Stakeholder Participation in AIaaS Introduction: An Interview Study on Expectations

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Abstract

Artificial Intelligence as a Service (AIaaS) is widely considered as an approach to support the widespread adoption of AI-driven solutions. However, the successful integration of AIaaS hinges not solely on technological aptitude but also on the extent to which employees and other organizational stakeholders embrace the change. This paper examines how organizational stakeholders anticipate their participation in enterprise AIaaS initiatives and which conditions they expect to support trustworthy organizational uptake. It employs a method that combines systematic literature analysis with semi-structured interviews and qualitative content analysis to derive methodological implications. Results indicate that participation should start in the conception phase and focus on work-relevant use cases to strengthen perceived usefulness. Transparency, dialogical communication with feedback loops, precise role definitions, and strong governance are essential for building trust, alongside usability and data protection. The study highlights risks such as hidden resistance, deskilling, delayed benefits, and implementation overhead, underscoring the need for a structured, participatory approach to AI-as-a-service implementation.

Keywords

AI-as-a-Service, AIaaS, stakeholder expectations, anticipation study

1. Introduction

In the context of industrial AI adoption and implementation, technological problems, such as selecting a suitable AI approach, and change management within the organization, i.e., adapting organizational structures and preparing affected stakeholders, are among the most frequently cited challenges [1]. With the increasing use of AI in enterprises [2] and the growing number of different AI approaches, research addressing these challenges is gaining importance and should aim for results applicable in organizational practice. The focus of the work presented in this paper, is on implementing AI-as-a-Service (AIaaS) solutions, and on change management aspects related to the organizational stakeholders, such as the employees or members of the management team, potentially affected by the AI solutions.

AIaaS combines AI and cloud computing to make AI accessible to organizations without requiring the implementation of complex algorithms [3]. This development is designed to enable companies to utilize AI for internal business purposes without requiring extensive in-house resources and expertise. Research has confirmed that these changes substantially affect the business, application, and data architecture of a company [4].

This paper intends to contribute to this area by focusing on selected organizational stakeholders and their expectations toward participation in anticipated AIaaS use contexts. Understanding these expectations is crucial to design instruments and to support for change management processes. Building on a literature study that analyzes potential aspects relevant to user participation in IT projects, this paper conducts an interview study to explore the relevance of these aspects and the attitudes of potential organizational AI users and affected stakeholders towards the use of AIaaS. The following research

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question (RQ) is examined in more detail: *What participation expectations do affected stakeholders articulate in relation to the planned development and introduction of AIaaS solutions in organizations?*

The stakeholder in focus of our investigation are managerial and non-managerial employees. The main contributions of the paper are (a) the results of a literature analysis investigating factors of stakeholder participation and related work in the field, and (b) the expectations of selected stakeholder groups for fplanned AIaaS development and introduction.

The paper is structured as follows: Section 2 provides the background for our work on AIaaS and participatory system development. Section 3 provides a brief introduction to the research approach. Section 4 examines the literature in the field to identify related factors that affect technology acceptance. Section 5 presents the interview study with its design, data, results and limitations. Section 6 summarizes the findings and outlines planned future work.

2. Background

2.1. AIaaS

The rapid evolution of artificial intelligence (AI) has transformed it in recent years from a theoretical concept into a practical tool for businesses, promising decisive competitive advantages through data-driven insights. While implementing proprietary AI infrastructures has long been associated with high barriers to entry, such as significant investments in hardware and specialized personnel, the emergence of AIaaS has ushered in a paradigm shift [5]. AIaaS enables organizations to access advanced AI functionalities via cloud platforms without the need to develop them internally, which opens up new opportunities for scalability and cost efficiency [6]. This enables flexible and cost-efficient use of modern AI solutions: instead of high investments in hardware and development, AI algorithms and computing power are purchased as needed (pay-per-use). This eliminates the expense of installation and maintenance, allowing users to focus on their core competencies [7]. Unlike generic AI or conventional IT adoption, AIaaS is characterized by a layered cloud architecture comprising AI infrastructure services, AI platform services, and AI software services [8], which creates specific dependency structures between the adopting organization and external providers. Consequently, the adoption of AIaaS is not merely a technical substitution but requires organizations to manage multi-layered provider dependencies alongside the integration into existing business processes and organizational structures. It has been shown that the success of AI initiatives depends largely on user acceptance and trust [9].

2.2. Participatory system development

The concept of participation is a key concept in labor and industrial sociology [10]. It refers to the level of authority an employee has to influence or participate in management decisions from various aspects. This level can be qualitatively defined, ranging from one-way communication, where employees merely receive information from their management, to two-way exchange, and then to consultation, where information, advice, and opinions from employees are welcomed. Higher levels include co-determination, where managers and employees collaborate in decision-making, and may even extend to mutual or employee control.

Research further indicates that greater employee participation is associated with substantial organizational commitment, increased openness to change, and enhanced job satisfaction [11]. Fundamentally, it is essential to understand employees' needs and to grant them an adequate level of influence [12]. Employee involvement in decision-making processes should be tailored to the target group and planned in advance [12].

In systems development, participatory development commonly denotes the involvement of organizational stakeholders in different activities of the development process. Studies confirmed the importance of user and stakeholder participation in information systems development (ISD), which also includes the area of AI-based solutions and AIaaS [13]. Examples for ISD activities that benefit from user participation are requirement elicitation, design of services and work processes, user interface design, deployment planning or IS testing. Nevertheless, AIaaS introduces participation challenges that extend beyond the scope of conventional ISD. These challenges include, but are not limited to, the engagement with issues of model uncertainty and explainability, shared responsibility between the organization and external service providers as well as data governance across organizational boundaries.

3. Research approach

The work presented in this article is part of a research project aimed at developing methods and technology support for implementing AI-as-a-Service solutions in enterprises. The project is structured according to the design science research (DSR) paradigm [14]. The envisioned artefact is a participative AIaaS implementation method, including tool support for organizational integration and change management for AIaaS structures and solutions. In this context, this paper focuses on the first phase of DSR, investigating and confirming problem relevance, and preparing for the second phase, which involves requirements analysis for the envisioned artifact. The main research question for this work was presented in the introduction.

Investigating problem relevance in DSR requires addressing relevance for both businesses and the scientific community. Thus, with the intention of addressing both aspects of significance, the research approach selected for the paper combines literature analysis, an interview study, and argumentative-deductive work. The first step is a literature analysis to identify the existing scientific literature on the participatory introduction of IT solutions that may be relevant to AI as a service. The purpose of this step is to identify theories, approaches, or technologies that could be relevant for user or stakeholder participation. The research method used for the literature study is described in Section 4, together with the results. Based on the results of the literature review, an interview study was prepared and conducted. The data collected in the interviews are analyzed using qualitative content analysis (QCA), as discussed in Section 5. Based on the interview and QCA results, there is a need to support stakeholder participation in the implementation of AIaaS solutions methodically. In this context, it is necessary to identify essential expectations of stakeholders. This argumentative-deductive part of our work is discussed in sections 5.2 and 6.

4. Literature analysis

4.1. Identification of relevant publications

This section presents the current state of research and the theoretical foundation of our work. The focus here is on existing literature on AIaaS, technology acceptance, and employee participation in transformation processes. To ensure the relevance and quality of the research used and to make the process transparent, a systematic literature review (SLR) was conducted. Relevant scientific publications were identified using the Scopus, Google Scholar and Web of Science literature databases. The basic search terms and search strings were developed to optimally cover the core topics of AI adoption in companies, technology acceptance, and employee or stakeholder participation. The entire research and selection process for the studies, including the phases of identification, screening, suitability assessment, and final inclusion, was documented in accordance with the guidelines of the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) 2020 Statements [15]. The specific search string of the systematic literature search as follows:

AI adoption, AI implementation (AND companies), technology acceptance (model), technology acceptance AND employees, technology acceptance AND AI.

As illustrated in Figure 1, the literature analysis was conducted in a three-step, systematic process consisting of identification, screening, and inclusion. In the identification phase, relevant publications were systematically searched for, compiled, and cleaned up (in particular by removing duplicates) using defined scientific databases and registers. In the subsequent screening phase, the titles and abstracts of the remaining studies were meticulously evaluated against predetermined inclusion and exclusion

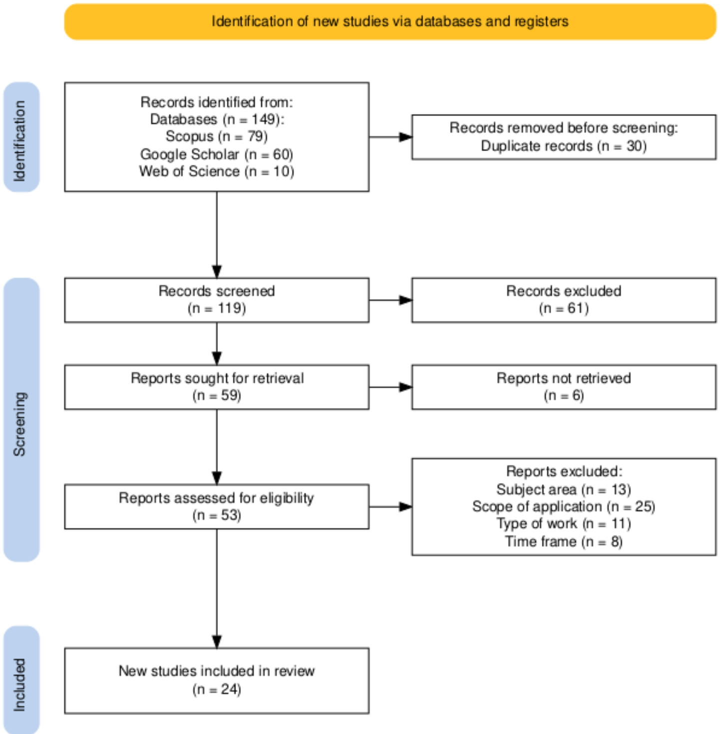

Figure 1: PRISMA flow chart of the study selection process [16].

criteria. The studies that did not meet these criteria were excluded from the review. Following the application of the aforementioned exclusion criteria, a total of 24 studies were selected for inclusion in the review.

4.2. Studies on AI-adoption

Research into the adoption of artificial intelligence (AI) in business is still a relatively young field, due to the recent technological advancements and the associated competitive relevance. While technical infrastructure requirements have already been studied extensively, the human factor is increasingly becoming the focus of scientific attention.

Early theoretical foundations for human-centered AI (HCAI) were laid by [17]. Their SMART model (Stimulating, Mastery, Agency, Relational, Tolerable demands) defines AI not as a substitute, but as a collaborative team player and heuristic for responsible human-AI work design. Key determinants for successful interaction are user competence, the experience of self-efficacy (agency), the appropriateness of requirements, and the stimulating nature of the work. In contrast to an often technology-centered implementation perspective, the focus here is not primarily on infrastructure or system issues, but on employee-related factors (acceptance, trust, role, and competence issues). Recent studies, such as those by [18] expand on this HCAI approach, focusing on small and medium-sized enterprises (SMEs) and identifying potential for optimization in existing implementation models through systematic literature reviews. The importance of employees for the effective and efficient use of AI systems is often given too little attention, as the focus is predominantly on technology [19].

Choi (2021) explicitly examines determinants of employee acceptance of AI technology. Key predictors identified include role clarity (clear roles for both users and AI) and skills/ability in dealing with AI. Privacy concerns inhibit acceptance by weakening the connection between role clarity and willingness to accept AI [20]. To prevent the failure of AI projects, [21] systematize empirical challenges in a “map of challenges.” This serves as a basis for expanding established process models such as CRISP-DM/ML or PAISE® to meet the specific requirements of AI and machine learning projects. Finally, [22] examine starting points for designing operational AI innovation processes (without an exclusive focus on human-centered AI) based on qualitative interviews. Trust, transparency, and encouragement are particularly emphasized; additionally, the authors highlight the role of key internal stakeholders, including the works council and rollout partners, in the implementation process.

4.3. Factors affecting technology acceptance

In contrast to the relatively young field of AI adoption, research into technology acceptance has a decades-long tradition, with the Technology Acceptance Model (TAM) developed by [23] based on psychological theories forming its central foundation. At the core of this model are the constructs of perceived usefulness and perceived ease of use, which determine actual system use via behavioral intent. This approach was substantially expanded by TAM2 [24], which integrated social influences and cognitive-instrumental processes, and by TAM3 [25], which addressed additional variables such as computer self-efficacy and computer anxiety. In parallel, [24] established the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which consolidated dimensions such as performance expectancy, effort expectancy, and social influences.

Meta-analytical findings by [26] confirm a significant correlation between usefulness and acceptance, while user-friendliness is considered to have weaker predictive power. In addition, [27] identified organizational, technological, and individual moderators that significantly influence acceptance processes. Further theoretical differentiations were made by including technology readiness [28], which consists of the drivers' optimism and innovativeness, as well as the barriers of discomfort and uncertainty. Additionally, domain-specific adjustments were made for the adoption of automation [29].

For the specific context of artificial intelligence, [30] developed the Employee Digitalization Acceptance Model, which supplements the classic TAM factors with personal resources such as a growth mindset and organizational resources such as empowering leadership. Explicit adaptations can also be found in the AI-TAM by [31], which focuses on trust and the quality of AI output, as well as in the AI-specific UTAUT models by [32, 33]. While [33] demonstrate the fundamental applicability of established models to AI systems and expand them to include contextual variables such as company size, [32] proposes transparency, explainability, anthropomorphism, and ethical values as additional determinants. Current literature reviews confirm the empirical validity and dominance of TAM in AI research, with trust and cross-sector attitudes acting as key factors and emphasizing the simultaneous existence of willingness to use and rejection [34].

5. Interview study

5.1. Study design

In addition to the literature review detailed in Section 4, this study adopts a qualita-tive research design, specifically utilizing semi-structured interviews. This approach aims to critically examine the expectations identified within the literature and evaluate their applicability in the current context, thereby providing an answer to our core re-search question. This approach appears applicable to the present work, especially concerning a relatively young field of study such as AIaaS, since it allows for the comparison of subjective opinions from employees on one hand, and managers and experts on the other.

The sample was selected to include both managers and employees from various organizations where AI has either been partly implemented or is planned for implementation in the near future. The interviews, initially captured using recording software, were subsequently transcribed. A deliberate choice was made to employ a basic semantic transcription protocol. This methodological decision is justified by the fact that the analytical focus of this study is placed exclusively on the thematic content of the discourse, prioritizing the informational substance of the narratives over any affective or particular linguistic characteristics [35].

A total of five interviews were successfully conducted. Details of participants are as of follow:

Table 1
Overview of Participants

Nr.	Gender	Age (years)	Position	Organizational tenure	Position
P1	**Male**	46	Executive Assistant to the Board	5 years	Arts and Culture
P2	**Male**	33	Lead Developer Digitalization & Project Manager	7 months	Football Club
P3	**Male**	33	Teamleader	15 years	Public Administration
P4	**Female**	62	Recruitment Consultant	34 years	Public Administration
P5	**Male**	61	Senior Project Manager	14 years	Healthcare Industry

The data were evaluated using Qualitative Content Analysis. The central methodological step involves data coding, where statements or observations are grouped into conceptual categories [36]. In this case, an inductive analysis was performed using the transcribed interviews. Following Mayring's framework, this study employs summarizing content analysis. This method focuses on three primary steps: paraphrasing, generalization, and reduction of the material [37].

The analytical process can be described as follows, following the inductive category development framework:

- Step 1: Definition of the units of analysis.
- Step 2: Paraphrasing the content-bearing text segments (utilizing grammatical short forms).
- Step 3: Generalization of the paraphrases (determining the target level of abstraction).
- Step 4: First reduction (selection and elimination of redundant paraphrases with identical meanings).
- Step 5: Second reduction (bundling, construction, and integration of paraphrases at the target level of abstraction).
- Step 6: Compilation of the new statements into a final category system.

This rigorous procedure ensures that the qualitative material is distilled into a concise and structured system of categories. The analysis was structured into three distinct units to ensure a systematic evaluation of the data. First, the evaluation unit encompasses the entire body of material, consisting of all five interviews. Within this framework, each individual interview with employees or managers serves as a context unit. Finally, the coding unit represents the most granular level of analysis, focusing on specific sentences, meaningful phrases, or individual words that constitute the primary components for categorization [37].

5.2. Data analysis

The initial coding frame was established deductively from the interview guide, focusing on the primary thematic domain: „what expectations do users and stakeholders have in the context of the development and introduction of AIaaS solutions in companies?" To ensure a systematic methodological approach, the interview questions were sequenced according to the five phases of the change management framework [38]: initialization, conceptualization, mobilization, implementation, and consolidation. The analytical level of abstraction was defined as follows: All statements within the material pertaining to expectations associated with the adoption of AIaaS.

The analysis commences with the initialization phase. The interview guideline incorporated specific inquiries designed to explore technology readiness, computer self-efficacy, and computer anxiety, factors identified during the literature review in section 4 as potential determinants of technology acceptance. Four out of the five respondents expressed significant enthusiasm regarding the adoption of AI-as-a-Service (AIaaS), citing its transformative potential for daily operations. In contrast, P4 from the public sector viewed the transition as an inevitable development beyond her influence. While this individual identified as a 'late adopter,' the other participants characterized themselves as 'tech-savvy' or 'early adopters. During the Initialization phase, a recurring theme emerged regarding the necessity of early-stage employee involvement. A participant from the healthcare sector (P5) emphasized that collaboration between internal subject matter experts and service providers is critical for operational safety and precision: "When introducing AI in clinical settings, physicians - as the medical experts - must work closely with providers during the development phase. The medical field is a high-stakes environment where AI errors can lead to fatal consequences. Cooperation [. . .] is essential to ensure that AIaaS is tailored precisely to the organization's specific needs." Similarly, within the public sector, specifically the Federal Employment Agency, two interviewees P3 and P4 noted that a pilot project is currently underway. This initiative "aims to ensure that the development of AI services is precisely aligned with our specific operational tasks." All participants further highlight the importance of training and opportunities for feedback, which should ideally be initiated during Phase Two (Conceptualization) and consolidated throughout Phase Three (Mobilization).

Even the self-identified late adopter P4 acknowledged the value of structured support, stating: "With proper training and a manual on the intranet, I believe I will be able to adapt." She continued: „Our employer usually sends us surveys on various topics to gather our anonymous feedback. I have noticed that the leadership team takes our input seriously and acts upon it." Furthermore, "tech-savvy" colleagues and team leaders appear to play a vital role in the daily integration of AIaaS. P2, who is a department leader from a professional football club noted the importance of peer-to-peer support and internal advocacy: "If any of our colleagues remain concerned about the utility of AIaaS, I will motivate them, like: see, you could save so many times using these tools." Across all five interviews, participants highlighted data protection as the cornerstone of establishing trust. Respondents noted that data security was their "most significant concern, specifically questioning the degree to which they could "trust the AI tool with the data provided." Beside security, the risk of deskilling emerged as a secondary concern. P5 warned of the potential loss of expertise: 'If there were a system failure and no one retained the skills to perform the task manually; the organization would face a critical problem". For brevity, we present only a few illustrative examples in this section, with detailed results deferred to Section 5.3.

5.3. Results

The interview analysis reveals a broad spectrum of AIaaS applications across various industries, highlighting its significant potential. Key benefits include work support, task simplification, and acceleration, leading to increased efficiency and optimized process streamlining through the processing of large datasets. Crucially, the findings indicate that AI is perceived not as a replacement for the human workforce, but rather as a complementary and supportive tool. The expectations of the participants are as follows: In selecting a provider during the preparation process, employee suggestions should play a vital role alongside provider marketing. In sensitive sectors like medicine, co-development and close collaboration between providers and internal experts should be preplanned. Extensive cooperation with providers is deemed essential to align the AI with specific departmental needs and to ensure continuous optimization during the implementation phase. Furthermore, pilot projects involving highly motivated employees serve as an effective pre-implementation strategy. Key selection criteria include usability, data protection, professional relevance, and individualization.

Successful implementation requires not only a robust technical infrastructure but also an innovative and culture-friendly corporate environment. It is imperative to establish favorable framework conditions and clarify roles and responsibilities as early in the process as possible. Beyond executives, who act as role models and provide essential support, project managers, department heads, and "Ambassadors" or "Key Users" play important roles. These Key Users are employees who demonstrate a high level of enthusiasm for the technology and are capable of motivating colleagues by demonstrating its utility and purpose. Furthermore, several challenges were identified. Beside the time-lagged effects of disruptive technologies, which necessitate the careful management of long-term expectations, hidden resistance may arise from fears of job displacement. Additionally, the risk of de-skilling remains significant; as AI assumes control, employees may lose the expertise required to intervene manually during system failures. These issues are further compounded by implementation overhead, as the intensified workload during the transition phase can become problematic.

Regarding the participants' opinions, the success factors include comprehensive data protection, employee education, careful monitoring, and a combination of mandatory and optional training. Early employee involvement, transparent dialogic communication with feedback loops, and a focus on perceived usefulness are critical for building trust. Following [38], participation should begin in the conceptual phase. Needs and expectations must be identified collaboratively, potentially involving the provider to find solutions [38].

Mobilization involves informing stakeholders about planned changes and convincing them of the technology's value. Training serves both to establish a fundamental understanding and to qualify employees. Trust-building depends on data privacy, transparency of the technology's functionality, early testing opportunities, and the credibility of leadership. Employees must perceive AI as an opportunity rather than a threat. While usability is a core criterion, it is not automatic; providers must optimize systems based on feedback, supported by tech-savvy employees who can bridge the gap for their peers.

Communication strategies are the highest priority, serving to reduce anxiety, build trust, and ensure active participation. Rewarded, is effective for boosting motivation during the implementation process.

5.4. Limitations

Several significant limitations of the present study must be acknowledged. First, it is worth noting that none of the organizations represented by the interviewees has yet undertaken a full-scale implementation of AIaaS. Consequently, the study lacks the concrete empirical data that would have provided more profound insights. As a result, many analyzed aspects remain at a stage of theoretical speculation or conjecture.

A second critical limitation concerns the composition of the sample. While a sample size of five interviewees is generally considered sufficient for qualitative research, the professional distribution of participants is suboptimal. Four of the respondents hold leadership positions, while only one represents the employee level. This imbalance precludes a meaningful comparative analysis between the perspectives of management and staff. However, the observed discrepancies are noteworthy; for instance, the fact that managers consistently perceive themselves as "early adopters" whereas employees tend to be skeptical "late adopters" - these findings are insufficient for broader generalization. A balanced confrontation of viewpoints, featuring an equal number of managers and employees (e.g., four from each group), would have been more effective.

6. Summary and conclusions

The present study examined stakeholder expectations regarding their involvement in the development and introduction of AI-as-a-Service in companies, as well as the socio-technical conditions that promote successful organizational integration. Methodologically, a systematic literature review on technology acceptance, AI adoption, and participation was combined with a qualitative interview study, based on semi-structured interviews and qualitative content analysis, as described by Mayring. The findings indicate that the perceived usefulness of AIaaS is contingent upon its consistent alignment with specific work contexts and prioritized use cases, as well as the initiation of user participation at the earliest stages of development, ideally during the conception phase. Transparent, dialogical communication and reliable feedback loops are particularly crucial for managing expectations and fostering trust, complemented by clearly defined roles. Managers play a pivotal role as sponsors and points of reference, while key users and ambassadors support everyday use as the interface between the specialist department and technology. Furthermore, the text emphasizes the significance of continuous empowerment through workplace-oriented training, knowledge transfer, and readily available documentation, along with robust governance structures, in effectively addressing uncertainties, implementation costs, and risks such as de-skilling. Two factors constrain the significance of the findings. Firstly, the sample size was limited, resulting in a small and imbalanced study population in terms of roles. Secondly, in several cases, a full AIaaS implementation had not yet been established. Future endeavors should include the expansion of the sample, the accompaniment of real implementation projects over extended periods, and the translation of the identified participation dimensions into an evaluated, practical implementation methodology.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using these tool(s)/service(s), the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

References

[1] L. Oldemeyer, A. Jede, F. Teuteberg, Investigation of artificial intelligence in smes: a systematic review of the state of the art and the main implementation challenges, Management Review Quarterly 75 (2025) 1185–1227. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85183752152&doi=10.1007%2fs11301-024-00405-4&partnerID=40&md5=d8af9e4801fb1cdddad0256ca929dddc. doi:10.1007/s11301-024-00405-4.

[2] Statista Research Department, Artificial intelligence (ai) market size worldwide from 2020 to 2031, 2025. URL: https://www.statista.com/forecasts/1474143/global-ai-market-size.

[3] R. Elshawi, S. Sakr, D. Talia, P. Trunfio, Big data systems meet machine learning challenges: towards big data science as a service, Big data research 14 (2018) 1–11.

[4] J. D. Rittelmeyer, K. Sandkuhl, Effects of artificial intelligence on enterprise architectures-a structured literature review, in: 2021 IEEE 25th International Enterprise Dis-tributed Object Computing Workshop (EDOCW), 2021, pp. 130–137.

[5] P. Juyal, The role of artificial intelligence in enhancing decision-making in enterprise information systems, Journal of Information Systems Engineering and Management 10 (2025) 196–205. doi:10.52783/jisem.v10i3s.371.

[6] L. Griesch, J. Rittelmeyer, K. Sandkuhl, Towards ai as a service for small and medium-sized enterprises (sme), in: J. P. A. Almeida, M. Kaczmarek-Heß, A. Koschmider, H. A. Proper (Eds.), The Practice of Enterprise Modeling, Springer Nature Switzerland, Cham, 2024, pp. 37–53.

[7] J. Cobbe, J. Singh, Artificial intelligence as a service: Legal responsibilities, liabilities, and policy challenges, Computer Law & Security Review 42 (2021) 105573. doi:10.1016/j.clsr.2021.105573.

[8] S. Lins, K. D. Pandl, H. Teigeler, S. Thiebes, C. Bayer, A. Sunyaev, Artificial intelligence as a service, Business & Information Systems Engineering 63 (2021) 441–456. doi:10.1007/s12599-021-00708-w.

[9] I. Glassberg, Y. B. Ilan, M. Zwilling, The key role of design and transparency in enhancing trust in ai-powered digital agents, Journal of Innovation & Knowledge 10 (2025) 100770. doi:10.1016/j.jik.2025.100770.

[10] T. Haipeter, M. Wannöffel, J.-T. Daus, S. Schaffarczik, Human-centered ai through employee participation, Frontiers in Artificial Intelligence 7 (2024) 1272102. doi:10.3389/frai.2024.1272102.

[11] A. Ullrich, M. Reißig, S. Niehoff, G. Beier, Employee involvement and participation in digital transformation: a combined analysis of literature and practitioners' expertise, Journal of Organizational Change Management 36 (2023) 29–48. doi:10.1108/JOCM-10-2022-0302.

[12] T. Lauer, Change Management. Grundlagen und Erfolgsfaktoren., Springer, 2011. doi:10.1007/978-3-642-04340-6.

[13] K. Sandkuhl, U. Seigerroth, Participative or conventional enterprise mo-delling? multiple-case analysis on decision criteria (2020).
[14] A. R. Hevner, S. T. March, J. Park, S. Ram, Design science in information systems research, MIS quarterly (2004) 75–105.
[15] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M. M. Lalu, T. Li, E. W. Loder, E. Mayo-Wilson, S. McDonald, L. A. McGuinness, L. A. Stewart, J. Thomas, A. C. Tricco, V. A. Welch, P. Whiting, D. Moher, The prisma 2020 statement: an updated guideline for reporting systematic reviews, BMJ (Clinical research ed.) 372 (2021) 1–9. doi:10.1136/bmj.n71.
[16] N. R. Haddaway, M. J. Page, C. C. Pritchard, L. A. McGuinness, Prisma2020: An r package and shiny app for producing prisma 2020-compliant flow diagrams, with interactivity for optimised digital transparency and open synthesis, Campbell systematic reviews 18 (2022) e1230. doi:10.1002/cl2.1230.
[17] A. Kluge, G. Ontrup, V. Langholf, U. Wilkens, Mensch-ki-teaming: Mensch und künstliche intelligenz in der arbeitswelt von morgen, Zeitschrift für wirtschaftlichen Fabrikbetrieb 116 (2021) 728–734. doi:10.1515/zwf-2021-0112.
[18] C. Böhme, C. Graf-Pfohl, K. Meusinger, Human centered implementation process of ai in smes – conditions for success, First Working Conference on Artificial (17 April 2024) 83–99. doi:10.1007/978-3-658-43705-3{\textunderscore}7.
[19] M. Jung, J. von Garrel, Mitarbeiterfreundliche implementierung von ki -systemen im hinblick auf akzeptanz und vertrauen, TATuP - Zeitschrift für Technikfolgenabschätzung in Theorie und Praxis 30 (2021) 37–43. doi:10.14512/tatup.30.3.37.
[20] Y. Choi, A study of employee acceptance of artificial intelligence technology, European Journal of Management and Business Economics 30 (2021) 318–330. doi:10.1108/EJMBE-06-2020-0158.
[21] A. Duschik, M. Goeken, Vorgehen in ki- und ml-projekten und gründe für ihr scheitern analyse phasenspezifischer herausforderungen: Projektmanagement und vorgehensmodelle 2023 - nachhaltige it-projekte, Gesellschaft für Informatik e.V. (2023).
[22] C. Silbernagl, M.-C. Fregin, K. Erbacher, et al., Verrauen, transparenz, ermutigung: Ansatzpunkte für die gestaltung betrieblicher ki-innovationsprozesse (2024).
[23] F. D. Davis, User acceptance of information systems : the technology acceptance model (tam) (1987). URL: https://www.researchgate.net/publication/30838394_User_acceptance_of_information_systems_the_technology_acceptance_model_TAM.
[24] V. Venkatesh, M. G. Morris, G. B. Davis, F. D. Davis, User acceptance of information technology: Toward a unified view1, MIS quarterly 27 (2003) 425–478. doi:10.2307/30036540.
[25] V. Venkatesh, H. Bala, Technology acceptance model 3 and a research agenda on interventions, Decision Sciences 39 (2008) 273–315. doi:10.1111/j.1540-5915.2008.00192.x.
[26] Q. Ma, L. Liu, The technology acceptance model, ????, pp. 112–128. doi:10.4018/978-1-59140-474-3.ch006.
[27] H. Sun, P. Zhang, The role of moderating factors in user technology acceptance, International Journal of Human-Computer Studies 64 (2006) 53–78. doi:10.1016/j.ijhcs.2005.04.013.
[28] C.-H. Lin, H.-Y. Shih, P. J. Sher, Integrating technology readiness into technology acceptance: The tram model, Psychology & Marketing 24 (2007) 641–657. doi:10.1002/mar.20177.
[29] M. Ghazizadeh, J. D. Lee, L. N. Boyle, Extending the technology acceptance model to assess automation, Cognition, Technology & Work 14 (2012) 39–49. doi:10.1007/s10111-011-0194-3.
[30] M. Höyng, A. Lau, Being ready for digital transformation: How to enhance employees' intentional digital readiness, Computers in Human Behavior Reports 11 (2023) 100314. doi:10.1016/j.chbr.2023.100314.
[31] I. Baroni, G. Re Calegari, D. Scandolari, I. Celino, Ai-tam: a model to investigate user acceptance and collaborative intention in human-in-the-loop ai applications, Human Computation 9 (2022) 1–21. doi:10.15346/hc.v9i1.134.
[32] M. Fetaji, Dvising a modl ai-utaut by combining artificial inteligence ai with unifid thory of

accptanc and us of tchnology (utaut), SAR Journal - Science and Research (2023) 182–187. doi:10.18421/SAR63-06.
[33] A. Nascimento, F. S. Meirelles, An artificial intelligence adoption intention model (ai2m) inspired by utaut (2022).
[34] S. Kelly, S.-A. Kaye, O. Oviedo-Trespalacios, What factors contribute to the acceptance of artificial intelligence? a systematic review, Telematics and Informatics 77 (2023) 101925. doi:10.1016/j.tele.2022.101925.
[35] T. Heinze, Qualitative Sozialforschung Einführung, Methodologie und Forschungspraxis Thomas Heinze, reprint 2016 ed., Oldenbourg Wissenschaftsverlag, Berlin and Boston and Berlin and Boston, 2016.
[36] U. Flick, Mapping the field in the sage hb of qualitative data analysis. (2014) 3–18.
[37] P. Mayring, T. Fenzl, Qualitative inhaltsanalyse, in: N. Baur, J. Blasius (Eds.), Handbuch Methoden der empirischen Sozialforschung, Springer Fachmedien Wiesbaden, Wiesbaden, 2019, pp. 633–648. doi:10.1007/978-3-658-21308-4{\textunderscore}42.
[38] W. Krüger, N. Bach, W. Krüger, Excellence in Change, 5 ed., Gabler Verlag, Wiesbaden, 2014. doi:10.1007/978-3-8349-4717-8.