# Human-Centered Exploration of Organizational Readiness for AI Adoption Before Deployment*

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**Abstract**

Emerging Artificial Intelligence (AI) technologies are increasingly recognized as transformative technologies with the potential to augment decision-making, automate cognitive tasks, and reshape organizational workflows. However, despite rapid advances in technical capabilities, the organizational adoption of AI-based systems remains uncertain. This paper presents an exploratory study conducted through participatory industry engagements of students within the Engineering Complex Systems course. The exploratory study involved interdisciplinary student teams from computer science and economy studies who visited two industrial companies: a food production company and a manufacturer of specialized stainless-steel kitchen equipment for hotels and restaurants. Through observations, discussions with practitioners, and post-visit reflective analyses, the study investigated organizational readiness for AI adoption, perceived opportunities, and anticipated barriers. The findings reveal that while companies recognize significant opportunities for process optimization, knowledge management, predictive support, and customer interaction, concerns related to trust, explainability, workflow compatibility, workforce skills, and governance remain central barriers to adoption. The paper proposes a structured analytical perspective for studying AI adoption readiness and discusses implications for human-centered AI engineering and socio-technical system design.

*Keywords: Large Language Models, Socio-Technical Systems, AI Adoption, Organizational Readiness, Industry-Academia Collaboration*

## 1 Introduction

Emerging Artificial Intelligence (AI) technologies are increasingly being integrated into organizational processes to support decision-making, automate cognitive tasks, and improve access to organizational knowledge. Recent advances

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have demonstrated considerable potential across domains including software engineering, manufacturing, healthcare, education, and business operations. Recent research demonstrates that organizational AI adoption is a multidimensional phenomenon influenced not only by technological capabilities but also by organizational, environmental, and socio-technical factors, including organizational capabilities, governance, stakeholder engagement, organizational knowledge, and resource availability [1, 2]. However, despite this growing body of research, important organizational implementation challenges remain insufficiently understood, particularly during the pre-adoption phase, when organizations evaluate potential opportunities, barriers, and implementation strategies before investing in AI technologies [3]. Throughout this paper, the term *AI* refers to contemporary generative AI technologies, with particular emphasis on Large Language Models (LLMs), which were the primary focus of the organizational discussions investigated in this study.

Human-centered AI research emphasizes that AI solutions should be designed to support human goals, maintain appropriate levels of human oversight, and foster trust and transparency in decision-making processes [4]. At the same time, recent studies have highlighted a variety of risks associated with LLMs, including hallucinations, bias, lack of accountability, and challenges related to governance and explainability [5]. Furthermore, successful industrial adoption depends not only on technical capabilities but also on organizational processes, human trust, workflow compatibility, explainability, governance, and regulatory requirements [6]. Although these socio-technical challenges are increasingly recognized, existing studies predominantly investigate AI solutions after deployment, and relatively little empirical evidence is available on how organizations assess their readiness for AI adoption, perceive potential benefits, and anticipate organizational challenges during the pre-adoption phase.

This work investigates the pre-adoption phase of organizational AI integration that remains comparatively underexplored. The objective is to understand organizational readiness for AI adoption, anticipated adoption barriers, and human-centered factors shaping emerging AI adoption. The main research question studied was:

**RQ**: How do organizations perceive opportunities and challenges associated with AI adoption?

We engage participatory and exploratory industry studies in two real-world SMEs and investigated potential opportunities and barriers related to future AI integration. Furthermore, the reserach design is situated within graduate university study laboratory aiming to explore the potential of interdisciplinary industry–academia collaboration as a mechanism for experiential learning and generating exploratory empirical evidence from real cases. Findings were interpreted through technology adoption theories embodied by a nine-dimensional framework defined in [9]. The main contributions of this paper are:

- exploratory empirical evidence on organizational AI readiness before deployment in two industrial SMEs.

- identification of recurring human-centered readiness factors across two industrial contexts;
- interpretation of these recurring patterns through complementary socio-technical perspectives, enabling analytical generalization that may support future organizational AI adoption studies and developing implementtion strategies.

In addition to investigating organizational readiness, the study explores the value of participatory industry–academia collaboration as a mechanism for collecting exploratory evidence from authentic industrial settings.

Sect. 2 presents the research methodology. Sect. 3 reports the results of the cross-case analysis, structured through the proposed analytical dimensions. Sect. 4 discusses the results in relation to socio-technical organizational context, and Sect. 5 concludes the paper.

# 2 Research Design

This study employed an exploratory multiple-case study design to investigate organizational readiness for Artificial Intelligence (AI) adoption during the pre-adoption phase. Rather than evaluating deployed AI solutions, the study examined how organizations perceive opportunities, barriers, and socio-technical requirements associated with future AI integration. Following the guidelines for exploratory case study research [10, 11], the objective was analytical rather than statistical generalization, aiming to identify recurring organizational patterns across heterogeneous industrial contexts.

## 2.1 Study Context

The research was conducted through an interdisciplinary industry–academia collaboration involving graduate Computer Science and Economics students at Juraj Dobrila University of Pula. The educational activities were informed by principles of experiential learning [14] and aimed to expose students to authentic organizational environments to collect exploratory evidence on organizational readiness for AI adoption.

The study investigated two Croatian SMEs operating in different industrial sectors: GASTRO-TIM, a manufacturer of customized stainless-steel kitchen equipment, and HISTRIS, a food production company. The organizations were selected using purposive sampling because both operate in knowledge-intensive environments, are actively pursuing digital transformation initiatives, had not yet adopted AI-based systems, and expressed interest in exploring opportunities associated with emerging AI technologies. Their contrasting organizational characteristics enabled comparison across different industrial contexts while supporting analytical generalization and are summarized in the Table 1.

## 2.2 Research Procedure

The primary educational objective was to help students understand the interactions between technology, organizations, society, and human stakeholders, and to develop the ability to analyze complex socio-technical systems from multiple perspectives with common emphasis on systems thinking, organizational analysis, responsible innovation, and the management of technological change. The research procedure, aligned with this educational objective, consisted of six consecutive phases depicted in Fig. 1.

In the initial phase, students were introduced to a structured framework for analyzing complex systems and their behavior within environmental, orga-

Table 1: Characteristics of the investigated organizations

| **Characteristic** | **GASTRO-TIM** | **HISTRIS** |
|---|---|---|
| Industry Sector | Hospitality equipment manufacturing and engineering services | Food production and processing |
| Business Model | Customized project delivery | Standardized product manufacturing |
| Primary Activities | Design, consulting, production, installation, service | Production, quality assurance, packaging, distribution |
| Knowledge Intensity | High | Moderate to high |
| Regulatory Intensity | Moderate | High |
| Documentation Requirements | Technical documentation and project records | Compliance, traceability, quality records |
| Customer Interaction | Highly customized projects | Product-oriented customer relationships |
| Production Characteristics | Engineer-to-order | Process-oriented manufacturing |
| Potential AI Opportunities | Design support, documentation, maintenance, customer communication | Quality management, compliance support, training, documentation |
| AI Adoption Status | Not adopted | Not adopted |

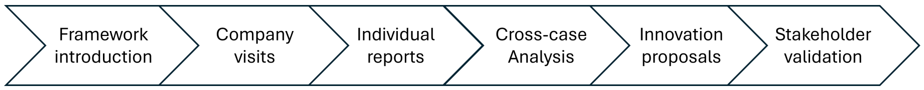


Figure 1: Overview of the research procedure.

nizational, technological, and societal constraints. The framework emphasized understanding the interactions between local and global system behavior, emergent system properties, stakeholder objectives, available resources, risks, and other contextual factors. The framework was already validated in a student course and results were reported in [13]. Students first applied these guidelines to hypothetical scenarios in order to familiarize themselves with the analytical framework. During the company visits, students observed organizational processes, participated in discussions with managers and practitioners, and recorded presentations and guided tours. Following the visits, each student prepared an individual analytical report addressing organizational context, business processes, stakeholder interactions, resources, challenges, and opportunities for future AI adoption. Multiple sources collected during company visits, along with individual student reports, served as the primary input for the subsequent cross-case analysis, in which recurring themes were identified and synthesized as described in the next subsection 2.3. Finally, students synthesized findings into prototype solutions that were presented to company representatives for discussion and validation.

## 2.3 Data Analysis

The study employed methodological triangulation by combining multiple complementary sources of evidence:

- Two organizational presentations and guided tours delivered by company representatives in duration of 6 hours;
- Student personal observations collected during industrial visits (12 students);
- Audio recordings and transcripts of company visits (approximately one hour recordings);
- Individual student reflection reports prepared according to a common analytical framework (12 reports);
- Innovation proposals and prototype descriptions developed by interdisciplinary student teams (12 prototypes);
- Audio recordings and transcripts of prototype presentations (2 hours);
- Feedback and reflections provided by company representatives during prototype evaluation sessions (30 minutes of recording);

- Supporting organizational materials publicly provided by participating companies (Web pages, company internal documents).

The collected material was analyzed using thematic analysis inspired by Grounded Theory principles. Individual observations were iteratively coded, compared across data sources, and synthesized through cross-case analysis. The analysis was guided by the nine-dimensional analytical framework proposed in [9], comprising the dimensions *Problem*, *Solution*, *Human Interaction*, *Context*, *Evaluation*, *Challenges*, *Benefits*, *Transferability*, and *Process*. These dimensions with explanations are presented in the first column of Table 2. These dimensions served as analytical lenses for cross-case comparison, aiming to identify similarities and differences between the two organizations with the objective of analytical generalization, enabling the identification of recurring socio-technical patterns relevant to organizational readiness for AI adoption.

### 2.4 Study Limitations

This exploratory multiple-case study analytically investigated organizational readiness for AI adoption. Consequently, the findings reflect anticipated opportunities, barriers, and organizational readiness rather than deployment outcomes. However, the same instrument may be reused in other contexts. The study involved only two SMEs from the Istria region in Croatia, which limits the generalisability of the findings. Reliability was strengthened through methodological triangulation, a common analytical framework applied by all participants, multiple complementary data sources, and validation of student-developed prototypes through discussions with company representatives.

## 3 Results

The results are organized according to the nine analytical dimensions [9] to compare the two industrial cases and are summarized in Table 2. The analysis identified several recurring patterns concerning expected opportunities, organizational barriers, and factors influencing readiness for adoption that we present below.

### 3.1 Perceived Opportunities for AI Adoption

Participants consistently viewed AI solutions as technologies capable of supporting organizational knowledge, process, and coordination activities rather than fully automating human work. Both organizations perceive humans as the key central role in their processes. Across both organizations, anticipated value originated primarily from improving information availability, documentation quality, communication, and decision support. Knowledge management emerged as the most frequently discussed opportunity. Both organizations rely heavily on experienced employees whose expertise is only partially documented. Participants therefore considered AI-based knowledge assistants as a potential

Table 2: Cross-case synthesis according to the nine analytical dimensions

| Dimension | GASTRO-TIM | HISTRIS |
| --- | --- | --- |
| Problem - What organizational problem is being addressed? | Managing customized engineering projects, documentation, coordination among engineering, production, suppliers, and customers. | Maintaining quality, traceability, c pliance, process consistency, produc planning, and knowledge transfer in f production. |
| Solution - How is the problem currently solved or expected to be solved? | Expert knowledge, engineering experience, direct communication, project documentation, and ISO-based procedures; potential for design, documentation, service, and knowledge-management support. | Standardized production, quality-con procedures, HACCP practices, and m itoring; potential for compliance s port, documentation, training, and p cess optimization. |
| Human Interaction - How do people interact with processes, knowledge, and decisions? | Strong dependence on engineers, technicians, installers, service personnel, and managers exchanging tacit knowledge. | Interaction among production work quality managers, technologists, management through standardized p cedures and quality-control processes |
| Context - Under which organizational and environmental conditions does the problem occur? | Project-oriented manufacturing, customized products, engineering-intensive work, moderate regulatory requirements, and growing digitalization needs. | Process-oriented manufacturing, f safety regulation, traceability, qua certification, standardized product and compliance pressure. |
| Evaluation - How is success or performance assessed? | Customer satisfaction, project completion, product quality, service quality, and operational efficiency. | Product quality, compliance, food saf production efficiency, traceability, customer trust. |
| Challenges - What barriers or constraints limit improvement? | Knowledge loss, expert dependence, documentation burden, resistance to change, digitalization gaps, and integration complexity. | Workforce shortages, regulatory b den, documentation requirements, c sistency, compliance management, c talization readiness, and training nee |
| Benefits - What value could be created through improvement? | Faster knowledge access, improved documentation, reduced cognitive load, better project coordination, and onboarding support. | Improved traceability, documentation ficiency, quality-management supp knowledge transfer, process visibi and compliance assistance. |
| Transferability - Which findings may generalize beyond the specific case? | Knowledge management, documentation support, onboarding, decision support, workforce training, and human-AI collaboration. | Documentation support, compliance sistance, knowledge transfer, process ibility, quality assurance support, human oversight. |
| Process - How could similar improvements be reproduced in other contexts? | Capture tacit knowledge, structure organizational knowledge, identify bottlenecks, evaluate AI opportunities, validate with stakeholders, and pilot solutions. | Map quality-critical processes, iden documentation-intensive activities, e uate automation opportunities, as governance requirements, validate v stakeholders, and pilot solutions. |

mechanism for capturing organizational knowledge, facilitating onboarding of new employees, and reducing dependence on individual experts. Documentation support represented another recurring theme. Students and practitioners observed that considerable organizational effort is invested in producing technical documentation, reports, quality records, and customer communication. Consequently, automated document generation and intelligent information retrieval were perceived as realistic early applications of AI technology.

Although both organizations recognized similar categories of opportunities, their priorities reflected their operational contexts. In GASTRO-TIM, anticipated applications focused on engineering documentation, project coordination, supplier communication, maintenance support, and customer interaction. In contrast, HISTRIS emphasized compliance documentation, quality assurance, employee training, production traceability, and support for standardized operational procedures. The identified opportunities suggest that organizations currently perceive AI solutions primarily as cognitive support technologies capable of augmenting existing work practices instead of replacing human expertise.

Table 3: Emerging opportunities identified across both organizations

| Opportunity | Typical applications |
|---|---|
| Knowledge management | Knowledge retrieval, onboarding, expert support |
| Documentation | Technical reports, compliance documentation, document generation |
| Decision support | Information retrieval, recommendations, planning assistance |
| Training | Interactive learning, employee guidance, procedural explanations |
| Communication | Customer support, supplier interaction, internal communication |

Table 4: Recurring organizational barriers

| Barrier | Organizational implications |
|---|---|
| Trust | Verification of AI recommendations |
| Workflow integration | Compatibility with existing processes |
| Governance | Responsibility, privacy, compliance |
| Digital maturity | Availability of structured organizational knowledge |
| Skills | Employee competencies and AI literacy |

## 3.2 Organizational Barriers and Readiness Factors

While participants recognized considerable opportunities associated with AI adoption, discussions repeatedly emphasized issues related to trust, governance, workflow compatibility, and organizational preparedness, while technical feasibility was rarely questioned. Trust emerged as the most influential adoption factor. Employees expressed uncertainty regarding the reliability of AI-generated recommendations and highlighted the necessity of maintaining human oversight, particularly in situations involving engineering decisions, product quality, or regulatory compliance. Participants indicated that explainability would strongly influence their willingness to rely on AI-generated outputs. Workflow compatibility represented another recurring concern. Both organizations emphasized that future AI solutions would need to integrate seamlessly with existing organizational processes and enterprise information systems. Participants frequently noted that even technically capable AI solutions would have limited practical value if they introduced additional operational complexity or disrupted established work practices. Governance-related issues were also discussed extensively. Representatives from both organizations raised questions concerning responsibility for AI-generated recommendations, protection of organizational knowledge, confidentiality of business information, and compliance with existing regulatory requirements. These concerns were particularly pronounced within the food production company, where traceability and quality assurance represent fundamental organizational requirements. Digital maturity constituted another important readiness factor. Participants recognized that successful adoption depends not only on AI capabilities but also on the availability of structured organizational knowledge, existing digital infrastructure, workforce competencies, and management commitment to innovation.

The analysis therefore indicates that organizational readiness extends substantially beyond technological infrastructure and encompasses human, organizational, and governance dimensions.

## 3.3 Cross-Case Synthesis

Despite operating in different industrial sectors, both organizations demonstrated remarkably similar patterns regarding organizational readiness for AI adoption. The cross-case comparison indicates that perceived adoption readiness depends less on industrial domain than on organizational characteristics associated with knowledge-intensive work. Both organizations identified knowledge management, documentation support, and improved access to organizational information as the principal sources of expected value. Likewise, concerns related to trust, explainability, governance, and workflow integration consistently emerged across both cases, suggesting that these issues represent general socio-technical challenges rather than sector-specific problems. Important differences nevertheless reflect organizational context. GASTRO-TIM emphasized engineering collaboration, project coordination, customer communication, and technical documentation. HISTRIS focused primarily on quality management, regulatory compliance, traceability, and standardized production processes. These observations indicate that while implementation priorities vary according to organizational context, the underlying readiness factors remain similar across organizations. The cross-case synthesis further suggests that successful adoption requires alignment between organizational needs and technological capabilities.

# 4 Discussion

The results presented in Section 3 describe our analysis of *what* recurring organizational patterns emerged across the investigated SMEs. In this section, we focus on *why* these patterns are important and how they can be interpreted from complementary theoretical perspectives. Therefore, we structure this section as three theoretical reflections: technology adoption, human-centered AI, and experiential industry-based learning—to explain the broader implications of our findings.

## 4.1 Technology Adoption in Organizational Contexts

The observed similarities and differences among SMEs can be partially explained by the organizational characteristics presented in Table 1 and are consistent with established technology adoption theories such as Rogers' Diffusion of Innovations and the Technology–Organization–Environment (TOE) framework [7,8]. While technological opportunities associated with AI were recognized in both organizations, participants consistently interpreted these opportunities through organizational characteristics such as process maturity, workforce capabilities, documentation practices, and regulatory requirements. Recent research has increasingly moved beyond technology-centric perspectives towards socio-technical interpretations of AI adoption that emphasize stakeholder empowerment, organizational capabilities, and human-centered transformation rather than technological deployment alone [1,2,17]. Our findings are consistent with this perspective and further contribute by illustrating how these socio-technical concerns emerge during the pre-adoption phase across heterogeneous organizational contexts.

## 4.2 Human-Centered AI and Socio-Technical Systems

A second important observation concerns the dominant role of human and organizational factors in shaping adoption readiness. Across both organizations, participants rarely discussed technical characteristics of AI. Instead, discussions focused on issues such as trust, accountability, knowledge transfer, workflow compatibility, and human oversight. This suggests that organizations evaluate emerging AI technologies primarily through their anticipated impact on existing work practices rather than through technical capabilities alone. This finding supports recent research conceptualizing AI readiness as a multidimensional organizational capability extending beyond technological infrastructure [1]. Furthermore, this aligns closely with human-centered AI principles proposed by Amershi et al. [4], which emphasize that intelligent systems should support human goals while preserving transparency, control, and understanding. Interestingly, several themes identified in the results correspond to risks highlighted in the language-model risk taxonomy proposed by Weidinger et al. [5]. The fact that these concerns emerged before any actual deployment took place suggests that organizations begin evaluating socio-technical risks during the earliest stages of technology exploration. The present study complements these efforts by providing exploratory empirical evidence on how readiness factors emerge in organizational discussions during the pre-adoption phase. The contrast between the two cases further demonstrates how organizational characteristics influence the manifestation of these concerns.

### 4.3 Experiential and Industry-Based Learning

Beyond the organizational findings, the study also demonstrates the value of research design for investigating emerging technologies. Following principles of experiential learning [14], students were exposed to authentic organizational environments and were required to connect theoretical concepts with real-world challenges. The progression from systems analysis and field observation to reflective reporting, innovation design, and stakeholder validation encouraged students to move beyond purely technical perspectives and consider broader organizational and societal implications. The interdisciplinary composition of the student teams further contributed to the richness of the observations. Students from computer science and economy backgrounds often emphasized different aspects of the same organizational challenges. This combination of perspectives enabled a more comprehensive understanding of the interactions among technology, organizational processes, quality requirements, and human factors. From a research perspective, the educational setting functioned as a structured mechanism for collecting exploratory evidence about organizational readiness for AI adoption. The student reports, prototype presentations, and stakeholder feedback generated multiple complementary perspectives on the same phenomenon, thereby supporting triangulation and increasing confidence in the identified themes. The results suggest that industry-academia collaborations may serve not only educational purposes but also as valuable exploratory instruments for investigating emerging socio-technical phenomena.

## 5 Conclusion

This paper presented an exploratory investigation of organizational readiness for Large Language Model (AI) adoption through interdisciplinary industry-academia collaboration engaged in participatory study within two industrial organizations. By combining systems analysis, participatory observation, reflective reporting, innovation design, and stakeholder validation, the study explored how organizations perceive opportunities, challenges, and requirements associated with the introduction of emerging AI technologies. The presented results should be interpreted as exploratory rather than definitive. The study involved only two organizations and focused on the pre-adoption phase of AI integration. The study contributes the following directions.

For AI adoption practitioners, the findings confirm previous studies that AI adoption requires socio-technical designs. Our findings indicate that organizational interest in AI adoption is primarily driven by needs related to knowledge management, documentation support, process visibility, and decision support. At the same time, the identified barriers were predominantly organizational and human-centered rather than purely technical. Across both cases, concerns regarding trust, accountability, workflow compatibility, governance, and organizational readiness emerged more frequently than concerns regarding technical capabilities of the underlying AI technology. Therefore, we encourage practitioners to broaden the scope of AI adoption planning beyond pure technical considerations.

For researchers, we identified that organizational readiness may be investigated through transferable socio-technical factors, calling for future comparative studies across different organizational contexts. Although the investigated organizations differ substantially, knowledge-intensive activities, dependence on human expertise, documentation burdens, and the need for effective knowledge transfer appeared as common themes across both cases. Furthermore, from a methodological perspective, the study demonstrates that the previously proposed nine-dimensional analytical framework can be successfully applied to compare heterogeneous organizational contexts systematically.

From an educational perspective, we contribute to evidence on how industry–academia interdisciplinary collaboration can simultaneously support experiential learning and generate empirical evidence on emerging technology adoption processes, offering a replicable approach for future educational and research initiatives.

Future work will extend the study to additional organizations, sectors, and stakeholder groups. By systematically collecting evidence across industrial contexts, workshops, practitioner engagements, and adoption experiences, the long-term objective is to develop a broader understanding of recurring opportunities, barriers, and socio-technical patterns associated with responsible and human-centered adoption of AI technologies. Such knowledge may contribute to the development of practical adoption guidelines and support organizations in navigating the opportunities and challenges of emerging AI-enabled systems. Rather than providing prescriptive implementation guidelines, this work offers a structured analytical perspective that helps researchers, educators, and practitioners better understand organizational readiness before AI deployment, thereby supporting more informed and human-centered AI adoption decisions.

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