



Conceptual Framework Introducing the Success Factors for Implementing Intelligent Automation – A Qualitative Multiple Case Study

Johannes, Dirnberger-Wild*

University of Applied Sciences FH JOANNEUM, Institute of Industrial Management

johannes.dirnberger@fh-joanneum.at

Maximilian, Roth

University of Applied Sciences FH JOANNEUM, Institute of Industrial Management

m.roth.maximilian@gmail.com

ABSTRACT

Productivity increases in administration remained partially untapped during recent years. At the same time, the pressure on existing professions is being exacerbated by demographic trends in industrialized countries. This reveals the potential offered by process automation in the administrative area. Technological progress can help to overcome this situation. In the recent past, Robotic Process Automation (RPA), automating simple and rule-based tasks, gained traction. RPA alone is not sufficient for more complex tasks. Therefore, supplementing or substituting AI-based technologies such as Machine Learning up to fully autonomous AI solutions, which we refer to as Intelligent Automation at its highest level, can be adopted. While RPA is regarded as an established technology, Intelligent Automation is still in its infancy. Therefore, research on successful practical examples is necessary for its dissemination. To this end, this paper conducts a qualitative multiple case study analysis based on guided semi-structured interviews aiming to identify success factors in the adoption of Intelligent Automation. To unravel the key factors, a framework comprising 45 success factors is introduced. This framework, along with its novelty to the scientific community, has the potential to facilitate practical implementation of Intelligent Automation. Yet, our investigation revealed that the identified use cases in the analyzed companies haven't reached the maturity level expected for Intelligent Automation. Consequently, the findings pertain to the early stages of Intelligent Automation development. This study distinguishes itself from prior research by incorporating additional cases from various institutions and sectors, utilizing a study design rooted in a broader scientific knowledge base. Given that a limited number of companies could be recruited despite extensive systematic acquisition efforts, this subject area deserves further research efforts.

CCS CONCEPTS

• **Applied computing**; • **Enterprise computing**; • **Business process management**;

*Corresponding author.



This work is licensed under a Creative Commons Attribution International 4.0 License.

ICCTA 2024, May 15–17, 2024, Vienna, Austria
© 2024 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-1638-6/24/05
<https://doi.org/10.1145/3674558.3674560>

KEYWORDS

Framework, Qualitative Study, Business Process Management, BPM, Process Automation, Intelligent Automation, IPA, Artificial Intelligence, Empirical Study, Semi-structured Interviews

ACM Reference Format:

Johannes, Dirnberger-Wild and Maximilian, Roth. 2024. Conceptual Framework Introducing the Success Factors for Implementing Intelligent Automation – A Qualitative Multiple Case Study. In *2024 10th International Conference on Computer Technology Applications (ICCTA 2024)*, May 15–17, 2024, Vienna, Austria. ACM, New York, NY, USA, 7 pages. <https://doi.org/10.1145/3674558.3674560>

1 INTRODUCTION

"When I started, it was definitely the case that our goal was to automate tasks that didn't really add value to the company. And you can imagine, (...) there are a lot of them. (...) [Then] we moved on to defining automation (...) in such a way that we only want to involve a human colleague if there is an exception. I think that's also going to change radically in the next six to twelve months when we see what's happening in AI right now."¹

Digitalization is progressing. Although many companies are still lagging, the transformation is continuing as indicated for the European Union by the Digital Economy and Society Index (DESI) – an index monitoring the "(...) overall digital performance and (...) progress of EU countries in their digital competitiveness" [1]. Since 2017, the *DESI Overall Index* has increased from 33.7 % to 52.3 % in the European Union [2]. Thus, business processes run primarily through IT systems nowadays [3]. Alongside emerging technologies, like the nearly established Robotic Process Automation (RPA) [4], new opportunities for process automation are evolving as a result.

Historically productivity gains in administration remained comparatively untapped compared to production (and there are studies indicating that little has fundamentally changed in this regard²). Due to the prevalence of non-transparent inefficient procedures in business processes, process automation opportunities are promising from an economic point of view. [5], [6] However, the automation of processes to the greatest possible extent is no longer to be pursued solely based on economic considerations. In western industrialized countries, the shortage of skilled workers is being compounded by demographic trends with a shift in the age pyramid and an impending wave of retirements. In addition, the attitudes and values

¹Translated quote from an interview conducted in August 2023 for this study.

²Assessing and generalizing these studies is often challenging due to their reliance on surveys.

(visible results, meaningful work, . . .) of the “Gen Z” entering and undertaking the labor market require or inevitably entail a redesign of work. [7], [8]

The automation of rule-based recurring tasks wherever the degree of standardization is high, the focal point of RPA, falls short on complex business processes rich in variants and exceptions. For this purpose, more advanced applications based on Artificial Intelligence (AI) are suitable. [9] In accordance with [9] we refer to them as “Intelligent Automation”. Compared to RPA, the extension of AI towards Intelligent Automation offers potentials such as processing and analyzing large amounts of unstructured data and making decisions faster, more precise, and therefore more cost-effective than humans. The scope of automation can therefore be extended from individual process activities to entire processes. However, challenges for example arising from necessarily manual processes, fragmented systems, the currently still high costs of AI and the limited expertise within companies impact its adoption. [10], [11] Additionally, some skeptics contend that Intelligent Automation will remain confined to rule-based applications. [12] Ultimately, Intelligent Automation remains a niche topic, even in its simplest form, as RPA extended by AI decisions. [4] Considering the advantages, challenges, the technology’s penetration rate and the fact that research in this field is still in its infancy, we consider Intelligent Automation as an area deserving scientific effort to increase its dissemination. Therefore, this paper aims at identifying and exploring the factors fostering the implementation of Intelligent Automation and addresses the following research question: *Which success factors foster the implementation of Intelligent Automation?*

By answering the research question, the aim of this paper is to propose a framework to systematically consider the factors contributing to the successful implementation of Intelligent Automation. For this purpose, we conduct a qualitative multiple case study with 5 industrial and 2 consulting companies, to methodically appropriately enrich the theoretical perspective in this comparatively new field of research [13]. Flechsig (2021) conducted a multiple case study analysis on Intelligent Process Automation (IPA), concentrating on purchasing and supply management, and identified success factors [14]. Our study, however, distinguishes itself from [14] by its focus on Intelligent Automation across various functional areas, thereby offering a broader perspective.

2 FROM RPA TO IPA

RPA is a software that follows a specified set of rules and a predefined sequence of activities to perform processes and tasks in one or more connected or disconnected systems [15]. Technological limitations, such as explicit rule coding, restrict the applicability of RPA. Additional challenges arise from standardized inputs and deviations that require human intervention. [16], [17], [18] Likewise, RPA does not include comprehensive exception handling, making it unable to bypass various exceptions in the process. [17], [19], [20] Clear definitions for synchronizing system dependencies and interfaces are necessary, as well as communication of changes for smooth execution. [21]

For these reasons, there is a need for a technology capable of processing unstructured data while following a flexible decision logic. By integrating RPA and AI, more complex and less defined

tasks can be addressed. The technology developed for this purpose requires problem-solving capabilities similar to those of humans. These problem-solving capabilities include, for example, resolving or bypassing system errors, dealing with unknown system behavior, or adapting to changing conditions in systems. [20], [22] A technology that possesses these problem-solving capabilities, at least partially, is called IPA. It is a combination of RPA technology with AI technologies, allowing the extension of the applicability and utilization of RPA technology. IPA combines business rules, determination logic, and decision criteria with the aim of executing processes, tasks, and activities with little or no human intervention. [15]

The increased use of various technologies results in the broader applicability and capabilities of IPA compared to RPA. Besides the use of structured data with RPA, IPA can also process semi and unstructured data and additionally is able to carry out more extensive tasks with extended capabilities due to the use of AI. [21], [23], [24] This results in increased complexity and therefore higher costs and extended implementation duration during installation of IPA projects. Consequently, the complexity and costs associated with interventions in ongoing operations increase too. [21]

IPA surpasses RPA due to its higher tolerance for input formats and expanded capabilities. Additionally, it can recognize patterns, comprehend documents, and model predictions. This allows for greater scalability and flexibility in the application of IPA. Simultaneously, it empowers workforce to focus on more challenging tasks, enhancing job satisfaction. [23], [25] Through machine learning algorithms, IPA provides faster and error-free task execution, increasing the potential for cost savings. When evaluating return on investment (ROI), it’s essential to factor in the increased implementation and operational costs of IPA. Nevertheless, research by Flechsig (2021) indicates that the ROI of IPA generally exceeds that of RPA, as the potential benefits of broader application outweigh. [14]

3 INTELLIGENT AUTOMATION

IPA solutions require regular maintenance, as AI models need frequent training to adapt to changes in processes or data. [14], [26] Creating IPA solutions also involves data preparation and feature engineering before integrating AI features. Training data may also be manipulated or contain biases related to ethnicity, gender, or ideology. To tackle more complex tasks, it will be necessary to combine multiple IPA solutions to facilitate their collaboration and coordination. [11], [12] The fear of job loss is often a concern of employees, especially when intelligent robots can automate complex and creative tasks. [14]

More complex tasks and processes, which include non-rule-based decision logics and require technologies such as Natural Language Processing (NLP), are suitable for Intelligent Automation. Within the framework of Intelligent Automation, cognitive technologies can apply holistic thinking and provide context-specific responses. The business benefit arises not from the selection of a specific technology but from the combination of various technologies to leverage the full potential of automation. The choice of the required Intelligent Automation technology depends on criteria such as the complexity of processes, the IT systems to be integrated, and the

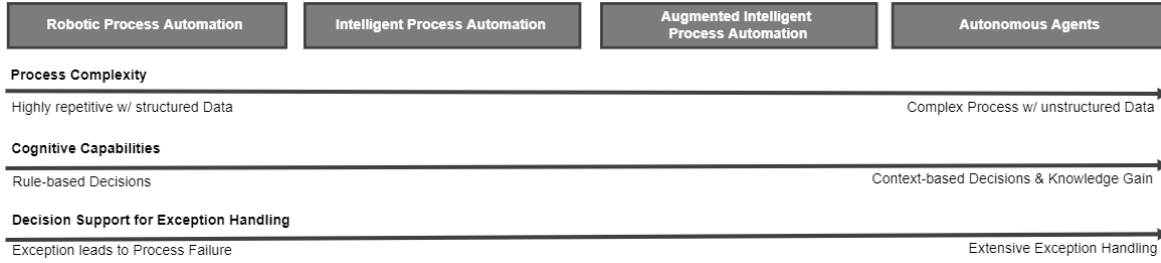


Figure 1: Development stages of intelligent process automation according to [9].

implementation effort. [9], [24] Authors aggregate various technologies under the term Intelligent Automation. Flechsig (2021) subdivides it into RPA, IPA, Cognitive Automation, and Cognitive Computing, using subsets in his framework. [14] Richardson (2020), on the other hand, distinguishes between two stages: namely RPA and Cognitive Process Automation (CPA), corresponding to Flechsig’s (2021) Cognitive Automation. [27] Shidaganti et al. (2023) categorize intelligent process automation technologies into RPA 1.0 to RPA 4.0. While RPA 1.0 still requires user interaction, RPA 4.0 encompasses complex automation solutions. [28] Ng et al. (2021) divide Intelligent Automation into RPA, IPA, Augmented Intelligent Process Automation (AIPA), and Autonomous Agents (AA) as shown in Figure 1.

It’s important to note that while RPA plays a key role in process automation, it serves merely as the foundation for Intelligent Automation and lacks inherent intelligent components. To recognize RPA’s substantial role within Intelligent Automation, this study adheres to Ng et al.’s classification. AIPA and AA have few to no applications at present. Before these become practical and widely used in the industry, additional best practices must be developed, implementation costs reduced, and the necessary expertise built within companies. Intelligent Automation, in its entirety, represents the ideal state, while in practice, only certain aspects of AI are applied.

4 METHODOLOGY

Using multiple case studies in research allows for comparisons to verify whether a result is specific to a single case study or can be replicated across multiple case studies. Additionally, employing multiple case studies enables a more precise description of phenomena and their relationships, as it is easier to derive precise definitions and appropriate levels of abstraction from a variety of case studies. Due to this a multiple case study analysis is applied to identify the success factors, wherein data is gathered via semi-structured interviews. This part of the study adheres to a procedural framework commonly employed in qualitative research, consisting of five stages as outlined by Stuart et al. (2002). The model includes the definition of research questions, development of the interview guideline, selection of suitable cases, data analysis, and publication of results. Because the fifth stage pertains to the publication and dissemination of research results, it is not covered in this chapter. [29] The first 4 stages are described as follows.

4.1 Research Questions

The research question presented in the introduction was embedded in a broader study that, in addition to the success factors, also addressed companies’ expectations of Intelligent Automation, use cases implemented, and barriers to implementation. By answering the research questions regarding the success factors, the goal is to close the existing knowledge gap in the field of Intelligent Automation as outlined in the introduction and provide valuable insights for businesses, decision-makers, and the scientific community.

The research questions defined are based on similar studies. In 2022, Flechsig, Anslinger, and Lasch conducted multiple case studies to identify potentials and barriers in RPA implementation within purchasing and supply management. Their work serves as a vital reference for gaining insights within this specific domain. In 2021, Ng et al. conducted an extensive literature review, identifying skills, drivers, and requirements for Intelligent Automation implementation, while also examining challenges. Comparing our study’s findings with these references contributes to furthering the research field and strengthens the validity of the insights.

4.2 Development of the Interview Guideline

The interview guideline exclusively employs open-ended questions to gather as much information as possible without biasing interviewees. [30] Unlike the typical standardized survey in quantitative research, this qualitative approach adopts a semi-structured format, allowing for deeper insights into company activities. [31] This format offers a clear structure while enabling flexibility to adjust question order and pose tailored queries based on responses. [32] To address the success factors of Intelligent Automation implementation, the following questions have been asked: What did you expect from the introduction of Intelligent Automation? What has happened? Why? What went well?

4.3 Selecting Suitable Cases and Corresponding Interview Partners

The challenge in selecting suitable interviewees is to find individuals with sufficient knowledge who are willing to share it. [33] The recruitment process begins by leveraging the authors’ network. The search is expanded through targeted keyword searches on LinkedIn and posting in Discord servers focused on Intelligent Automation. Additionally, speakers from conferences such as the Intelligent Automation Summit are identified and approached for participation. The recruitment process prioritizes diversity among companies,

Table 1: Description of the interview partners

Interviewee	Industry	Sales (in Billions)	Employees
Comp 1	Energy	> 30	> 50.000
Comp 2	Engineering	> 5	> 15.000
Comp 3	Energy	> 30	> 20.000
Comp 4	Pharmaceutical	> 5	> 10.000
Comp 5	Audio Electronics	> 0.5	> 1.000
Cons 1	Consulting	-	-
Cons 2	Consulting	-	-

considering organizational size, geographical location, and industry. This approach allows for a thorough exploration of the subject and facilitates meaningful comparisons across diverse contexts, enriching the study and providing informed insights into Intelligent Automation. [32] However, the acquisition of interviewees proves to be a significant challenge due to the heterogeneity in the implementation of process automations and AI across companies, especially in small and medium-sized enterprises. This constraint leads to a limited diversity within the interview panel. Despite numerous personal inquiries, many remained unanswered, with respondents often citing a lack of expertise in AI or compliance-related constraints as reasons for non-participation. These challenges highlight the complexity of empirical research in this field, demonstrating potential barriers researchers may face, particularly in dynamically evolving research areas. However, 7 interviewees from the German-speaking “DACH region” were identified and interviewed. An overview of the participants is presented in the following table.

The table represents different interview partners, divided into surveyed companies (Comp x) and interviewed consulting experts (Cons x). The interviewees have different experiences with AI in process automation. While Comp 3 already has used various AI technologies in process automation across different business areas, Comp 1 and Comp 5 are currently in the phase of testing available technologies and have occasionally implemented use cases to draw results from them. It is also noteworthy that Cons 1 is an automation expert with a focus on production processes. Nevertheless, Cons 1 possesses expertise in automating administrative processes and identifies common success factors and challenges in the application of AI across both administrative and production domains.

All interviews were conducted online and recorded using the Microsoft Teams communication platform between June 26, 2023, and August 11, 2023. In one instance, consent for recording could not be obtained, leading to the creation of written notes during the interview. In the other cases, the audio files were transcribed, proof-read, and revised according to predetermined transcription rules adhering to Kuckartz (2012) [34]. In the following, the transcripts were imported into the computer-assisted qualitative data analysis software MAXQDA for a qualitative content analysis following Kuckartz’s (2012) methodology.

4.4 Qualitative Content Analysis

Initially, coding categories were deduced from the interview guide’s sections. However, an inductive approach was later employed, generating additional categories directly from the material. [34], [35] This involved cross-checking and revising construction and assignment rules based on theoretical considerations when necessary. [35] Following the completion of interviews, including recording, transcription, and coding, an analysis was conducted through a content-structuring content analysis. The coded text passages were consolidated, paraphrased, and evaluated to derive success factors, aiding in structuring interview content and gaining insights [35]. The factors were then contextually assigned to an inductively formed category and to one of 5 deductively defined perspectives. The perspectives, drawn from Best and Weth (2010) [36], encompass “processes and organizational structure”, “technology”, “performance measurement”, “personnel”, and “corporate culture”. They serve to systematically analyze processes from different perspectives. [36]. Our framework assesses the factors from *organizational*, *technological*, *cultural* (including leadership aspects to address the common challenge of resource scarcity, which is why management should prioritize process digitalization [3]) and *people* perspective. The “performance measurement” perspective is substituted by a *finance* perspective, acknowledging that performance evaluation is possible only post-implementation, and financial factors often impede process digitalization and/or automation [3]. Accordingly, our framework can help to identify weaknesses in the actual processes during Intelligent Automation implementation, following the principle of “digitalization acts as a driver of analogue process optimization” [37] or, in the words of Bill Gates: “The first rule of any technology used in a business is that automation applied to an efficient operation will magnify the efficiency. The second is that automation applied to an inefficient operation will magnify the inefficiency.” [38] The results are represented in the next section.

5 RESULTS

We identified 45 success factors – including multiple answers in different contexts – across 5 perspectives, 16 categories, and 34 unique factors. The framework is illustrated in Figure 2 using a sunburst diagram to make the hierarchization from perspective to category to factor transparent.

The “People” perspective stands out with 17 factors, placing particular emphasis on the “Skills and competencies” category. Table 2 presents this category as an extract of the qualitative content

Table 2: Extract from the qualitative content analysis for the Skills and competences category of the People perspective

<i>Interviewee</i>	<i>Factor</i>	<i>Paraphrased factor</i>
People – Skills and competences	Comp 1	Transformation skills
	Comp 2	IT know-how
		Process know-how
	Comp 3	Experience
	Comp 4	Business process management
		Developers
		Education and training
		Process specialists who could assess potential improvements in day-to-day business may lack the motivation to familiarize themselves with automation tools which is why a person knowing the process, understanding the technology, and possessing communication skills is required.
		Include people in the team who are familiar with the existing system (e.g. ERP system) and can assess whether the use of a software robot is advisable, or whether a solution within the ERP system itself is feasible.
		Involve people on the team who are familiar with the processes and can assess the manual effort involved.
		Unlike with RPA implementation, integrating Intelligent Automation requires the involvement of technologically proficient individuals from the project’s outset.
		Businesspeople need to understand the processes and document them in a way that software developers can understand what needs to be automated, otherwise a lot of time is wasted in creating that understanding.
		One success factor is highly skilled software developers who must be flexible and deeply immersed in the business to understand it.
		Train the businesspeople to really understand the processes and document them in a way that the software developers understand what needs to be automated, otherwise a lot of time will be wasted in creating that understanding.

analysis supporting the framework, ensuring transparency in the analysis process.

It is interesting to note that in terms of skills and competencies (see Table 2), Comp 2 indicates that knowledge of both the existing IT landscape and the processes themselves is required to evaluate the automation solution. In addition, Comp 1 also refers to the necessary communication skills, which are summarized under the factor “Transformation Skills”. In the know-how category – which differs from the skills and competencies category in that the focus here is on domain knowledge – Comp 1 again points out that domain knowledge, both in terms of the process and the technological capabilities and data, is critical to success. In addition, Comp 4 explicitly addresses business process management skills by emphasizing proper documentation of the processes to be automated for delivery to developers. Thus, for the people involved in Intelligent Automation projects, the combination of IT, process, and process management skills, competencies, and know-how is critical to success, but also experience (Comp 3). As for the developers, they should not only be highly skilled programmers, but also deeply immersed in the business (Comp 4). Finally, the skills and competencies category highlights the importance of education and training to ensure that automation requirements are properly identified up front and time is not wasted.

In the “Organization” category, “Use case selection” (or process selection) is the factor most frequently cited, as mentioned by Comp 2, 3, 4, and 5. This highlights the need for companies to set the right priorities. The interviewees point out that use cases should be implemented that benefit employees or stakeholders, as this increases the acceptance of Intelligent Automation (Comp 2 and 3). Comp 4 also indicates that once the team experiences functioning automation, the buy-in is high. However, the process must also be technically suitable for automation with the desired solution (Comp

5). Once the technical setup is set a proper change management is necessary to communicate and support the transformation towards Intelligent Automation (Comp 2 and 4).

In addition to the findings that can be derived from the various factors, some additional interesting aspects should also be described. On the one hand, it is interesting to note that “citizen development”, which is often praised in the context of RPA, is also viewed critically. In this context Comp 2 recommends using professional developers to automate business processes, rather than citizen developers, who may be slower, deliver inadequate quality, and are overall too expensive and therefore better suited for other tasks. The potential of low-code or no-code programming is also somewhat tempered by the respondents who point out that programming skills are still required (Comp 2, 4, 5 and Cons 1). However, Cons 1 acknowledges in this context that there will be “a lot” in the AI sector in the future. The use of the right tool for the right automation is only addressed by Comp 5, and this relates to the dependency on the available input data. Critically, this is where Intelligent Automation tries to dock and, unlike RPA, can also work with unstructured data, for example. At this point, however, we would like to reiterate the critical voices that assume that the scope of Intelligent Automation will remain rule-based [12].

6 CONCLUSION

In this article, we investigated the success factors for the implementation of Intelligent Automation. For this purpose, we developed a framework based on 5 perspectives, 16 categories and 34 factors, which – including multiple answers in different contexts – comprises a total of 45 success factors. The qualitative analysis of the case studies – 5 industrial and 2 consulting companies – shows that the areas of “people” and “organization” are seen as particularly critical to success in the organizations studied. Accordingly, it is

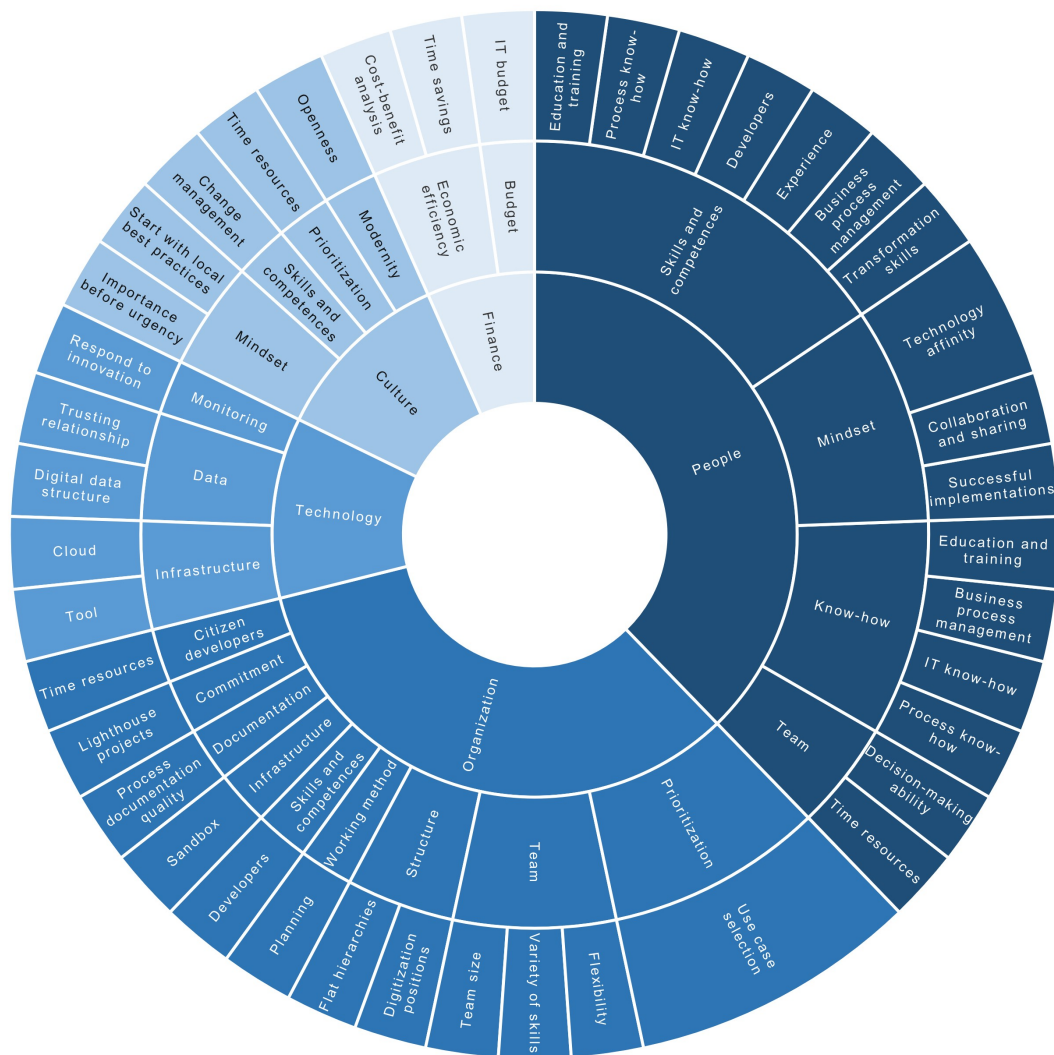


Figure 2: Factor Framework for Successful Intelligent Automation Implementation

crucial for the successful implementation of Intelligent Automation to consider the people involved and affected and to take the necessary organizational precautions. However, there are some limitations to our research. First, a critical point to note is that the boundaries between success factors and barriers are blurred. For example, some respondents answered the question about success factors with barriers that have been removed, which made contextual analysis challenging. Second, despite careful analysis, deriving categories and assigning the identified factors to those categories and the predefined perspectives is not always clear. For this reason, all factors, including their categorization, were visualized using a sunburst chart to make our considerations transparent. This provides an opportunity to question or refine this categorization in further studies. Thirdly, the potential interactions between the individual factors were not considered in the present research.

Therefore, future research could start here and investigate the relationships between different factors. Fourth, this qualitative study did not examine specific industries or functions. As a result, future work on this topic could conduct further studies similar to, for example, Flechsig (2021). Finally, and this was particularly striking to us, even large companies that are comparatively advanced in terms of process automation are still at the beginning of the development stages of Intelligent Automation according to Ng et al. (2021). The question of success factors was therefore partially answered from the perspective of RPA, i.e. the first stage of development. Therefore, while our results can be seen as a contribution to the implementation of Intelligent Automation, they should not be generalized to all possible development stages. In the future, when several advanced solutions have been implemented in practice, further investigation will be required to revise our framework.

In addition to that, future research projects should focus on exploring additional regions characterized by lower wage costs to gather more universally applicable conclusions. Furthermore, research on the ethical impact of generative AI in working environments needs to be explored in more detail.

Nevertheless, the developed framework serves as a starting point, offering orientation and decision support for companies undergoing Intelligent Automation implementation. This facilitates the transition towards relieving employees of tedious tasks or aiding them in complex decision-making processes. Moreover, it contributes to the strengthening of meaningful activities, thereby enhancing attractiveness as an employer for young talent. Lastly, it enhances productivity, addressing challenges such as the growing shortage of skilled workers.

REFERENCES

- [1] 'Digital Economy and Society Index (DESI) 2022 | Shaping Europe's digital future', European Commission. Accessed: Jan. 17, 2024. [Online]. Available: <https://digital-strategy.ec.europa.eu/en/library/digital-economy-and-society-index-desi-2022>
- [2] 'Digital Decade DESI visualisation tool', European Commission. Accessed: Jan. 17, 2024. [Online]. Available: [https://digital-decade-desi.digital-strategy.ec.europa.eu/datasets/desi-2022/charts/desi-compare-countries-progress?indicator=\\$desi_total&breakdown=\\$desi_total&country=\\$EU&unit=\\$%pc_desi](https://digital-decade-desi.digital-strategy.ec.europa.eu/datasets/desi-2022/charts/desi-compare-countries-progress?indicator=$desi_total&breakdown=$desi_total&country=$EU&unit=$%pc_desi)
- [3] M. Röglinger, D. Fischer, and F. Baumgarte, 'Prozessdigitalisierung für das „New Normal“', Fraunhofer FIT & ABBY, Oct. 20, 2021. [Online]. Available: <https://www.abbey.com/de/company/news/studie-von-abbey-und-fraunhofer-untersucht-prozessdigitalisierung-in-unternehmen/>
- [4] S. L. Roth and T. Heimann, 'Studie IT-Trends 2023 - Datenpotenziale endlich ausschöpfen', Capgemini, 2023. Accessed: Jan. 17, 2024. [Online]. Available: <https://prod.ucwe.capgemini.com/de-de/wp-content/uploads/sites/8/2022/03/Studie-IT-Trends-2023.pdf>
- [5] 'Schlendrian im Büro - Studie belegt 30 Prozent Verschwendung in der Administration', OTS.at. Accessed: Jan. 17, 2024. [Online]. Available: https://www.ots.at/presseaussendung/OTS_20100503_OTS0023/schlendrian-im-buero-studie-belegt-30-prozent-verschwendung-in-der-administration
- [6] M. Höhne, P. Fahr, T. Schabicki, S. Schnägelberger, and U. Feddern, 'Prozesse effizient managen und nachhaltig verbessern - Process Management & Analytics Studie', BearingPoint & BPM&O, 2021. Accessed: Jan. 17, 2024. [Online]. Available: <https://www.bearingpoint.com/de-de/downloadformular/>
- [7] M. Maloni, M. S. Hiatt, and S. Campbell, 'Understanding the work values of Gen Z business students', *The International Journal of Management Education*, vol. 17, no. 3, p. 100320, Nov. 2019, doi: 10.1016/j.ijme.2019.100320.
- [8] E. S. W. Ng and J. M. Johnson, 'Millennials: who are they, how are they different, and why should we care?', in *The Multi-generational and Aging Workforce*, R. J. Burke, C. Cooper, and A.-S. Antoniou, Eds., Edward Elgar Publishing, 2015, doi: 10.4337/9781783476589.00014.
- [9] K. K. H. Ng, C.-H. Chen, C. K. M. Lee, J. (Roger) Jiao, and Z.-X. Yang, 'A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives', *Advanced Engineering Informatics*, vol. 47, p. 101246, Jan. 2021, doi: 10.1016/j.aei.2021.101246.
- [10] M. Gotthardt, D. Koivulaakso, O. Paksoy, C. Saramo, M. Martikainen, and O. Lehner, 'Current State and Challenges in the Implementation of Smart Robotic Process Automation in Accounting and Auditing', *ACRN Journal of Finance and Risk Perspectives*, vol. 9, pp. 90–102, May 2020, doi: 10.35944/jofrp.2020.9.1.007.
- [11] Kofax, 'Intelligent Automation Benchmark Study'. Accessed: Jan. 25, 2024. [Online]. Available: <https://www.tungstenautomation.com/learn/reports/kofax-2022-intelligent-automation-benchmark-study>
- [12] C. Coombs, 'Will COVID-19 be the tipping point for the Intelligent Automation of work? A review of the debate and implications for research', *International Journal of Information Management*, vol. 55, p. 102182, Jul. 2020, doi: 10.1016/j.ijinfomgt.2020.102182.
- [13] M. N. K. Saunders, P. Lewis, and A. Thornhill, *Research methods for business students*, Eighth Edition. New York: Pearson, 2019.
- [14] C. Flechsig, 'The Impact of Intelligent Process Automation on Purchasing and Supply Management – Initial Insights from a Multiple Case Study', pp. 67–89, 2021, doi: 10.1007/978-3-030-85843-8_5.
- [15] 'IEEE Guide for Terms and Concepts in Intelligent Process Automation', IEEE Std 2755-2017, pp. 1–16, Sep. 2017, doi: 10.1109/IEEESTD.2017.8070671.
- [16] Christian Langmann and Daniel Turi, *Robotic Process Automation (RPA) - Digitalisierung und Automatisierung von Prozessen*. Wiesbaden: Springer Fachmedien. Accessed: Jan. 25, 2024. [Online]. Available: <https://www.springerprofessional.de/robotic-process-automation-rpa-digitalisierung-und-automatisierung/19654776>
- [17] R. Syed *et al.*, 'Robotic Process Automation: Contemporary themes and challenges', *Computers in Industry*, vol. 115, p. 103162, Feb. 2020, doi: 10.1016/j.compind.2019.103162.
- [18] S. Moreira, H. S. Mamede, and A. Santos, 'Process automation using RPA – a literature review', *Procedia Computer Science*, vol. 219, pp. 244–254, Jan. 2023, doi: 10.1016/j.procs.2023.01.287.
- [19] P. Hofmann, C. Samp, and N. Urbach, 'Robotic process automation', *Electron Markets*, vol. 30, no. 1, pp. 99–106, Mar. 2020, doi: 10.1007/s12525-019-00365-8.
- [20] D. Kedziora, 'Botsourcing, Roboshoring or Virtual Backoffice? Perspectives on Implementing Robotic Process Automation (RPA) and Artificial Intelligence (AI)', *Human Technology*, vol. 18, no. 2, Art. no. 2, Oct. 2022, doi: 10.14254/1795-6889.2022.18-2.1.
- [21] F. A. Lievano-Martínez, J. D. Fernández-Ledesma, D. Burgos, J. W. Branch-Bedoya, and J. A. Jimenez-Builes, 'Intelligent Process Automation: An Application in Manufacturing Industry', *Sustainability*, vol. 14, no. 14, Art. no. 14, Jan. 2022, doi: 10.3390/su14148804.
- [22] W. M. P. van der Aalst, M. Bichler, and A. Heinzl, 'Robotic Process Automation', *Bus Inf Syst Eng*, vol. 60, no. 4, pp. 269–272, Aug. 2018, doi: 10.1007/s12599-018-0542-4.
- [23] P. S. Kholiya, A. Kapoor, M. Rana, and M. Bhushan, 'Intelligent Process Automation: The Future of Digital Transformation', in 2021 10th International Conference on System Modeling & Advancement in Research Trends (SMART), Dec. 2021, pp. 185–190, doi: 10.1109/SMART52563.2021.9676222.
- [24] M. Lacity and L. Willcocks, 'Becoming Strategic with Intelligent Automation', *MIS Quarterly Executive*, vol. 20, no. 2, Jun. 2021, [Online]. Available: <https://aisel.aisnet.org/misqe/vol20/iss2/7>
- [25] A. Perdana and K. Yong, 'Intelligent Automation', May 2021.
- [26] T. Chakraborti *et al.*, 'From Robotic Process Automation to Intelligent Process Automation', in *Business Process Management: Blockchain and Robotic Process Automation Forum*, A. Asatiani, J. M. Garcia, N. Helander, A. Jiménez-Ramírez, A. Koschmider, J. Mendling, G. Meroni, and H. A. Reijers, Eds., in *Lecture Notes in Business Information Processing*. Cham: Springer International Publishing, 2020, pp. 215–228, doi: 10.1007/978-3-030-58779-6_15.
- [27] S. Richardson, 'Cognitive automation: A new era of knowledge work?', *Business Information Review*, Nov. 2020, doi: 10.1177/0266382120974601.
- [28] G. Shidaganti, S. Salil, P. Anand, and V. Jadhav, 'Robotic Process Automation with AI and OCR to Improve Business Process: Review'. Accessed: Jun. 03, 2023. [Online]. Available: <https://www.sciencegate.app/document/10.1109/icesc51422.2021.9532902>
- [29] I. Stuart, D. McCutcheon, R. Handfield, R. McLachlin, and D. Samson, 'Effective case research in operations management: a process perspective', *Journal of Operations Management*, vol. 20, no. 5, pp. 419–433, 2002, doi: 10.1016/S0272-6963(02)00022-0.
- [30] C. Züll and N. Menold, 'Offene Fragen', in *Handbuch Methoden der empirischen Sozialforschung*, N. Baur and J. Blasius, Eds., Wiesbaden: Springer Fachmedien, 2022, pp. 1127–1134, doi: 10.1007/978-3-658-37985-8_75.
- [31] B. von dem Berge, 'Teilstandardisierte Experteninterviews', in *Fortgeschrittene Analyseverfahren in den Sozialwissenschaften: Ein Überblick*, M. Tausendpfund, Ed., in *Grundwissen Politik*, Wiesbaden: Springer Fachmedien, 2020, pp. 275–300, doi: 10.1007/978-3-658-30237-5_9.
- [32] J. Gläser and G. Laudel, *Experteninterviews und qualitative Inhaltsanalyse als Instrumente rekonstruierender Untersuchungen*, 3. Überarb. Aufl. in *Lehrbuch*. Wiesbaden: VS Verlag für Sozialwissenschaften, 2009.
- [33] M. Hiltz and H. R. Otten, 'Qualitative Expert*inneninterviews', in *Empirische Sozialforschung für die Polizei- und Verwaltungswissenschaften: Eine Einführung*, S. Hollenberg and C. Kaup, Eds., Wiesbaden: Springer Fachmedien, 2023, pp. 169–198, doi: 10.1007/978-3-658-39803-3_9.
- [34] U. Kuckartz, *Qualitative Inhaltsanalyse: Methoden, Praxis, Computerunterstützung*, 4th ed. Weinheim: Beltz Juventa, 2012.
- [35] P. Mayring, *Qualitative Inhaltsanalyse: Grundlagen und Techniken*, 12. Überarbeitete Auflage. Weinheim Basel: Beltz, 2015.
- [36] E. Best and M. Weth, *Process Excellence*. Wiesbaden: Gabler, 2010, doi: 10.1007/978-3-8349-8950-5.
- [37] R. Hierzer, *Prozessoptimierung 4.0: den digitalen Wandel als Chance nutzen*, 1. Auflage, in *Haufe Fachbuch*. Freiburg München Stuttgart: Haufe Gruppe, 2017.
- [38] M. Sevilla, 'Esoar - A unique and straightforward transformation methodology', Capgemini. Accessed: Mar. 09, 2024. [Online]. Available: <https://www.capgemini.com/solutions/esoar/>