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A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives

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ABSTRACT

With the recent developments in robotic process automation (RPA) and artificial intelligence (AI), academics and industrial practitioners are now pursuing robust and adaptive decision making (DM) in real-life engineering applications and automated business workflows and processes to accommodate context awareness, adaptation to environment and customisation. The emerging research via RPA, AI and soft computing offers sophisticated decision analysis methods, data-driven DM and scenario analysis with regard to the consideration of decision choices and provides benefits in numerous engineering applications. The emerging intelligent automation (IA) – the combination of RPA, AI and soft computing – can further transcend traditional DM to achieve unprecedented levels of operational efficiency, decision quality and system reliability. RPA allows an intelligent agent to eliminate operational errors and mimic manual routine decisions, including rule-based, well-structured and repetitive decisions involving enormous data, in a digital system, while AI has the cognitive capabilities to emulate the actions of human behaviour and process unstructured data via machine learning, natural language processing and image processing. Insights from IA drive new opportunities in providing automated DM processes, fault diagnosis, knowledge elicitation and solutions under complex decision environments with the presence of context-aware data, uncertainty and customer preferences. This sophisticated review attempts to deliver the relevant research directions and applications from the selected literature to the readers and address the key contributions of the selected literature, IA's benefits, implementation considerations, challenges and potential IA applications to foster the relevant research development in the domain.

1. Introduction

Robotic process automation (RPA), which is able to yield a high level of operational efficiency, risk management and adherence to quality and compliance, has attracted considerable interest among businesses. Routine tasks such as workflow processing, automated email query processing, scheduling systems, data acquisition from online sources and automated inventory replenishment can be performed by an expert system equipped with automatic software agents and bots [1]. RPA can automate repetitive business processes, which plays a key role in mimicking routine manual tasks and workflow processes via the advancement of information technology (IT). RPA has emerged and attracted the attention of practitioners for deployment, given the fact that RPA could work automatically in rules-based decision making in business processes. Although RPA is a powerful tool, its applications are only limited to highly rule-based, structured, mature, standardised, repetitive and well-documented decision logic for easy tasks/processes with digitised structured data input [2,3]. Industries are now seeking more intelligent and innovative RPA to tackle the decision-making processes with cognitive computing and embedded intelligence. The increase of smartness of such systems implies an increase in technological capabilities to perform high-level process automation and value creation for stakeholders [4–6]. Furthermore, some occupations demanding manual and basic cognitive skills are seeing a diminishing

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trend [7]. We could expect that human workers will work alongside intelligent and innovative RPA in the near future, as robots, software agents and intelligent decision support systems are able to take up more and more cognitive decisions in business processes [8]. RPA is a well-established business process automation technology that has received increasing attention over the past decade, although its potential still requires further exploration and adaptation in more complex, dynamic business environments.

Computational capacity has been increased exponentially, contributing to the recent developments in artificial intelligence (AI) [9,10]. For example, analysing large-sized datasets in a complex model can be completed quickly with the recent advancements in machine learning (ML) approach. Massive data can be generated for AI training as the development of context-aware computing and real-time data acquirement from online sources mature [11]. Powerful graphics processing units increase compatibility in handling complex deep learning and reinforcement learning algorithms [12]. All these factors contribute to the breakthrough in AI and the development of embedded intelligence in other engineering applications and are brought together in integrated systems. RPA can take advantage of AI to perform cognitive decision making that can further expand in different engineering applications. The integration of RPA and AI, namely intelligent automation (IA), can further expand technological capabilities, technological readiness and process automation potential in different engineering and business applications. The cognitive decision-making power of IA can overcome the challenges of RPA implementation in handling unstructured data, computer vision, natural language processing, fuzzy rule-based decision, decision analytics, real-time decision and content-aware computing and supervise the performance of rules-based RPA [13–15]. Embracing IA in process automation promises considerable benefits in the form of return on investment (ROI), productivity and brand equity [16]. Due to the widespread use and synthesis of wireless sensing technologies, Internet-of-Things (IoT) and cyber-physical systems (CPS), the decision quality of AI enjoys the benefit of recent advancements in human-centric and context-aware computing [5]. The amplification of intelligence in AI, namely augmented intelligence or AI augmentation, can yield a solution that outperforms human decision making [17,18].

Indeed, IA undeniably could be a catalyst for growth in the value chain of business processes and offer insight to optimise business processes with virtual assistants for routine and complex tasks. However, the description and functionalities of IA in commercial products are sometimes exaggerated. For this reason, IA is still an abstract topic for the public. Furthermore, the research in IA is still in its infancy, despite the potential of IA to bring enterprise efficiency improvement, error reduction, lower-cost scalability, better customer experience and quality in business processes [19]. It is difficult for an organisation to commit their organisational goals and business process to IA and incorporate more intelligence in their systems and processes at this stage [20]. Even though the advancement of AI is mature, IA is an application-driven technology and the approaches are largely different in terms of organisation strategies, company vision, maturity of in-house R&D and readiness level for system integration among current IT systems. Organisations need to have a full background of what types of business processes can be automated, their technological readiness and the resource capabilities for setting up an IA solution in their company. Such differences mark the technological transfer of one successful case of IA adoption for a company to be imitated by others or as a reference.

The issues of implementation, consideration, challenges and potential applications of IA are yet to be explored in the literature. There is a growing need to investigate the research and development of IA; accordingly, we attempt to outline the state of the art, survey the advancement of IA, potential engineering applications and research directions in this review article. To provide a more concise and in-depth review and supplement the existing research development, five main research questions were developed:

- Research question 1: how can we harness the capabilities in intelligent automation to catalyse the business growth?
- Research question 2: what are the drivers and requirements for intelligent automation implementation?
- Research question 3: what are the insights and managerial implications of intelligent automation that can be derived from other industrial cases?
- Research question 4: what are the challenges of implementation of intelligent automation?
- Research question 5: what are the future research directions of intelligent automation?

The outline of the review article is as follows: After the introduction, the research methodology for the systematic literature review and statistical analysis of the selected studies are presented in **Section 2**. We present the paradigm changes in IA and contributions of the survey to provide a general idea of the basic notions to the readers, in **Section 3**. The key findings about IA, including the key elements, operational and strategic benefits, implementation and consideration of IA, are given in this section. Readers can have a more in-depth understanding of the benefits and deployment limitations of IA. After the discussion of the key findings on IA from the literature, we will further the discussion of managerial implications and challenges of IA adoption to provide more clear, concise and dense information to the readers in **Section 4.1** and **Section 4.2**, respectively. **Section 5** provides the potential applications in different engineering and business domains and research directions of IA before the concluding remarks (**Section 6**).

2. Research methodology for systematic literature review

2.1. Selection process of the literature

We aim to outline and consolidate the scattered knowledge of the current research in the literature systematically and further provide a comprehensive analysis on the technical and implementation challenges of IA in real-world applications. The systematic literature review contributes to the research progress of RPA and IA. The review process follows the steps proposed by Mayring [21]. Readers can refer to the detailed flowchart of the review process in Ng, Lee, Chan and Lv [10]'s work. The literature search process in this review article is shown in Fig. 1.

The authors carried out the literature search from electronic library databases, including *IEEE Xplore Digital Library*, *ScienceDirect*, *Taylor & Francis Online*, *Springer Online Journal Collection*, *Emerald Insight*, and *Web of Science*. The search strings included "*robotic process automation*", "*intelligent process automation*", "*intelligent automation*", "*artificial intelligence & robotic process automation*" and "*business process automation*". Only peer-reviewed journal and conference articles written in English were selected. The total number of articles in the initial search for the search string "*intelligent automation*" and other search strings were 4615 and 816, respectively. We found that the term "*intelligent automation*" in the current literature is ambiguous, which includes articles from the field of industrial automation, artificial intelligence in edge computing, instrumentation, non-process type entities and self-driving automobiles. Therefore, we revised the search string from "*intelligent automation*" to "*intelligent automation & business process*". We ended the initial search with 1010 articles (816 + 194) (last accessed on 1st May 2020). According to our preliminary search, the first article with the "*robotic process automation*" string in the title was published in 2016.

We further delimited the primary studies with the following inclusion and exclusion criteria. We performed the basic content checking of the 1010 articles in the next step. Only peer-reviewed journal and conference articles were considered. As RPA is a well-developed commercial tool, RPA/IA articles in engineering, system design and business review aspect are considered in this literature review, except empirical research articles (e.g., acceptance level/trust of RPA/IA). The primary

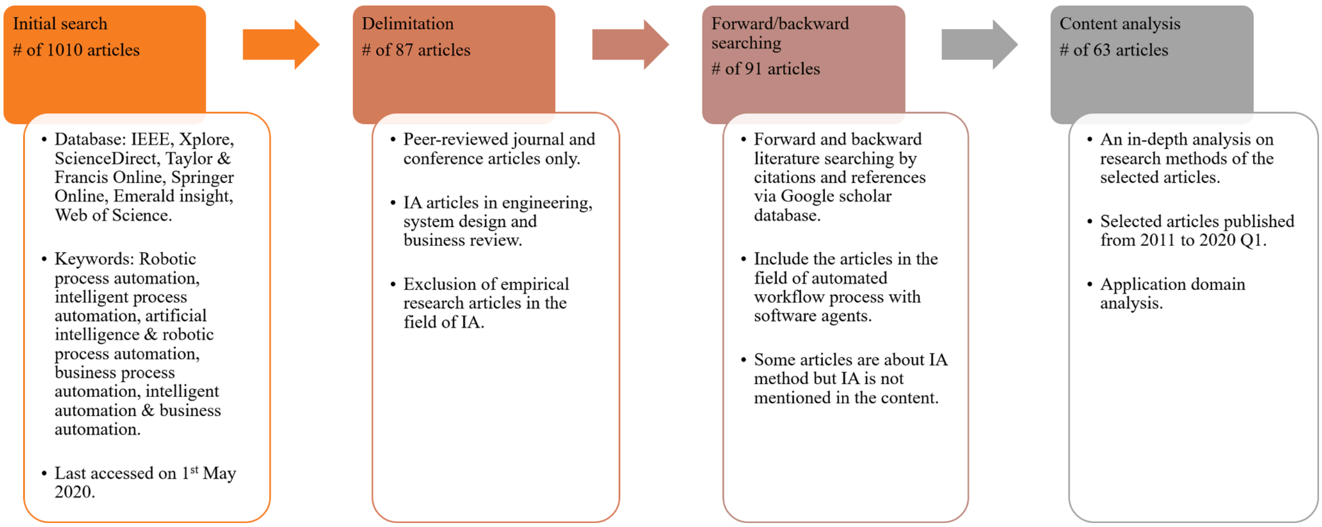


Fig. 1. Literature search process.

search yielded 87 articles.

Forward and backward literature searching based on citations were also performed to ensure a more comprehensive literature search. We performed forward searching based on the reference lists of the 87 articles, while the backward searching was performed using the function *cited by* in the *Google scholar* database. Forward and backward literature searching helped to locate 91 articles. We found that some articles do not include the keywords of RPA/IA, but their methods are related to the automated workflow process with software agents, as published in 2011. We also included those articles among the selected articles.

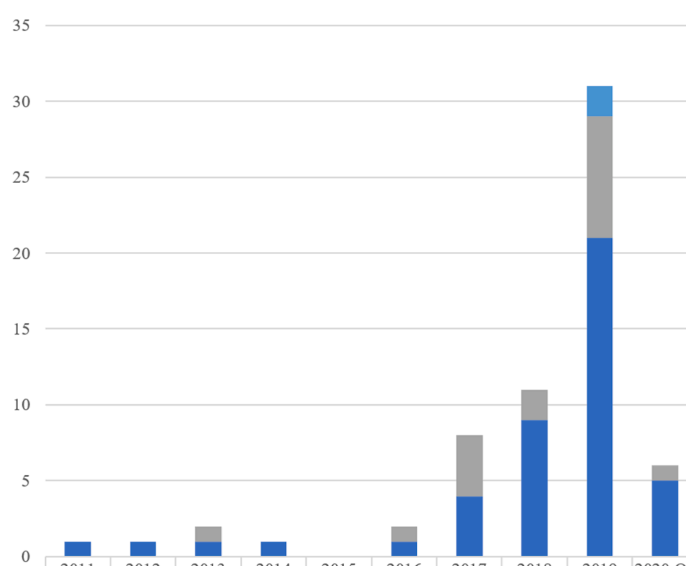
Then, an in-depth analysis was performed to further filter for those articles where the main theme is not RPA/IA. We reviewed the methodology of the selected literature that contributes to the workflow or process automation via robot, chatbot or software agent. Eventually, 63 articles were extracted for the purpose of this review.

2.2. Statistical analysis of the selected studies

This section presents the statistical analysis of the selected articles from 2011 to 2020 Q1 and illustrates the distribution of the publications by application domain. This summary enables readers to quickly refer to the literature and define possible research directions.

The number of publications IA kept increasing from 2016 to 2019. We classified the research methodology into RPA, intelligent process automation (IPA) and augmented intelligent process automation (AIPA). More details regarding the classification of IA technology are provided in **Section 3**. Fig. 2 illustrates the publication distribution of RPA, IPA and AIPA from 2011 to 2020 Q1. Most of the publications are in the RPA domain, whereas IPA and AIPA are relatively new research domains.

The articles distribution by application domains and the cross matrix of research methods are presented in Fig. 3 and Table 1, respectively. The application domains of IA application in the literature are mainly from business process management, information system, computer science, finance, industrial engineering, and social services. We classify the



	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020 Q1
Augmenting intelligent process automation	0	0	0	0	0	0	0	0	2	0
Intelligent process automation	0	0	1	0	0	1	4	2	8	1
Robotic process automation	1	1	1	1	0	1	4	9	21	5

Fig. 2. Publication distribution timeline.

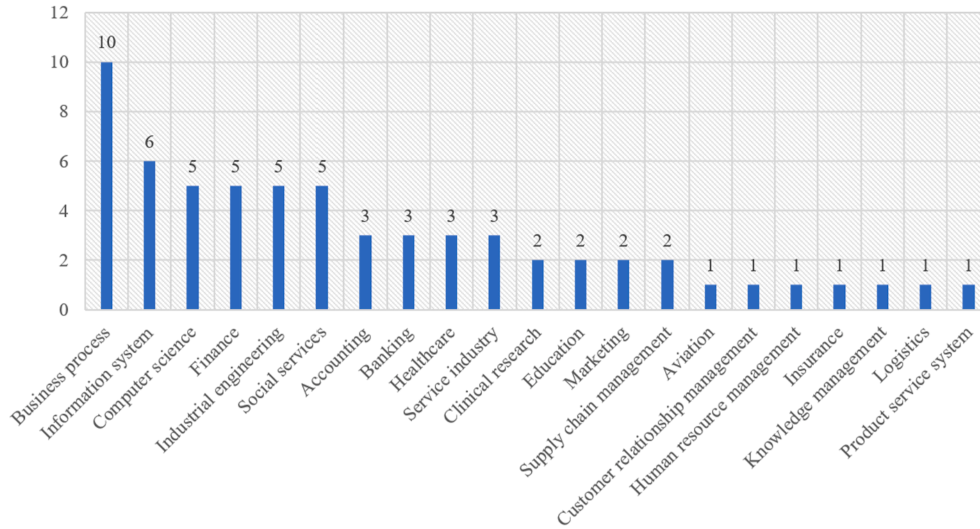


Fig. 3. Articles distribution by application domain.

Table 1
Cross matrix by application domain and research methods.

	Robotic process automation			Intelligent process automation			Augmenting intelligent process automation
Application domain	Engineering	System design	Business review	Engineering	System design	Business review	Engineering
Business process	[22,23]	[24,25]	[26–28]	[29,30]		[31]	
Information system	[32,33]	[34]	[35,36]	[37]			
Computer science	[38–41]						[14]
Finance	[4,42]		[43]		[3]	[44]	
Industrial Engineering	[45]	[16]		[7]	[34,46]		[15]
Social services		[47]	[48,49]	[50,51]			
Accounting		[1]	[52,53]				
Banking		[54]	[55,56]				
Healthcare	[57,58]			[59]			
Service industry			[8]	[60,61]			
Clinical research			[62]		[63]		
Education	[64]			[65]			
Marketing			[66,67]				
Supply chain management	[68,69]						
Aviation			[70]				
Customer relationship management						[71]	
Human resource management			[72]				
Insurance		[73]					
Knowledge management				[13]			
Logistics		[2]					
Product service system	[74]						

research methods by three major aspects. Articles in the group of Engineering aspect indicate that the research method of the selected articles contributes to the IA methodology. Articles belongs to the group of system design aspect illustrate that the selected article focus on the system architecture and design framework of IA application, while articles in the group of business review imply that the selected articles analyse the performance of commercial or brought-in IA application.

3. Key findings of intelligent automation

3.1. Paradigms changes of intelligent automation

RPA is defined as a form of automation technology to accelerate rule-based decision making in an efficient manner with highly structured data and limited human supervision in business process management that is empowered by robots, chatbots or software agents [75–78]. RPA is a well-developed technology, and various commercial products can be seen that aim to mimic routine tasks by humans in business process management, which improves agility and ease of compliance management or shorten the administration process in an organisation [76,78,79]. The classical examples of RPA include help desk, sales process support, scheduling systems, form processing and call centre operations. These tasks must be highly structured, and the decision logic is typically rules-based and repetitive with prescription instructions. Organisations enjoy the benefits of RPA that can automate part of the business process and free up more labour from repetitive and mundane business activities. The role of the human workforce then tends to be to engage in critical thinking and cognitive tasks. Routine and repetitive tasks can be handled by RPA without any human intervention [23,41,79]. Organisations can thus achieve a high level of efficiency in business processes and step into the new era of human-robot collaboration in the future workplace.

The advancement of AI has brought the evolution of RPA to another level, which ought to be coordinated with other technologies in real-world applications. Automated cognitive tasks are demanding but not amenable to automation using traditional approaches. Emerging AI and

ML improve the industry and business processes, equipping these with smartness [6,80]. More importantly, AI enables decision making to perceive, analyse and adapt to the actual environment. More complex tasks with judgemental activities in business process and human perceptual ability are well suited for IA applications using computer vision, natural language processing (NLP) and fuzzy logic, which makes IA not just a buzzword but endows it with practical insight [16,78]. Human-like judgement and perceptual ability have increased IA's applicability in various research domains and applications. As mentioned, IA is an application-driven technology. The solution designs of IA are subjected to various criteria, including procedure/workflow of the business process, method of integration to the current IT system and implementation effort and scale.

IA technology can be classified into RPA, IPA, AIPA and autonomous agents (AA). Their functionality and performance and application scenarios of IA are summarised in Fig. 4 and Fig. 5, respectively.

RPA can automate workflows or business processes that are highly repetitive with structured data input. Their decision logic can be formulated in rule-based decisions. However, the business process or workflow must be of a low level of process complexity and zero or limited cognitive capabilities. Therefore, RPA has a low level of exception handling capability and smartness.

IPA integrates RPA and AI technology and has the cognitive capabilities to perform prescriptive analytics and decision logic with unstructured data input, such as image, text, videos and vocals. IPA can provide a certain level of cognitive decision with the support of AI and soft computing (SC) techniques and can imitate human decision. Compared with RPA, IPA requires exception handling in decision logic, as the decision-making process is not rule based. Therefore, only a low level of human intervention is necessary. The IPA engines could use supervised or unsupervised learning, but they require experts to fine-tune the performance and accuracy of AI. Most of the commercial applications of IA adopt IPA techniques. Chatbot in BPM is the best-known IPA application. The online customer assistance via chatbot helps to foster the automated BPM and extract the text content for conversation analysis and review of customer preferences and comments [71]. Other evidence shows that IPA can be merged with the NLP algorithm to handle appointments and for contact information competency according to regulations from text information [3,59,63].

In contrast to IPA, AIPA achieves the next level of cognitive decision quality to enable a holistic approach to automating business workflow and digital processes. The AIPA system must be equipped with decision engines with deductive analytics with quick judgement, and the cognitive level of AIPA is close to human intelligence [14]. Learning from human decisions is also one key feature of AIPA engines [15].

The knowledge augmentation in AA allows the system to make better decisions than human intelligence. Exception handling capability, zero human intervention and self-learning ability to achieve high levels of decision smartness, quality control and decision support for exception handling are the major features of AA. AAs are software programmes that able to respond to the events and request independent without any human interventions and directions [81]. Depends on the task complexity, AA is required a certain corresponding cognitive ability to achieve the automated functions in engineering applications [82–84]. Robotic agents, computational agents, intelligent software agents and agent-based model are the sub-group of AAs. Given an interactive and reliable computer-based decision-making system, an expert system can deal with daily business workflow and process automatically. Various types of expert system, such as knowledge-based system, knowledge graph techniques and case-based reasoning, attempted to mimic human behaviours in automated decision-making [85–88]. Multi-agent system (MASs) are the promising research areas in the field of automated business process and workflow [89]. MASs aim to operate the automated decision-making process by a group of distributed AI via agent-communication language in a flexible manner [90–92]. Each agent has particular knowledge, cognitive level and capabilities for problem-solving. With the decentralised decision architecture, an interoperate decision-making via organisational paradigms, including hierarchical, team-based, coalitions and congregations agent-based organisation, can achieve better solution quality than a single intelligent agent [85,93]. Albrecht and Stone [84] illustrated that the transfer learning and learning of new tasks are still challenging to develop an efficient AA. Similar research literature and applications have been well studied for decades, but yet to be improved to meet the business needs with high cognitive level due to the limitations of technological advancement. The increase in process complexity, cognitive capabilities and decision support for exception handling, quality control and smartness required a more ground-breaking AA with contemporary AI algorithms [94,95]. In business workflow and process management, unistructural data becomes an important source of decision-making, and we expected that more cutting-edge AA will be developed to match the business needs in automation in near future.

The selection criteria of proper IA technology are based on the degree of automation needed in the business process, the complexity of the process and the required level of solution intelligence, as shown in Fig. 5. Readers can get a sense that only parts of the industrial automation and instrument automation belong to the group of IA, but they can serve as enablers of IA with a certain level of business process management. For example, smart product-service systems are equipped with context-aware sensors and Internet-of-Things (IoT) networks [87,88]. The user-generated and context-aware data can be further analysed to support the next-generation product configuration design.

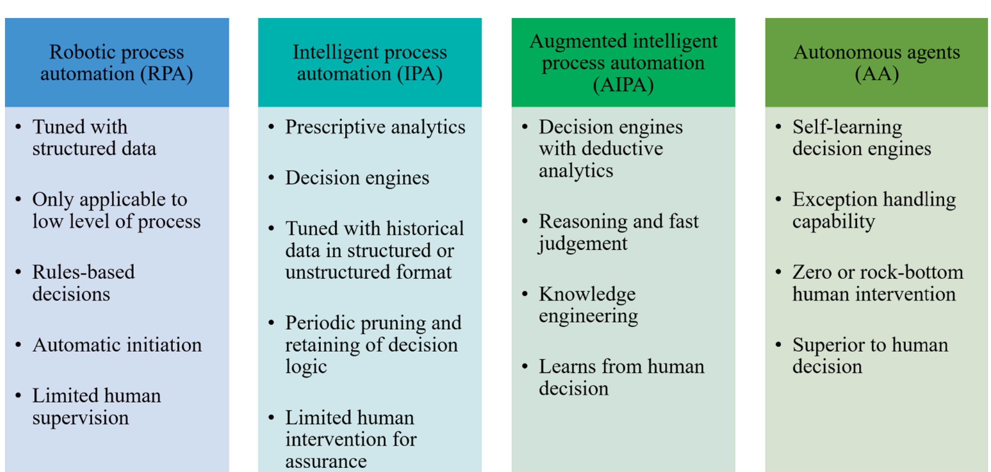


Fig. 4. Types of IA technology.

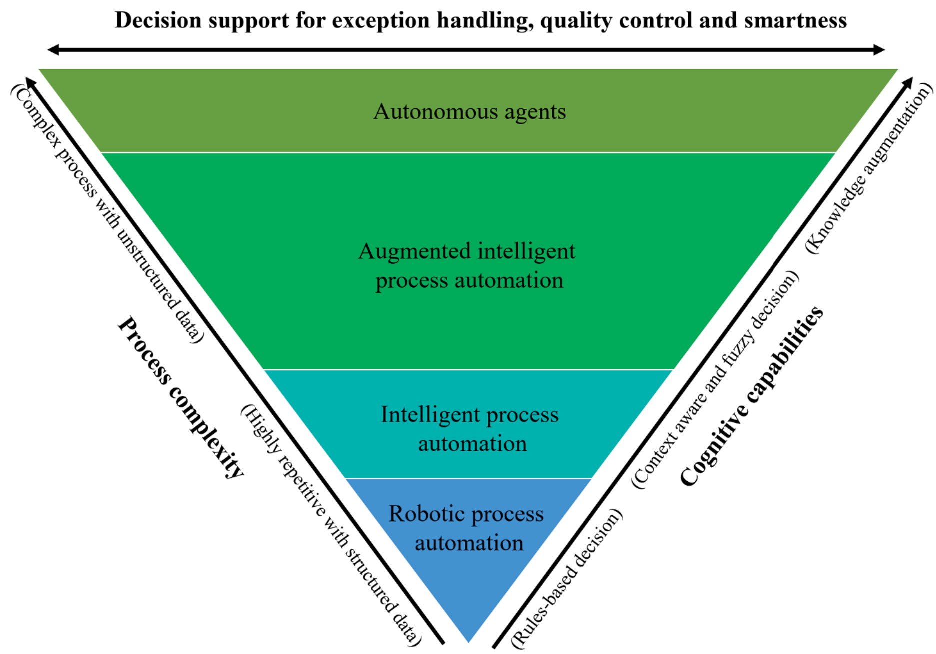


Fig. 5. An overview of IA application scenarios.

We can see many different IA definitions from the commercial products but not in academic literature. Because the definition of IA is ambiguous and inexplicit, we have consolidated different ideas from the literature and define IA as *a technology that is not only an integration of automation technology, RPA, AI, SC and other technologies but also incorporates the synergy of the technologies to empower rapid end-to-end business process automation and accelerate the digital transformation that delivers cognitive reasoning, fast judgement, knowledge discovery and prescriptive and deductive analytics resulting in better practical efficacy, operational efficiency, adaptation to changes in the business environment and outperformance of human intelligence*.

3.2. Operational and strategic benefits of intelligent automation

To answer research question 1 (How can we harness the capabilities of intelligent automation to catalyse the business growth?), this section summarises the operational and strategic benefits of IA applications as indicated in the selected literature. The ultimate goal of IA is to provide automated business workflow and digital process, and at the same time increase value creation for the stakeholders, offer labour-saving solutions and extend the IA applicability to replace more cognitive processes that are labour-intensive or manual tasks.

3.2.1. Cognitive technologies with human-like capabilities

The key aspects of cognitive technologies with human-like capabilities indicated in the literature are presented in Table 2. As mentioned, RPA aims to provide rule-based automation and replace highly routine work. However, it is impossible for RPA to formulate a complex network and rule-based decisions for cognitive processes. The approaches of AI and SC algorithms, including fuzzy logic, neural network and evolutionary computing, attempt to solve problems in imitating the logical thinking of human intelligence and adjust the IA model when facing errors and wrong decisions [14]. These features enable the acceleration of end-to-end business processes and create agile, speedy and efficient cognitive decisions with human-like capabilities in IA [7,61]. Cognitive decisions can be achieved by processing the structured and unstructured data in BPM through NLP, image and video processing and big data analytics. The extant cognitive technologies in AI are able to mimic conversations using a chatbot in online customer assistance services [71], fuzzy-logic-based interpretation of machine process and workflow

Table 2
Key examples from the selected literature of IA contributing cognitive technologies with human-like capabilities.

Application domain	Refs	Proposed approach/ application	Main contributions to cognitive technologies
Customer relationship management	[71]	IPA adoption strategies for retailers	Human language mimicking and conversations using chatbot to provide customer services
Finance	[44]	Virtual bot executed without the risk of human error. Recommendations prediction for investment banks	Optimisation of client-servicing channels to drive predictive recommendations
Healthcare	[59]	Classification of secure messaging via patient portals	Automated classification of the content of patient portal messages via NLP
Industrial engineering	[7]	Support vector machine (SVM) and genetic algorithm based cutting parameters tuning algorithm Real-time control of machine process via open architecture motion controller	Fuzzy-logic-based interpretation and decision making based on machine performance and workflow
Knowledge management	[13]	Automatic search queries for community question-answering system.	Sentiment analysis on linguistic attributes and annotation of the content of the corpus via automatic List-Net, ListMLE, RankNet, Ranking SVM and LambdaRank algorithm
Service industry	[61]	Genetic framework of IPA in service industries	Real-time view of customer profiles, product search and customer queries via service robot
	[60]	A theoretical framework for the determination of level of automation, substitution and cooperation between service robotics and human labour	Distinguishing routine and non-routine tasks and orchestration of humans and robots via software agents

[7], search queries for community question-answering system [13], customer profiles mining via service robot [61] and roster orchestration of human workers and robots via software agents [60].

The current research also suggests that the human-like behaviours and characteristics in IA applications are more favourable for digital question-and-answering platforms, which increases the trust level of clients and service exchanges' value in BPM [96]. For example, a chatbot in IA can provide holistic thinking and context-specific responses for online customer assistance [71]. A chatbot is not only a digital assistance agent, but it can work as a user-centric intelligent module in IA. Client servicing and user comments can be extracted from text and voice to foster the decision process of IA, instead of using manual input [15,59]. Cronin, Fabbri, Denny, Rosenbloom and Jackson [59] proposed an NLP model using logistic regression and random forest classifiers to handle patient appointments, contact information and prescriptions of medication via patient portal messages. Their method achieved better accuracy of classification than RPA. Figueroa [13] proposed an automatic generation of search queries via knowledge-based systems for community question-answering problems with assorted linguistically motivated properties. This information can further support customised client services based on historical data and contributes to the value co-creation of BPM in the service industry [60,61].

3.2.2. Data-driven operational efficiency

The examples of IA from the selected literature which contribute to data-driven operational efficiency are presented in Table 3. With the adoption of IA and more automated processes by replacing the manual tasks and workload in BPM, operational time, cost and human resources can be reduced [76]. In general in the service industry, human resource-related and transaction processing costs are significant in BPM [61,76]. RPA can automate the highly repetitive and routine tasks with structured input, such as in continuous auditing, accounting, job matching systems and staff recruitment processes in 24/7 non-stop operations [1,49,52,72]. Cost effectiveness, productivity and skill capabilities can be increased in managing employee experiences.

IPA leverages the data-driven optimisation and pattern mining for automating business processes to interpret the user behaviours and undeniably works as a catalyst for business growth. AI advancement has provided a solid foundation for IPA to boost process efficiency in automated and optimised workflow and business processes, enabling every decision process with data-driven recommendations and decisions [80]. For instance, the context-aware data in a product-service system can automatically obtain user behaviour and deliver a more service-oriented and customised product design based on customer preference and requirement excitation via ML and AI along the product life cycle [74]. Lean operations can be performed to have better control of inventory, delivery and supply chain processes in pharmacies [57]. Baril, Gascon and Brouillette [57] proposed an RPA dispensing system for the medication-use process to resolve the labour shortages in hospital pharmacies. Digitalised and automated medical-use process also ensures a critically low rate of medication errors and eliminates the wasteful and non-valued added activities along the medical supply chain. Yin, Zhang, Xu and Wang [14] proposed an adversarial feature sampling learning method for visual tracking for human–computer interactive IA systems. Their proposed method can achieve better competitive accuracy than the state-of-the-art visual trackers and is able to augment the deep convolutional features of object recognition with time-dependent appearance changes over a time span.

3.2.3. Visibility and process transparency enhancement

IA not only offers an optimised organisational process experience but also provides visibility enhancement of the process performance. Relevant literature is presented in Table 4. With enterprise-wide implementation, the top management can unlock the performance of a business process quickly, as the automated business process and workflow are digitalised [3,74]. The automation of workflow and processes greatly improves the corporate visibility of the decision process with the support of emerging real-time monitoring technologies, including cyber-physical systems (CPS), IoT and sensing technology [11,97]. The visibility enhancement continually improves the tactical and strategic decision making, given the overview of digitalised business workflow and

Table 3
Key examples from the selected literature of IA contributing to data-driven operational efficiency.

Application domain	Refs	Proposed approach/ application	Main contributions to operational efficiency
Accounting	[52]	Evaluating the functionality of RPA in advisory services, assurance services and client relations management	Reducing cost incurred in accounting firms compared to traditional approach
	[1]	RPA for continuous auditing	Increase in accuracy of item check in auditing
Aviation	[70]	An evaluation method of arrival management with the adoption of automated workflow processes	Workload reduction of air traffic controllers with the adoption of automated workflow processes and increased situation awareness in human controller
Clinical research	[63]	Code reuse implementation for pharmaceutical drugs	code reuse and process repeatability to enhance efficiency and consistency
	[62]	An evaluation method of error-prevention approach and medical errors with the adoption of automated control system in documented medical information	Optimal product quality outcomes and reduction of human inefficiency in medical certification process
Computer science	[14]	Tracking by detection-based trackers via adversarial feature sampling learning	self-learning to keep leading tracking accuracy and accelerating the tracking speed
Finance	[3]	ML module in IPA that supports customer advisors via Q&A. Review of the performance of RoboPlatform at ING Slaski Bank in Poland	Five-and-a-half times faster than manual script typing
	[4]	Credit-card fraud detection	Suspicious case discovery and further processing by financial analysts for manual review
Healthcare	[57]	Automated dispensing systems in pharmacies	Delivery time reduction from 35 days to 4 days and packaging time improvement
Human resource management	[72]	Exploratory analysis of RPA adoption in staff recruitment	Automates several HR processes in recruitment and hiring
	[2]	A payroll service using RPA in OpusCapita postal and logistics service	Automatic payroll process and management
Industrial engineering	[7]	*Referred to* Table 2	Operating time, lead time, productivity reduction and reliability of design manufacturing process
Product service system	[74]	A service-oriented manufacturing system to assist system engineers during the whole product life cycle	Agile, flexible and reconfigurable service-oriented manufacturing IA systems
Service industry	[60]	*Referred to* Table 2	Collaboration between robot and labour to achieve high level of skills and performance capability
Social service	[49]	An employment search engine with RPA	Cost reduction and faster case management for job matching

Table 4
Key examples from the selected literature of IA contributing to visibility enhancement.

Application domain	Refs	Proposed approach/ application	Main contributions to visibility enhancement
Computer science	[38]	Aspect-oriented model driven engineering for real-time system in UAV application	Conflict resolution, checklist compliance with civil aviation rules
Finance	[3]	*Referred to* Table 2	Generate annual reports, salary slips, invoices and income statement
Industrial engineering	[15]	Support vector machine (SVM) and genetic algorithm based cutting parameters tuning algorithm Real-time control of machine process via open architecture motion controller	Safe workplace in remote control processes and automatic robot through vision control
Product service system	[74]	*Referred to* Table 3	Web-based application for virtual enterprise

process. Annual report, salary slips, invoices and income statements can also be generated with an IA system [3,74]. Operational visibility enhancement is another distinctive advantage of IA implementation. All decision processes are digitalised, and the IA system can ensure compliance with the rules and regulations. The activities of remote-control processes and automatic agents by vision control can be closely monitored in a human-robot collaboration workplace [15] and in civil aviation [38].

3.2.4. *Adaptation strategy under uncertainty and exception handling*

Traditional RPA is not able to handle uncertain information and exception handling, as the required business process and workflow that are going to be automated are highly routine and repetitive [76]. Creating such kinds of rules-based decision trees with exhaustive decision rules may be inefficient for solution quality and computation time for complex decisions. Contemporary AI and ML methods such as neural networks, knowledge graphs and deep learning can extract rules and formulate the data pattern to perform prediction [98,99].

Computing modules in IPA and AIPA with AI and ML engines can interact with real-time context-aware data to obtain environment information [5,80]. A summary of the relevant literature is provided in Table 5. Pantano and Pizzi [71] utilised the customer behaviour from social media platforms and further configurated the IPA for a more customised solution. Adaptation to frequently changing rules and legislation in human resource management can also be performed with the support of IPA [2]. Parameter adjustment for environment adaptation using machine context-aware data and 3D scanning of the real manufacturing process can reduce the uncertain factors in IPA and AIPA compared to RPA applications [7,15].

Table 5
Key examples from the selected literature of IA contributing to adaptation strategy under uncertainty and exception handling.

Application domain	Refs	Proposed approach/ application	Main contributions to adaptation strategy and exception handling
Customer relationship management	[71]	*Referred to* Table 2	User behaviour Extraction from social media platforms to provide more customised solutions
Industrial engineering	[7]	*Referred to* Table 2	Machine content-aware data and correct parameter adjustment to environment adaptation
	[15]	*Referred to* Table 2	Content-awareness by 3D scanner of real manufacturing environment in real time
Human resource management	[2]	*Referred to* Table 3	Adaptation to relatively complex and frequently changing legislation

3.2.5. *Effective monitoring and error reduction*

The key examples of IA from the selected literature that promote effective monitoring and error reduction in BPM are provided in Table 6. The accuracy and efficiency of the digital worker, robot and software agent for handling routine and complex tasks in IA outperform the human worker in different ways [100]. The number of manual inspections required can significantly reduce as error prevention and compliance of regulations can be performed simultaneously with each digitalised decision process with the use of IA. For example, RPA can detect any erroneous human input in the work papers in accounting [1], extract contents from patents, legal documents [101–103] and validate the medical processes that satisfy the drug regulations in healthcare and clinical research [57,62,63]. Nonetheless, valuable insights for model correction can also be accomplished when the IA faces error. The self-learning mechanism in IA can eventually decrease the exceptions, achieving a high level of error reduction and reducing the number of wrong decisions, using a data-driven approach. Carneiro, Figueira and Costa [4] proposed a continuous credibility assessment for credit-fraud detection in online retail. Furthermore, fault diagnosis is a complex, nonstationary, nonlinear time-series decision under mixed abundant background noise and environment factors [98,104,105]. Though the advancement of fuzzy logic decision, AdaBoost, neural network and other fault prediction algorithms, significant changes in operational efficiency and quality of operations can be achieved for intelligent fault management automation [106–108].

3.3. *Implementation considerations of intelligent automation in an organisation*

According to the Harvard Business Review, approximately 61% and 28% survey respondents indicated that their company are now experimenting with IA technology or have had very limited trials of IA in their daily business operations respectively [109]. Oracle [109] illustrated that their respondents just do not want to fall behind their rivals in market share competition. However, adopting IA may be risky, as several concerns and considerations of implementation must be well-organised and well-developed in an organisation before stepping into the era of IA. In responding to the research question 2 (What are the drivers and requirements for intelligent automation implementation?), we have summarised several prerequisites that enable the IA technology.

Table 6
Key examples from the selected literature of IA contributing to effective monitoring and error reduction.

Application domain	Refs	Proposed approach/ application	Main contributions to effective monitoring and failure detection
Accounting	[1]	*Referred to* Table 3	RPA for detecting human error in work papers
Clinical research	[63]	*Referred to* Table 3	Compliance with drug regulations and human error avoidance
	[62]	*Referred to* Table 3	automation of core error prevention for interpretative medical errors
Finance	[4]	*Referred to* Table 3	Risk score implementation to estimate the creditworthiness of the merchant
Healthcare	[57]	*Referred to* Table 3	Medication returns, patients' risk reduction and medication error detection
Industrial engineering	[7]	*Referred to* Table 2	Limited human intervention and fewer human errors

3.3.1. Technological readiness

The digital transformation of current BPM could be a challenge without a front-end digitisation, process discovery, documentation, straight-through-processing workflow design and technological readiness in an organisation. The most important element driving automated business workflow and process is the technological readiness within an organisation. Oracle [109] revealed that most of the companies attempt to get into the field of IA, but without much knowledge regarding the implementation requirements. Robotic process automation is the gateway to the implementation of intelligent automation. Starting from RPA is the easiest way to explore the benefits of automated BPM at the initial stage. A company is required to investigate which types of workflow or processes are highly repetitive, routine and labour-intensive [76], and rethink the improvement to process standardisation and digitalisation to support smooth decision making [2,4]. Digitalised BPM in information flow provides the benefit of streamlined, speedy and optimised workflows and processes to replace routine manual tasks [4,67,71]. The digitalisation of material flow in workflows or processes requires identification and tracking technologies, such as barcode, radio-frequency identification (RIFD), near-field communication (NFC), wireless sensing networks (WSNs) and Wi-Fi. These technologies are the major enablers of RPA. As for IPA and AIPA, organisations must have clear business workflows, processes and sufficiently large size of historical data to train the AI engines [13,38]. Compared to RPA, expertise is required to supervise the performance and fine-tune the parameter setting of AI engines at the introductory stage of IPA [61].

3.3.2. Resources capabilities and automation at runtime

Several studies have highlighted that the resource capabilities are critical to the successful implementation of IA. To ensure the safe and successful adoption of IA, human-in-the-loop is required to calibrate the AI engines. During the transition stage of phasing out manual processes and pulling in IA in BPM, stakeholders such as domain experts, employees, managers and major users are required to closely monitor any exception cases in operation [76] and suggest an appropriate, gradual and continual change of the automation level [70]. Furthermore, historical data of business processes and IA adjustment at runtime are necessary to build a robust and trustworthy AI engine, and to validate the accuracy of the decision [60,63]. This override decision by human intervention helps improve the quality of automated decisions via trial and error and data-driven learning in the business-as-usual stage. Process transparency, standardisation, compliance environment and flexible and scalable IA at runtime must be provided to achieve better augmentation level of decision quality and enhance business operations with an augmented virtual workforce [5,15].

3.3.3. Technological roadmap

The technologies mentioned in **Section 3.3.1** are quite mature and can be found in commercial use. However, IA is not just brought-in digitalisation process of BPM and material flow but involves fundamental changes in the way a business delivers to its clients and customers [110]. An organisation should define which types of business workflows or processes can be automated that will benefit overall operational efficiency. Furthermore, it is necessary to construct a strategic plan for IA adoption and indicate the resources required from executives, management and IT professionals within an organisation in a long-term collaboration [109].

4. Managerial implications and challenges of intelligent automation adoption

In this section, we summarise the managerial insights and the challenges of IA adoption with regard to the research question 3 (What are the insights and managerial implications of intelligent automation that can be derived from other industrial cases?) and research question 4 (What are the challenges of implementation of intelligent automation?). We intend to provide top management with the right direction in identifying proactive goals, an effective management style and correction measurements for IA progress. In the meantime, we point out the possible management issues that may lead to organisational failure and disruption of operational performance.

4.1. Managerial implications

The managerial implications of intelligent automation provide readers the management traps to avoid organisational and technological failures in IA implementation. The adoption of IA may completely revamp the current systems to achieve specific concerns and business goals, which required a totally different managers' mindset for the effective management on IA. The authors would like to point out that IA is not something that is very novel or innovative, but the top management needs to recognise the identify the possible areas of IA adoption in their business flow management. We would like to discuss the scalability of IA system integration, function of IA, exception management and management style in the following subsections.

4.1.1. Risk assessments and system integration at scale

IA, indeed, provides many competitive advantages to further enhance operational efficiency, adaptation to environmental changes and human-based BPM for an organisation. This innovative investment in IA can help to repeat routine, repetitive and complex business workflow and processes using automation technology in a cost-effective way [42,43]. Many companies are intrigued by the potential of IA, but wary of failure in the IA adoption and of a setback in the IA race [109]. Top management should be aware that the introductory stage of IA will make fundamental changes to their current BPM and that the system integration must be at scale [55,73]. The system designers should carefully evaluate the right configuration of IA at the proof-of-concept stage and align it to the current business workflows and processes. As already mentioned, the introduction of IA must be step by step, and the organisation should carefully assess the risk and uncertainties during the transition from manual BPM to automated BPM [44]. Risk control matrices and risk assessment mapping of critical processes based on the importance of each process logic and the likelihood of system failure can provide top management with a generalised transition roadmap by automating the non-critical processes first and the critical processes later [4,61]. System engineers should be aware of the vulnerabilities and compliance adherence, and design solutions and operating procedures without much impact on their usability for stakeholders when gradually adopting IA in each decision logic [4].

4.1.2. The myth of hands-free intelligent automation

There is no doubt that intelligent decision making via IA can streamline the decision process automatically. However, IA adoption does not mean zero human intervention and employee layoffs but the synergy of robotic efficiency with human judgement and human resource reengineering [3]. Staff can be allocated to mission-oriented work and cooperate with software agents to handle repetitive work, by improving employee engagement [3]. IA empowers human resources and agile decision processes with intelligence, which enables improvement of customer experience, process efficiency and optimising workforce productivity in the human-robot interaction workplace [87,88]. The AI engines in IPA and AIPA need an adequate upgrade, parameter tuning and retraining by external consultation, investment in human capital or development of an in-house AI team to increase the credibility of system and process robustness of BPM, even for the enterprises naturally equipped to adopt IA [13,71]. Employee engagement is an indispensable resource in change management, and it is critical to help employees be comfortable and thereby mitigate resistance to new IA in the current BPM.

4.1.3. Preparation for exception management

Enterprises should prepare for exception management during the implementation of IA. From a client perspective, the automated BPM should not deviate too much from previous BPM, to achieve a similar level of technological acceptance. However, in the system aspects, enterprise digital data infrastructure, employee training and education, system development and IT support are required to support change management to new IA technology. The design quality of AI engines mainly depends on the service exchange benefits between clients and enterprises. This is the most effective way to improve the AI engines' performance and accuracy in an ongoing endeavour using context-aware and corporate operational data from IA [13]. Besides, system failure and errors in IA at runtime and exception cases are inevitable in normal business process operations [108]. Enterprises should consider a human-in-the-loop approach and recognise the exception cases for further cognitive improvement of IA by retraining AI engines. Therefore, incorporating the IA evolution initiatives at runtimes, human-in-the-loop and exception management benefit the transformation programme of business workflows and processes and enable staying competitive with up-to-date AI engines [71].

4.1.4. Open-mindedness to organisational changes

To make IA pay off, it is essential to rely on strong business process reengineering and an open-minded management style. The IA adoption may fail due to a conservative management style. Top management should be the sole originator and must constitute an IA team as an auxiliary implementer of IA. IA is a problem-dependent application, and therefore concerns raised by the major stakeholders can help the IA development thrive and reach successful automation of BPM in an ever-evolving business environment [5,6,80].

4.2. Challenges of intelligent automation implementation

As mentioned, IA required changes on the current system and business flow management to better cope with its functionality. Management need to keep in mind several challenges that may face when they are going to implement IA in their current system. We will further our discussions on the problem dependency, expert reliance, cultural readiness, workforce skill upgrading and issues of system integration in this section.

4.2.1. Problem dependency and expert reliance issues

There is no generic IA framework, as BPM has problem dependency. Without the presence of artificial general intelligence, practitioners must delicately determine the right AI engines to perform the cognitive decisions, as the cognitive limits are strictly dependent on the data pattern, problem formulation and cognitive complexity in BPM applications [111,112]. The unpredictable business activities, process complexity and adaptation to change require a continuous situational awareness and context awareness in near-time decisions to polish the decision logic of AI engines [112]. In addition, the transformation of BPM is required to take cognisance of domain knowledge, user experiences, current IT infrastructure and cognitive operations in BPM. The reengineering stage of BPM may require domain experts, in-house IA teams and consultancy to deliver a proper IA solution design [57].

4.2.2. Cultural readiness and workforce reskilling

Disruptive IA technology presents an opportunity to adapt business environment changes, digitalised business workflows and processes, and judgement using intelligent software agents. This brings about a significant change in operational processes, and the vast majority of cognitive tasks can be automated with little human intervention due to the technological advancement in cognitive computing [38]. Top management keeps an eye on technological acceptance, trust level and barriers to IA adoption in the human-robotic collaboration environment. Visionary management should encourage their employees to view IA as a digital worker and provide sufficient education, time and training on the use of IA. Apart from that, management must have a clear outlook that IA adoption is not about employee replacement, but human resource reengineering [72]. Employees should consider IA's role as supporting and collaborative and human workers' role as supervisory in managing IA performance and exception handling. The physical, manual and basic cognitive tasks can be handled by software agents and higher-level cognitive, social, emotional and technological tasks can be handled by human workers [72]. The human–robotic collaboration environment with IA can provide knowledge augmentation and improve the talent management process within an organisation [1,60].

4.2.3. Issues of integrating with legacy systems

Prompt decision making enabled by IA creates a good corporate image and reduces customer churn. However, the system integration must be at the right place to ensure seamless and automated business workflows and processes [38]. The reengineering of legacy systems is necessary to ensure low latency and the usability, consistency and quality of activities logs, event triggers and data in business processes [16,71]. A comprehensive and automated data governance framework can reduce the risks from IA adoption or any shortcomings in the analytical performance of IA. The current business process systems are required to open application programming interface (API) connectors that allow data extraction and retrieval and event triggers by the AI and ML. Additional sensing technologies are required for the IA system to perform context-aware computing and accumulate sufficient operational data for future IA upgrades and retraining. Better integration with legacy systems in IA adoption will provide a smooth IT upgrade following IA adoption.

5. Potential research directions, future perspectives

This section presents the potential research directions and future perspectives in IA research and applications with respect to the research question 4 (What are the challenges of implementation of intelligent automation?) and research question 5 (What are the future research directions of intelligent automation?). Most of the selected literature belongs to the group of RPA applications. IPA and AIPA are a rather new concept for industries, commerce and academe.

5.1. Key (potential) applications of intelligent automation

It is well known that IA applications in the field of business process, information systems, computer science, finance, accounting, banking, service industry, healthcare and clinical research are mature. We wish to help readers identify possible IPA and AIPA applications in other engineering and business domains as well.

5.1.1. Intelligent automation in aviation

Regarding the BPM in airline management, flight cancellations, rebooking, refunds, seat upgrade and pricing issues are usually requested using IT systems but processed manually [113]. Sometimes, change requests and refund processes may take weeks to handle, and this long processing time has a huge influence on customer satisfaction and loyalty to the airline [114]. Another application in civil aviation is to utilise the flight GPS, automatic dependent surveillance – broadcast (ADS-B) and trajectory information and estimate more accurate flight information and delay estimation to enhance the customer experience [10,115–118]. In the operational aspects, IA can assist the back office to arrange an urgent flight cabin crew roster and significantly reduce the ground staff workload by incorporating IA technology and eliminating manual BPM.

5.1.2. Intelligent automation in supply chain and city logistics

The digitalisation of supply chain and city logistics can support the IA development in inventory and demand fulfilment prediction, customer demand estimation and tracking of last-mile delivery. Retail point-of-sales can connect to the inventory management system and explore customer preferences and demand [119]. Cognitive computing enables the data patterns' analysis and requirement elicitation from customers. Furthermore, GPS tracking and sensing technology can improve the visibility in supply chain and logistics. For instance, enterprises can closely monitor the product condition and movement using IoT technology attached to the containers in the cold chain and valuable items delivery. These technologies in supply chain and city logistics are well developed but are not yet being integrated with IA [120].

5.1.3. Intelligent automation in portfolio management

In wealth, asset and portfolio management, the operating costs are significantly high as the dynamic changes to regulations and customer requirements create challenges to always maintaining an optimal condition in portfolio management. By applying IA and digitalisation of the business model, wealth managers can easily obtain a solution with respect to the resource constraints and achieve a high level of decision quality [43]. Furthermore, optimisation and AI engines can help the manager to evaluate the risk assessment and quickly deliver a solution with good ROI [4]. IA can also spot any inconsistencies from the historical data that human intelligence may not be able to handle manually.

5.1.4. Intelligent automation in product-service systems

Smart product-service systems (PSS) enable value co-creation in product configuration design by utilising the data of user behaviours and requirements for smart connected products [5,121]. The value co-creation process is driven by the embedded sensors, IoT, edge computing and CPS. The knowledge elicitation process can also be integrated with IA and can automatically retrieve user behaviours and demand for the next new products [5,6,80]. This customer-oriented business intelligence approach offers data-driven analytics, customer relationship management and value co-creation for developing new product designs [87,88]. The manual data analytics can merge with IA and deliver to top management a more sophisticated overview of user comments and requirements on their product in product lifecycle management [122].

5.1.5. Intelligent automation in building and construction

In building and construction, the workflows, processes and project management involve a lot of effort in document-related tasks, which occupy a significant proportion of labour hours and management time [123]. Delay in construction projects may occur due to inefficient management and failure to coordinate schedule and execution, thereby increasing the cost and negotiation and construction time with clients, contractors and consultants [124]. IA can take advantage of real-time data and enterprise resource planning (ERP) systems to closely monitor the activities' performance and provide automated workflows and evaluation of the construction schedule to mitigate unknown project risks and overhead costs due to poor construction management [125,126]. Furthermore, building information modelling can also be the working package as an input of the IA system to closely monitor and evaluate the construction process management and validate any design alternatives in the earlier planning stages [127,128].

5.1.6. Intelligent automation in manufacturing and industrial engineering

AIPA can orchestrate humans and industrial robots in the workplace [15]. IA can automatically train the industrial robot in virtual reality and perform the human–robot collaboration in actual environments [129]. The human–robot collaboration in the actual environment must comply with safe working conditions, energy, material saving requirements and low level of machine failure [104,107,108]. The robots attempt to replace routine manufacturing process and at the same time satisfy the documented rules and safety requirements [15]. The digitalised manufacturing and industrial processes can also integrate with CPS to achieve a high level of interoperable visibility of the performance of all the processes in a real-time manner [12,130].

5.2. Research directions

IPA and AIPA research are a new direction of IA. Therefore, several research directions of IA are addressed in this section to help readers identify their own research topics in the IA domain.

5.2.1. Holistic automation strategy

Current IA research focuses on cognitive decision making, but there is a lack of engineering applications in a holistic automation strategy. It is important to have a hybrid design concept of IA to stimulate application-oriented design solutions, as IA is an application-driven technology that consists of digital assistant, RPA, AI, cognitive automation and recognition processes in BPM. The case-based scenarios and rule-induction in the usage stage of IA can help to improve the quality of cognitive decisions and increase the cognitive capability of any changes in customer behaviours in an up-to-date manner [78]. Therefore, a holistic automation strategy automatically extracting event logs in real-time and periodically updating the AI engine via pruning, regularisation and retraining using real-world cases is necessary to improve the robustness of a solution generated by IA [78,131]. A data-driven, intra-routine self-learning and re-training approach using real-time data in IA research is lacking in the literature.

5.2.2. Self-adaptable to environment via context-aware computing

The major feature of IA is that it can adapt to environmental changes, providing context-aware data and customised service in business workflows and processes. Self-adaptation in IA is defined as an IA system that enables recognising a specific circumstance and reacting appropriately [122,132]. Sensing technology and context-aware computing support IA to achieve self-adaptation to the environment with limited human intervention, for assurance [5,6,80]. However, prior rational knowledge and expert knowledge in a declarative fashion as an input of AI engine may not be sufficient to ensure a low level of exception cases in actual operation [132]. IA must have the ability to accumulate the user-data, building a knowledge engine and reacting promptly with fast judgement and reasoning via context-aware computing [131]. More importantly, the IA system can learn from decisions, reduce the modelling uncertainty in data and further provide promising solutions for cognitive decision-making during runtime.

5.2.3. User-centric, cognitive-based and data-driven user design intention

Understanding users' needs and wants is important to value co-creation and the user experience in automated BPM. The IA framework is not a complex system, but the performance of the AI engine and software agents is the key to successful IA adoption. One may realise that at the current stage RPA, IPA and AIPA are yet to replace human labour entirely in BPM, as humans are more capable of handling customised business processes and of exception handling [3]. Text mining and analytics, NLP and voice recognition can assist the AI engine and software agents to understand customers' expectations, comments and queries and improve customer service interactions [13,133]. A more powerful AI engine to handle user-centric, cognitive-based and data-driven user requirements in BPM needs to be investigated in future research.

5.2.4. Real-time/near-time cognitive decision making and soft computing techniques

AI engines and intelligent software agents have proven to be a vital component of IA in BPM. Real-time decisions of IA, from acquisition to customer service, provide proactive and intelligent customer service in every decision process, which could enhance the customers' experience and their engagement with the company. Not only providing intuitive answers and decisions on customer queries and requests, prompt decisions are also an important element for virtual agents interacting with customers in BPM [113]. However, such capabilities are subject to the completeness of the knowledge database and the real-time/near real-time decision-making process of the AI engine or intelligent software agent. Soft computing techniques help to leverage the computational burden, but levels of analytical and prediction powers remain the same. Prompt decision making via real-time/near real-time AI and soft computing techniques is still a growing research trend in the domain.

5.2.5. Human-automation interaction and collaboration

One could expect that IA in BPM will be the catalyser of the research development of the human-automation interaction and collaboration, which increases the likelihood of its engineering applications in actual workplace. Function and task allocation by IA can further improve the overall productivity and achieve effective job allocations between humans and machines [134]. Basic function or low-level judgement of cognitive decision can be processed by software, while high level cognitive decision-making and exception handling required human workers' participation. Given this nature of function and task allocations, human workers can focus on the situational awareness, and response time and accuracy to alerts [135]. IA will take-in-charge of the non-safety critical engineering applications and advanced decision aids [136]. Indeed, trust issues, confusion and radical changes in workplace are inevitable in the future human-automation interaction and collaboration. However, this radical change can expedite the BPM, gain process efficiency and innovation [137], and totally redesign the workforce requirement and system design for business process in the future.

5.2.6. Affective computing

In the future IA, we can expect that a human-like BPM system can perceive human emotion and respond to user' emotions [138]. Kratzwald, Ilić, Kraus, Feuerriegel and Prendinger [139] suggested that affective computing will be the key to future decision support system to undertake the complex, customised and ambiguous cognitive decision. The state-of-the-art content analysis and content-based e-discovery lead to the advanced pattern examination via text, audio, video or image [140–142]. The affect computing can amplify the effectiveness of emotion elicitation and increase the intellectual experience in customer service or BPM [143]. AIPA with affective computing can reduce the impact on human trust issues and confusion of tasks by identifying a customer's attitude recognising the user emotion via sentimental analysis automatically.

6. Concluding remarks

This paper presents a holistic review of the literature on IA applications, covering the aspects of operational and strategic benefits, implementation considerations, managerial implications, challenges, potential industrial and business applications and research directions. IA is a new research direction that aims to develop intelligent software agents to handle business workflows and processes automatically, and consequently, a unified and fundamental understanding of IA research and applications is lacking in the literature. To foster the research and development for IA, we conducted a survey of articles to help readers identify their research directions in IA and achieve the vision of the interconnection and interoperation of relevant technologies. The major contributions of this review of articles based on the analysis of the latest IA literature can be summarised as follows:

- A comprehensive analysis of IA benefits in operational and strategic aspects as investigated in the literature has been carried out. The development of IA metrics and the key contributions of the selected literature is provided to guide the readers regarding the application domains and the state of the art in IA research.
- In order to assist readers, scholars and practitioners in having an overview of the IA implementation process, several implementation considerations, managerial implications and challenges are illustrated with examples. Practitioners will get an in-depth understanding of IA implementation and the underlying principles in real-life contexts and for successful IA adoption in commerce.
- Commercial IA applications so far are mainly in the field of business process, information systems, computer science, finance, accounting, banking, service industry, healthcare and clinical research. We further elaborate the possibility of IA adoption in other engineering and business domains to foster relevant research and development in the field.
- Current research focuses on the cognitive level of AI but lacks research publications on holistic automation strategy, context-aware computing and user-centric and data-driven decision making in the IA context. Research methods that consider the process complexity and cognitive technology can provide valuable insight in the context of IA and offer a sophisticated IA architecture that ensures a high quality of cognitive decision making by software agents, a high level of adaptability to context-aware data and environment and distinctive and customised service and customer experiences.

It can be concluded from the selected literature that IA research is a promising area and can have a great impact on societies in future automated business workflows and processes using software agents, chatbot and robot. The authors hope this systemic review can be regarded as a foundation to support more relevant research, engineering applications and business reviews in the IA domain and to identify research directions, implementation considerations and challenges among academics, industries and practitioners, providing new insights.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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