Challenges in AI Implementation: Perspectives from Practice and Research

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Abstract: Artificial Intelligence (AI) has become an inevitable topic for organizations across various sectors and sizes, offering promising applications as technological accessibility continues to expand. Despite its potential, practical implementation of AI-based Systems remains difficult with particular challenges tied to specific organizational contexts. Often companies invest heavily in AI development but encounter problems such as failure to achieve market readiness of the prototype or the systems struggling to deliver expected benefits. These setbacks often stem from flawed implementation strategies, excessive reliance on technology, or inadequate integration into existing organizational frameworks. Therefore, this paper addresses these challenges encountered at different phases of AI implementation projects. To this end, we initially conduct a Rapid Structured Literature Review (Armitage and Keeble-Allen, 2008), examining the literature on AI implementation cases and associated scholarly reviews. Extending the initial analysis, we experiment with AI driven document analysis as a means to integrate findings of a greater amount of publications into the review. The literature review is subsequently complemented by insights from our own consultancy experiences from the field of AI consultancy. The paper gives an overview of the most salient challenges in AI implementation projects and points out some approaches to mitigate those challenges. From a methodological standpoint it shows that AI driven reviews can yield similar results as conventional reviews, but may lack some explanatory depth. We find that a combination of manual and automated approaches tends to be the most effective strategy.

Keywords: AI implementation, Machine learning, Organizational challenges, Semi-automated literature review, AI security

1. Introduction

According to a recent publication by Gartner, "*Investment in AI has reached a new high with a focus on generative AI*"[1]. Yet at the same time, in Gartner's infamous Hype Cycle, the topic of Generative AI is at the peak of inflated expectations, likely nearing the edge of disillusionment as more and more organizations encounter issues when they try to implement AI into their undertakings . Although the technology has generated dazzling success stories for some early adopters, its suitability for the masses appears more and more questionable, as reports of failed AI initiatives are increasing. Many authors claim that AI technology seems to fall short of delivering the anticipated business value it promised, or fails to be operationalized, thus often remaining in a prototypical stage (e.g. Hopf et al., 2023). Thus, elucidating the issues that organizations encounter when trying to adopt AI technology seems an interesting avenue for research. And indeed the number of publications on AI implementation challenges is growing rapidly in many areas. For practitioners, however, it can be challenging to transfer those findings to their own endeavors, as scientific literature is not always easily accessible and the interpretation or generalization of often very specific studies poses another hurdle. Thus, with this review, we attempt to take a step of abstraction and analyze typical challenges in order to build categories of common pitfalls in AI implementation projects. This is beneficial for scientific knowledge transfer into practice but can also yield useful results for academia, as it reveals potential open ends or blind spots of the current discourse. Not least, recognizing common categories of issues paves the way to the development of appropriate solutions that will also be briefly addressed in the paper. Our analysis adapts a combination of manual and automated methods to identify AI implementation challenges from the literature. Therefore, In addition to addressing the content dimension, this article also enhances our understanding of AI's potential as a research tool for analyzing scientific literature and extracting relevant information.

2. Method

In order to examine the issues that organizations encounter when dealing with AI and its implementation into their operations, we conduct an exploratory literature review, adapting Armitage and Keeble-Allen's (2008) Rapid Structured Literature Review (RSLR) framework. Complementing this analysis, we also run an automated analysis over a greater sample of literature to cross check our findings against other publications. Where

[1] https://www.gartner.com/en/documents/5505695

possible, we also put the results in the context of our practical experience from our consulting work in the AI domain. Thus the research presented herein consisted of three steps: the first is an analysis of the literature and the extraction of common categories of issues that organizations would encounter according to the surveyed publications. The second step consists of a screening of a large sample of publications on AI implementation and respective challenges and the automated generation of categories of challenges to cross-check our initial findings. Lastly, we screen our own process documentations from about ten years of consultation projects. We then compare and contrast the data with the aim to integrate the findings from all sources.

For the manual review of the literature, we opted for Armitage & Keeble-Allen's methodological framework for conducting a RSLR (Armitage and Keeble-Allen, 2008; Armitage and Keeble-Ramsay, 2009), that is in alignment with our goal to get an overview of the rapidly growing literature on AI implementation issues. A Rapid Structured Literature Review (RSLR) consists of six stages: defining a research question, developing a search strategy (databases and keywords), conducting the literature search, screening and selecting relevant studies, extracting and synthesizing data, and reporting the findings in a structured format.

2.1 Research Question

In this phase, the most important aspect to consider is which facets of the research question are of particular importance to achieve a desired research output. For our purposes, we knew that the focus should be on AI projects, meaning that we wanted to address initiatives where an organization would try to implement AI into their undertakings, but exclude all organizations who rely on AI as their core business. What is more, our goal was to adopt a broad perspective on the challenges of AI implementation in order to uncover the true heart of the matter. This idea stems from practice, where we often found that its hardly purely technical issues that hindered project success but a diffuse combination of various aspects.

With the formulation "development and implementation of AI systems", we scope our search towards customized AI applications that go beyond the use of easily accessible AI tools such as Chat GPT and alike. Ultimately, these considerations led to the formulation of the following research question as a guideline for our study:

What are key problems and challenges, encountered in the development and implementation of AI systems within companies and other organizations, that hinder AI project success?

2.2 Identifying Relevant Studies

According to our goal to include a great variety of sources and ideally a mixture of case reports and, if available, existing reviews of AI implementation challenges, we initially aimed for multiple databases. The focus, however, was set to papers published in academic outlets to ensure a certain degree of objectivity and reliability of the data. We thus decided to use the databases of Scopus, ProQuest and Google Scholar to search for relevant publications using the search strings "AI implementation" AND challenges AND project (AND "literature review"); "machine learning implementation" AND challenges (AND "literature review").

Not surprisingly, the initial search yielded five-digit numbers of results, which confirmed the assumption that there is already a large number of publications and might indicate the relevance of the topic. However, numbers alone are no reliable indicator for relevance, as the whole field of information systems is extensive and relevant papers easily exceed tens of thousands (Wagner et al., 2022).

As a first means to filter out papers for the subsequent analysis, we went through the titles of those papers that the search engines marked as the most relevant and collected them in a separate folder to prepare the next step of the analysis. In addition to the systematic keyword search, we also added papers to our database that we either encountered before this research project or that we found by browsing the references of other papers using the snowball method. A noteworthy observation during the literature search was that the results from the online search engines produced some overlap, but each provided mostly unique results.

2.3 Study Selection

As the initial search led to a very large number of papers to be potentially included in the review, we were thinking of either reducing the sample through inclusion / exclusion criteria as suggested by the RSLR methodology (Armitage and Keeble-Allen, 2008; Armitage and Keeble-Ramsay, 2009), or automating the analysis using a language model to search for content that would help to answer the research question. Ultimately, we opted for a mixed approach: we filtered our sample for all those publications that best matched the original query for manual reading to get an idea of reoccurring topics and create a framework for the analysis of the remaining body of literature. The remaining sources were analyzed automatically using the platform Scispace[2], an application that allows for searching and analyzing scientific literature using large language models. For the initial manual analysis and development of the categories that guided the following analysis we used the following sources: Brock and Von Wangenheim (2019), Gabsi (2024), Lee et al. (2023), Mergel et al. (2023); Oldemeyer et al. (2024), Reim et al. (2020) and Viskova-Robertson (2023). The overall sample for the automated analysis consisted of 97 articles.

3. Automated Analysis

After the manual analysis of the aforementioned publications and the development of the categories as depicted in Table 1 and Table 2 in the columns titled "initial Dimensions", we began the automated analysis by uploading our sample of publications to the research platform Scispace (available via www.typeset.io). The application offers various features, including the automated analysis of pdf documents which we utilized for our sample. We analyzed the literature with regards to challenges and respective guidelines to overcome those. In order to extract the relevant data we ran a query that would summarize the key findings regarding AI implementation challenges of all the papers in our library. As a next step, we built thematic clusters on the basis of the summarized findings. This led to ten dimensions of AI implementation challenges as depicted on the right hand side in Table 1 and Table 2. After the analysis for implementation challenges led to promising results, we conducted the same procedure for proposed solutions in order to compare if challenges and solutions would match, as an indicator for reliability of the analysis.

4. Findings (Challenges and Potential Solutions)

In this section we present and overview of challenges and proposed solutions that we identified from the surveyed literature. We compare the dimensions of the initial manual analysis with the analysis using AI technology.

4.1 Challenges of AI Implementation

We first define six dimensions (Knowledge & Expertise, Financial Considerations, Data, Organizational Context, Technical issues, Security & Reliability) describing the types of challenges, organizations encounter when implementing AI that we derive from the manually surveyed articles. Then we progress to compare our own analysis with the automated version based on extracted sentences and keywords that describe AI implementation challenges in the remainder of the literature. Table 1 compares our initial dimensions, with the results of the automated analysis.

Table 1: Comparison of initial dimensions and automatically generated Dimensions

Initial Dimensions	Automated Analysis
Data	Data-related Issues
Security & Reliability	Ethical and Societal Concerns
	Transparency and Explainability Concerns
Technical Issues	Technological Barriers
	Adoption and Implementation Challenges
Organizational Context	Management and Governance Issues
	Integration with Existing Processes
	Cultural and Leadership Challenges
Knowledge & Expertise	Workforce and Skills Gap
Financial Considerations	Resource Limitations

The table shows that the overarching dimensions map fairly well, although the automated analysis yielded more dimensions than the manual analysis. When going into detail, we found that the overlap of identified challenges was even more compelling. Table 2 presents our analysis with all subcategories included and

[2] www.typeset.io

compares it to the results from the automated analysis, also including all subcategories. The automated analysis yielded very few results that were obviously out of place (e.g. the statement “Exclusion of relevant papers due to specific keywords used”) which we removed to keep the table concise. We also removed a few results that were too domain specific, resulting from the sample that contained many articles from specific domains (e.g. “challenges in developing construction robots due to the constantly changing environment”). Apart from these minor corrections, we depict the results as is. We found that the automatically generated subcategories are not as selective as the manually generated ones. Some subcategories in the automated column can be found twice in different dimensions. Yet, arguably the results from the automated analysis are pretty satisfactory when compared to the manual analysis, when the goal is to provide an overview of the challenges encountered.

Table 2: Detailed comparison of manual and automated analysis, including subcategories

Initial Dimensions	Initial Subcategories	Automated Dimensions	Automated Subcategories
Data	Data quality Availability of data Fragmented / Limited Training Data Data security Data Privacy Limitations through analog processes	Data-related Issues	Data quality Data privacy and security concerns Data management Lack of dataset availability Limited access to data Data ethics
Security & Reliability	related to the Data Dimension; two subcategories: A) Technical reliability & security Privacy concerns in public administration contexts Sensitive data related to processes, products and customers Particular challenges of regulated and/or critical industries (adherence to standards) e.g. aviation, medicine, infrastructure,… Hardware requirements	Ethical and Societal Concerns	Ethical considerations Ethical issues Algorithmic bias Privacy violations Discrimination Trust in AI technology Transparency and accountability Societal inequalities Fair access to transformative technology
	Biases in algorithms B) Ethical considerations Transparency and traceability Fairness & equity (especially in public admin.) Potential influence on societal values Accountability and responsibility	Transparency and Explainability Concerns	Lack of explainability in AI models Algorithm opacity Insufficient documentation and traceable logs
Technical Issues	Maintenance & ensuring continuous performance Scalability & Flexibility to accommodate changing requirements Interoperability, Integration of digital & existing technology AI implementation as a trial-and-error process Availability of technology (no off the shelf solutions) requires customized	Technological Barriers	Technical feasibility, regulatory norms, privacy concerns, and ethical concerns Integration challenges Technological challenges in developing construction robots due to the constantly changing environment High cost of implementation Non-standardization hinders automation and robotics efficiency

	solutions	Adoption and Implementation Challenges	Implementation barriers at tactical, operational, and strategic levels Lack of strategy to implement AI Resistance from employees Ambiguity in decision-making with AI
Organizational Context	Management support / resistance from management Resistance / support from workforce Trust & Accountability for failure Lack of leadership towards digitalization Internal / structural resistance to change Lack of organizational agility; emergent nature of AI projects (Brock und Von Wangenheim, 2019, p. 128) Challenging for SMEs (Oldemeyer et al., 2024, p. 24) Mutual misunderstandings of AI capacities in different departments / roles Productivity evaluation Complexity & effects on the organization Restructuring of organizational activities (transformational aspect)	Management and Governance Issues	Governance, scalability, and privacy issues related to AI implementation Lack of organizational capabilities related to data Lack of defined requirements for generating and maintaining records Organizational inertia
		Integration with Existing Processes	Alignment with existing processes and systems Compatibility issues with traditional business models
		Cultural and Leadership Challenges	Organizational culture Leadership challenges Misconceptions related to human and machine compatibility
Knowledge & Expertise	Availability of skilled workforce Upskilling of surrounding functions General understanding of AI in the organization Lack of example cases, hardly any empirical advice Little experience of consequences of AI Misconceptions of AI possibilities & limitations	Workforce and Skills Gap	Addressing workforce skills gap Lack of skilled personnel Insufficient employee qualification Human cognitive flexibility and capacity for learning skills Employee training and upskilling Knowledge and skills gap
Financial Considerations	High initial investments Sunk costs for abandoned projects Difficulties if expected results do not (yet) materialize	Resource Limitations	Budget constraints Resource constraints Limited access to AI expertise Infrastructure limitations

Looking at the findings themselves, we find that although it is possible to create distinct categories, those are strongly interdependent. An isolated view of one category or a respective intervention thus poses the threat of unintended consequences in one or more other dimensions. This illustrates the complexity that is mentioned as part of the organizational context dimension, which is mentioned in multiple publications. AI implementation might require organizations to revise their organizational structure charts (Viskova-Robertson, 2023), and on the other hand, in contexts like the public sector, where organizations cannot simply adapt their structure, AI initiatives need to be aligned with the organizational context (Mergel et al., 2023). Literature confirmed the relatively subordinate role that technical challenges play when compared to other aspects such as Knowledge and expertise. However, the related aspect of Data availability and quality is of utmost importance. However, regarding Data, we once more found strong ties to other dimensions, particularly the organizational context as well as Security & reliability and Ethical & Privacy considerations.

4.2 Proposed Solutions

After the analysis of challenges, we were curios to see what solutions the sample had to offer in comparison to the challenges. We analyzed the full sample of papers and extracted short sentences and keywords from the data. Those were subsequently clustered taking into consideration their frequency of occurrence and explanatory power.

The analysis showed that the most prominent suggestion concerned the issue of data management and quality which includes organizational capabilities to collect data in a systematic way and implement standardized documentation practices for data and respective models. The second cluster, matching the findings from the analysis of challenges concerns the acquisition of knowledge and skills development. Here, literature suggests continuous training and upskilling of employees in all aspects of AI related issues (technical, ethical, legal, managerial aspects) including the requirement for AI literacy training by educating bodies. The next important area to consider is to adapt a mid-, to long term perspective on AI. This means to develop a comprehensive AI strategy that covers both required technical steps as well as a strategy to develop organizational capabilities for AI implementation. Further, an AI strategy should deal with the alignment of AI with stakeholders needs and values. Recommendations for such comprehensive AI strategies indicate the interconnectedness of the challenges from an organizational perspective. Having a well done strategy in place that includes appropriate measures for project success at a given time can mitigate the aforementioned risk of abandoning AI initiatives too early, when expected results do not materialize at first. Closely tied to that requirement is inter-organizational communication and collaboration, especially between IT and business departments. Literature calls for collaborative problem-solving, trust and establishing clear communication channels. Trust is also a reoccurring topic with regards to the systems itself, meaning that whatever the use case, respective AI applications should be as transparent as possible and results should be reproduceable. Additionally, stakeholders should be involved in the process of implementation where possible. A separate category, however, closely tied to trust is ethics and governance, where literature recommends ethics- and privacy-based audits along with mechanisms to ensure transparency, accountability, and contextually relevant AI deployment. Considering the frequency of mentions, technical considerations (excluding data-related aspects) only appear at the bottom of the list.

Reading through this suggestions again illustrates the complexity of AI initiatives and the need for easily applicable frameworks or guidelines for practitioners. Some authors have already worked out respective approaches. Viskova-Robertson (2023) or Akbarighatar et al. (2023), for example suggests to understand AI systems as socio-technical systems. Lee et al. (2023) propose an Input-Process-Output model as the research framework to investigate the antecedences, processes, and consequences of AI implementation in organizations. Other examples include the TOE framework (Shahzadi et al., 2024) for AI in supply chain management, DIGITAL guidelines for successful AI Applications (Brock and Von Wangenheim, 2019) or a roadmap for Business Model Innovation in the context of AI (Reim et al., 2020). In the field of public administration, innovation labs or specified AI labs providing safe environments for emerging AI technologies have also proven successful (Mergel et al., 2023).

4.3 Limitations

Due to the somewhat experimental research design, we acknowledge that there are several limitations to the results of this study. First, although we searched only for scientific literature we did not perform any deeper quality assessment of the selected articles, however, we excluded articles that appeared as mere essays or opinion pieces or did obviously not meet academic standards. Second, as we derived initial categories of challenges from a relatively small sample of papers, we cannot assure with certainty that these categories would have emerged the same, had we started from different base-articles. Third, the way we conducted the analysis definitely has the advantage that it can take into account a very large body of literature, yet we must assume that a great share of context is lost through such automation. What is more, it is difficult to maintain traceability of individual arguments throughout the analysis as the approach tends to aggregate data into higher-level statements. While this can be acceptable for the purposes of a meta level exploratory study that aims to provide an overview of a large body of literature, it is definitely an issue to be addressed for more systematic and structured types of methodologies. From a researchers individual perspective, another interesting observation was that designing and experimenting with prompts for the analysis brutally uncovers the lack of “intentionality” of a large language model (i.e. the model does not share researchers curiosity and interest for the discovery of insights). From an objective standpoint, this is of course unsurprising, but it has the implication for research practice that intentionality and the specific research interest need to be incorporated into the prompts to achieve satisfactory results. Table 3 provides an example for the development of the query regarding possible solutions to overcome AI implementation challenges.

Table 3: Developing a prompt to analyze solutions to AI challenges in the sample using typeset.io

Solution Keywords v1	Solution Keywords v2	Solution Keywords v3	Solution Keywords v4
Provide keywords for solutions that the paper suggests to overcome the challenges presented in the paper.	Provide keywords for solutions that the paper suggests to overcome the challenges presented in the paper. Exclude everything that is domain specific. Exclude everything that has to do with medicine.	What are key problems and challenges, encountered in the development and implementation of AI systems within companies and other organizations, that hinder AI project success? Provide keywords for what the paper suggests to overcome these challenges presented in the paper. Exclude everything that is domain specific. Exclude everything that has to do with medicine.	What are key problems and challenges, encountered in the development and implementation of AI systems within companies and other organizations, that hinder AI project success? Give me keywords for what the paper suggests to overcome these challenges presented in the paper. Exclude everything that is domain specific. Exclude everything that has to do with medicine. Include only the proposed solutions, disregard keywords that only describe challenges

5. Conclusion

From our analysis of the literature and experience in consulting work, we can conclude that the challenges of AI implementation go beyond technical aspects and are in fact very diverse. However, the most prominent challenge for the successful implementation of AI, appears to be knowledge and expertise. This includes technical expertise but more importantly, a general understanding of the technology and its functioning beyond the specialized experts in IT departments. Understanding AI in that sense serves as a gatekeeper to the meaningful consideration of other issues which all rely on the organizational context that ultimately shapes the landscape for AI implementation. Here, the most salient challenges are financial constraints, availability and quality of data as well as security and reliability of the systems (especially in critical contexts). Challenges embedded in the organizational context also include support of management and leadership towards AI, sufficient agility of the organization and the complex issue of process- and eventually business model transformation elicited through AI implementation. Yet, it is noteworthy that not all AI initiatives must necessarily re-invent the wheel as "realistic AI" is said to prevail for quite some time, before technology will take over everything (Brock und Von Wangenheim, 2019, p. 129). When looking at proposed solutions to the challenges identified, we see a trend towards holistic frameworks (e.g. Brock and Von Wangenheim, 2019), taking a socio-technical systems perspective (Viskova-Robertson, 2023) that acknowledge the complexity of AI implementation and interconnectedness with other organizational domains. A general recommendation derived from these findings could be for organizations to prioritize foundational training in AI for all employees, with the aim of establishing a shared understanding and common knowledge base. This could benefit the systemic integration of AI within organizations, making expectations of the technology more realistic while also enabling a better recognition of its potential.

In further research, it would be interesting to gather and analyze empirical evidence of AI projects that take up such an integrated perspective on AI and see how such projects turn out in comparison to previous examples. Additionally, research could address the issue of AI literacy from a general perspective and develop strategies to convey an essential understanding of the technology to a broad audience.

From a methodological perspective, it becomes evident that large language models can indeed produce useful results for scientific reviews. However, at least in our case, the findings tended to be more abstract compared to the manual analysis. It also became clear that researchers must formulate their queries very precisely in order to obtain results that align well with the specific research objectives. Despite some minor inconsistencies that may have eventually been caused by less-than-optimally phrased inputs, we argue that the method of automated literature analysis can be useful for exploratory literature studies. Yet, from our experience from this trial, it might be less suited for in depth analyses where a more nuanced understanding of the content is required.

Note: More examples and data from the analysis as well as the full list of references underlying the analysis are available from the authors. The full list of references is also available here < https://shorturl.at/0IKRu > . Since this type of review is a novel approach, we highly welcome feedback and suggestions for improvements of the methodology.

References

Akbarighatar, P., Pappas, I., Vassilakopoulou, P., 2023. A sociotechnical perspective for responsible AI maturity models: Findings from a mixed-method literature review. Int. J. Inf. Manag. Data Insights 3, 100193. https://doi.org/10.1016/j.jjimei.2023.100193

Armitage, A., Keeble-Allen, D., 2008. Undertaking a structured literature review or structuring a literature review: Tales from the field. Electron. J. Bus. Res. Methods 6, 103–114.

Armitage, A., Keeble-Ramsay, D., 2009. The rapid structured literature review as a research strategy. US-China Educ. Rev. 6.

Brock, J.K.-U., Von Wangenheim, F., 2019. Demystifying AI: What Digital Transformation Leaders Can Teach You about Realistic Artificial Intelligence. Calif. Manage. Rev. 61, 110–134. https://doi.org/10.1177/1536504219865226

Gabsi, A.E.H., 2024. Integrating artificial intelligence in industry 4.0: insights, challenges, and future prospects–a literature review. Ann. Oper. Res. https://doi.org/10.1007/s10479-024-06012-6

Hopf, K., Müller, O., Shollo, A., Thiess, T., 2023. Organizational Implementation of AI: C RAFT AND M ECHANICAL W ORK. Calif. Manage. Rev. 66, 23–47. https://doi.org/10.1177/00081256231197445

Lee, M.C.M., Scheepers, H., Lui, A.K.H., Ngai, E.W.T., 2023. The implementation of artificial intelligence in organizations: A systematic literature review. Inf. Manage. 60, 103816. https://doi.org/10.1016/j.im.2023.103816

Mergel, I., Dickinson, H., Stenvall, J., Gasco, M., 2023. Implementing AI in the public sector. Public Manag. Rev. 1–14. https://doi.org/10.1080/14719037.2023.2231950

Oldemeyer, L., Jede, A., Teuteberg, F., 2024. Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. Manag. Rev. Q. https://doi.org/10.1007/s11301-024-00405-4

Reim, W., Åström, J., Eriksson, O., 2020. Implementation of Artificial Intelligence (AI): A Roadmap for Business Model Innovation. AI 1, 180–191. https://doi.org/10.3390/ai1020011

Shahzadi, G., Jia, F., Chen, L., John, A., 2024. AI adoption in supply chain management: a systematic literature review. J. Manuf. Technol. Manag. https://doi.org/10.1108/JMTM-09-2023-0431

Viskova-Robertson, A., 2023. Socio-Technical System and Organizational Ai Integration: An Integrative Literature Review. Acad. Manag. Annu. Meet. Proc. 2023, 1–6. https://doi.org/10.5465/AMPROC.2023.48bp

Wagner, G., Lukyanenko, R., Paré, G., 2022. Artificial intelligence and the conduct of literature reviews. J. Inf. Technol. 37, 209–226. https://doi.org/10.1177/02683962211048201