance, and enhance scalability and adaptability could provide essential support for organisations to overcome challenges and mitigate risks associated with IPA implementation.

Methodology and practices for data curation are needed to overcome the technical challenges of adopting IPA, which is essential to ensure access to good quality data critical for ML. Another major challenge in IPA is that the selection process for the used ML model is not optimal. This results in low-quality output in IPA. Research on reference models and ML model implementations is needed to overcome this shortcoming. The reference models should be published as open-source implementations, and the documentation should contain practical examples of use cases illustrating their optimal application. The third technological challenge is related to integration and may be overcome with standardisation work where good-quality interface and data standards are created, and the widespread uptake of the standards is facilitated.

Emerging Low-Code Development Platforms (LCDPs) are a significant phenomenon that requires further exploration as they will impact building process automation solutions. RPA and IPA were targeted and focused on the automation of particular business processes, whereas LCDPs go beyond simple process automation by aiming at building entire business applications, enabling persons with introductory software skills to develop fully functioning apps. In this context, integrating more technologies across the entire value chain shall enable further simplification and effectiveness of available tools. Hence, the relationship and opportunities resulting from integrating RPA and LCDPs will certainly become an important trend, as according to Gartner (2023), by 2027, low-code application development will be responsible for more than 70 per cent of application development activity globally.

These research trends reflect the diverse and evolving nature of intelligent automation. Researchers in this field will play a crucial role in advancing automation technologies and ensuring their responsible and effective use, as well as shaping the future of IPA across a wide range of industries, fostering innovation, and addressing the practical, technical, and ethical challenges that arise along the way. Additionally, addressing the potential impact on the workforce and engaging in collaborative efforts with experts and stakeholders is essential to navigating the challenges of human-centred design in the context of intelligent automation.

Conclusions

Integrating AI with RPA significantly enhances automation capabilities, empowering organisations to increase efficiency, reduce errors, enhance customer service, and remain competitive in a rapidly evolving business landscape. This combination provides a robust solution for organisations looking to streamline their processes and deliver added value. AI-powered RPA excels at handling unstructured data, utilising natural language processing (NLP) and applying machine learning to execute tasks that demand cognitive abilities, including understanding text, images, and speech. These developments expand the range of tasks that RPA can automate. AI's ability to identify patterns, predict outcomes, and suggest process improvements further enhances and refines operations. When seamlessly integrated with RPA, it streamlines workflows, ensuring heightened efficiency. AI's capacity to continually learn and adapt from new data and experiences makes RPA processes more agile and adaptable in dynamic environments.

Organisations encounter numerous challenges when adopting IPA or transitioning from RPA to IPA. These challenges are predominantly associated with organisational adjustments and the changing role of the human workforce, extending beyond technological concerns. The primary areas of organisational focus encompass (Geotzen et al., 2023) leaders as they are critical in navigating organisations through the complexity of IPA implementation. The ability of IPA leaders to provide strategic direction, foster cohesion, nurture the workforce, and effectively manage change and communication is essential for the success of IPA initiatives. Governance is the guiding structure for ensuring that IPA projects are carried out precisely and following the organisation's strategic objectives. It establishes engagement norms, dispute resolution processes, and scope definition and provides the required support for effective IPA implementation. Restructuring of operations and (re-)design of processes and tasks are necessary to maximise the cooperation between IPA bots and human labour. Challenges in this domain encompass several categories: data challenges, process and routine organisation, and task aspects and deficiencies. Notably, a significant challenge category pertains to corporate compliance hurdles, specifically focusing on legacy system integration and IT security issues. Robust cybersecurity measures are imperative to ensure secure IPA deployment and scaling. Furthermore, policies and guidelines should be updated to include audit capabilities for secure change monitoring.

The research highlights four key human-centred challenges in IPA implementation: the transformation of traditional job roles, the need for novel skill sets and competencies, the importance of trust and explainability of AI, and the necessity of mutual and iterative learning processes among diverse experts and managers from different backgrounds. These challenges must be addressed to facilitate collaborative and sustainable IPA-related human–AI systems. Many organisations plan to increase their workforce to support AI implementation, reflecting the emergence of new job roles and profiles in the industry. These advancements, however, are not without hurdles, such as the increased time and effort necessary for staff learning and training efforts.

The evolution of intelligent automation software has been influenced by technical limitations. The specific technical challenges encountered by organisations vary depending on the type of intelligent automation technology in use. The software was categorised into six common types of intelligent automation to provide a structured perspective: conversational AI (including generative AI), business process (task mining), intelligent OCR, information extraction, Machine Learning, and data science (including predictive analytics). Issues were underlined, e.g., hallucinations, where unreliable information is generated by large language models and concerns regarding bias and insufficient training data. Security and compliance challenges were identified as widespread issues in IPA, including conversational AI applications. The overarching importance of data quality in machine learning techniques employed in IPA is highlighted, given that many IPA approaches rely on ML. Business process mining and its reliance on historical data are recognised as a challenge, as changes in business processes or the environment may not be adequately considered. Infrastructure scalability challenges, which can negatively impact the entire IPA ecosystem, are discussed, emphasising the need for systematic updates.

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