# Understanding Organizational Decision to Adopt AI Technologies: A Qualitative Study

Maryam Gulzar[1[0000-0003-1632-7588]]

[1] Department of Software Engineering, Lappeenranta, 53850, Finland
maryam.gulzar@lut.fi

**Abstract.** Artificial intelligence (AI) continues to transform organizational operations by introducing advanced methods that enhance efficiency and productivity. However, many organizations struggle with critical decisions about when to adopt such technologies and how to integrate them effectively into their existing IT infrastructures. To address this gap, the current study conducted a multicase study and collected data through 15 semi-structured interviews. By applying Gioia's method, it identifies the motivations, triggers, and decision-making considerations that influence the adoption of AI within organizations. This work proposed a process model that reveals AI adoption is not driven by a single factor but emerges from a complex interplay of motivations, triggers, and evaluative logic that collectively shape an organization's decision for its adoption.

**Keywords:** AI adoption, motivations, challenges, decision making, organizational change

## 1 Introduction

Artificial Intelligence (AI) has evolved from a theoretical promise into an operational reality, encouraging organizations to explore and adopt AI-based tools and technologies [1]. This rapid AI advancement has played a positive role in transforming business processes from automation to integration of generative AI and machine learning technologies. A growing number of organizations now feel pressure to integrate advanced AI technologies into their operations to maintain innovation, relevance, and competitiveness, but often lack strategic clarity [2]. Many companies rush to implement AI tools without clearly understanding how these technologies align with their broader business objectives, which results in falling short of expectations [3]. Organizations vary widely not only in whether they adopt AI, but also in why they pursue it, when they decide to explore it, and how they evaluate its fit within their unique context.

Prior research works, such as the Technology Acceptance Model (TAM) [4], the Diffusion of Innovation theory [5], or the Technology–Organization–Environment (TOE) framework [6], mostly talked about technical implementation and performance outcomes or individual user acceptance models. Though these models are useful in explaining macro-level patterns and user-level behavior, they often overlook the complex, contextual, and interpretive processes through which organizations deliberate the

LUT Group Confidential - Other information (3Y)

adoption of emerging technologies like AI. In particular, they underrepresent the strategic thinking, internal debates, and evaluative considerations that shape AI adoption decisions at the organizational level. Recent studies acknowledge that AI adoption is not only a matter of technological readiness, but it involves deep strategic, cultural, and organizational reflection [7,8]. Organizations must determine whether AI aligns with their business goals, operational capacities, and ethical standards.

## 2 Research Methodology

This study explores how organizations make decisions about adopting AI technologies by applying the Gioia method [9]. For this purpose, we conducted a qualitative multi-case study, having 15 semi-structured interviews over 6 months (Nov 2024 to Apr 2025), ranging from 40-60 minutes. To gain a broad yet deep knowledge of AI adoption decision-making, we sampled organizations from diverse industries, and participants were chosen who were directly involved in the decision-making or implementation of AI initiatives. Table 1 presents the information about the organizations interviewed.

**Table 1.** Case organizations and interviewees' information.

| Case ID | Organization Name | Orgn. size | Interview’s Position |
|---|---|---|---|
| A | Business Consulting and Services | 800,000 | Senior Manager, Data & AI<br>Data & AI Lead |
| B | IT Development, Services, Consulting | 220000 | Data & AI Sales Director<br>Global AI Architect<br>AI and Analytics Sales Executive |
| C | Industrial Machine Manufacturing | 20,000 | Director of Data & AI Projects |
| D | | 18000 | Head of AI Development<br>Senior Manager |
| E | Educational Institute | 3400 | Leading Senior Advisor |
| F | | 1400 | Head of AI |
| G | IT Services and IT Consulting | 1000 | Innovation Lead<br>AI Principal<br>Lead developer |
| H | AI Solutions Lab | 500 | AI Consultants<br>Lead AI Solutions Strategist |

### 2.1 Data Analysis

We have transcribed the interviews as text and imported all transcriptions into NVivo for further qualitative analysis. This stage involved a detailed examination of texts to discover underlying patterns, themes, and dimensions. For this purpose, we have followed the three-stage coding process of the Gioia method [9] to analyze raw data. The following elaborates on each of the three-step processes.

LUT Group Confidential - Other information (3Y)

**Step 1: 1st-Order Coding.** This step began with open coding, where researchers adhered strictly to the participants' terms and tried to reduce the categories into a manageable number by labeling them or using some sort of phrasal descriptors. This resulted in a set of 1st-order codes representing the terms, concerns, and mental models used as participant-centric.

**Step 2: 2nd-Order Theme Development**. At this stage, the emerging first-order codes were organized into second-order theoretical developments based on the interpretation of the researchers. We examined first-order codes by constant comparisons to identify patterns, similarities, and relationships, grouping them into 2nd-order themes that captured the underlying structures of organizational reasoning.

**Step 3: Aggregate Dimension.** Finally, we make sense of the data at this stage, aimed at developing the data structure. We clustered 2nd-order themes into three aggregate theoretical dimensions that directly aligned with the objective of the study: Strategic Motivations (*Why*), Triggering Conditions (*When*), Decision Logic and Evaluation (*How*). A complete analytical coding process in the form of emergent terms, themes, and aggregate dimensions is presented in Table 2.

**Table 2.** Analytical coding process.

| Aggregate Dimension | 2nd-Order Theme | 1st-Order Coding |
|---|---|---|
| Strategic Motivations | Efficiency and optimization | Automation reduces time, effort, enhances work quality, improves employee operational efficiency, and productivity |
| | Bridging and retaining expertise | Addressing labor shortages and bridging knowledge gaps, retain & utilize the knowledge of retired employees |
| | Innovation-driven growth | Early adoption for learning and the emergence of new business models, enabling innovative approaches to compete |
| | Market and client responsiveness | Enhanced client advisory services, global trends, competitive pressure, and improved customer interactions |
| Preconditions & Triggers | Inter-Infrastructural barriers | Insufficient, inaccurate, and mismanaged data for AI tools, inconsistent data management standards, and integration issues |
| | Organizational need & growth | Ensuring value alignment, addressing business growth & organizational needs |
| | Process improvement & business transformation | Enable people to achieve more with fewer resources, improving operational tasks to transform business, and enhancing work processes |
| Evaluation Criteria | Problem identification & strategic alignment | Define actual problems to solve with AI, alignment with broader strategy & goals, focus on value creation and business case, prioritize and assess user-centered needs |
| | Organization capability & readiness | Organizations' readiness to support AI adoption, develop a change management plan, ensure employees' training, and in-house development to match needs |

LUT Group Confidential - Other information (3Y)

| | | |
|---|---|---|
| | Technical fit & compatible | Ensuring the tools comply with security protocols, analyze the cost, usability & accessibility of AI tools, and scalability & align with organizational infrastructure |
| | Expected ROI & value justifications | Cost justification by expected gains in productivity, needs financial modelling and benefit assumptions, AI tool evaluation to perform the required tasks |

## 3 Findings and Discussion

This study explores the reasoning processes behind organizational decisions to adopt AI technologies. It is mainly guided by three central questions: **why** organizations pursue AI, **when** challenges prompt exploration, and **how** decision-makers approach adoption. We developed a process model that demonstrates AI adoption as a multi-stage reasoning journey rather than a singular technical decision. The model reveals three interdependent dimensions: strategic motivations, preconditions and triggers, and evaluative criteria, each of which contributes to shaping the eventual adoption decision. **Strategic motivations** capture the underlying reasons why organizations initially chose to explore and pursue AI technologies. Rather than being driven solely by technological enthusiasm, AI adoption was motivated by a combination of internal strategic goals and external pressures. **Preconditions and triggers** encompass the conditions and triggers that prompted organizations to initiate active exploration of AI. These often-represented systemic limitations underscore the urgent need for and the more obvious adoption of AI. In **evaluation criteria,** once organizations are motivated to explore AI and confront practical challenges, they need to adopt a structured decision-making process to determine whether AI is worth pursuing. This dimension captures the evaluative reasoning of the “how” behind AI adoption. Building on these aggregate dimensions, we developed a process model (Figure 1) that illustrates how organizations move through various phases of AI adoption decision-making.

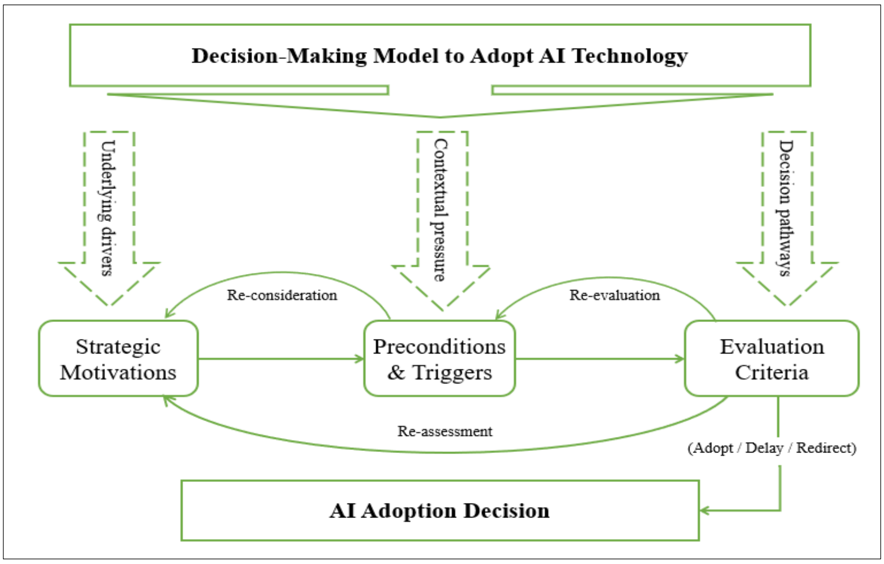


**Fig. 1.** Process model of organizational AI adoption decisions

LUT Group Confidential - Other information (3Y)

These stages collectively shape the ultimate decision to adopt, delay, or redirect AI initiatives. Importantly, the model also depicts feedback loops, signifying that AI adoption is not a linear process. Organizations often revisit earlier stages as new needs emerge, technologies evolve, or implementation challenges occur. Rather than being purely technical, the adoption journey is deeply interpretive, context-dependent, and shaped by both opportunities and constraints. Prior research on the adoption of technology has often emphasized efficiency gains and cost reduction as the principal drivers [11, 15]. However, beyond these central motivations, organizations also pursued AI adoption to bridge expertise gaps, retain organizational knowledge, respond to evolving client demands, and enable innovation-driven growth. Existing literature on AI adoption often treats challenges such as poor data quality, workforce resistance, and complexity as barriers that hinder adoption [10,12]. Our findings complicate this view. Rather than acting solely as inhibitors, these challenges and preconditions often served as catalysts that triggered the exploration of AI solutions.

The third dimension of our findings concerns how organizations approached AI adoption decisions. Traditional models often emphasize cost-benefit analyses, ROI, or technical feasibility [9]. While these factors were indeed central, our data reveals a more layered and iterative process. Organizations first emphasized problem identification and strategic alignment [13] that addressed real, high-impact business problems rather than irrelevant tasks. Second, they evaluated organizational readiness and capability [14], which included internal training, cultural acceptance, and infrastructure maturity. Third, technical fit, compatibility, and security considerations played a role, particularly concerning privacy, compliance, and enterprise-level scalability. Finally, organizations assessed ROI and outcomes but framed them not only in financial terms but also in broader organizational value creation and long-term positioning.

## 4 Conclusion

This study demonstrates that AI adoption is not a linear or purely technical decision, but a multi-stage reasoning process driven by motivations, preconditions & triggers, and evaluative logics. By framing adoption through the lenses of why, when, and how, we provide a process model that both advances theory and offers practical guidance. Ultimately, understanding AI adoption as organizational reasoning, rather than as a technical inevitability. This study has limitations as it draws on qualitative data from a specific set of organizations, which may limit generalizability. Future research could extend these insights across a number of industries or geographic contexts. Our study captures adoption reasoning at a particular point in time; longitudinal studies could reveal how motivations, challenges, and evaluation criteria evolve as organizations progress through implementation.

LUT Group Confidential - Other information (3Y)

## References

1. Dittmar, E. C. (2025). AI as a catalyst for organizational learning: moving beyond tool implementation to learning transformation. *Development and Learning in Organizations: An International Journal*.
2. Al-kfairy, M. (2025). Strategic integration of generative AI in organizational settings: Applications, challenges, and adoption requirements. *IEEE Engineering Management Review*.
3. Boo, C. (2025). When a customer meets AI failure: expectation discrepancy perspective. *Applied Economics Letters*, *32*(7), 1039-1043.
4. Davis, F. D. (1989). Technology acceptance model: TAM. AlSuqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption, 205, 219.
5. Rogers, E. M. (2003). Diffusion of innovations (Vol. 32, pp. 891–937). The Free Press of Glencoe.
6. Tornatzky, L.G. & Fleischer, M. (1990), The process of technological innovation, Lexington Books, United Kingdom.
7. Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2021). Organizational decision-making structures in the age of AI. *California Management Review*, *63*(3), 46-68.
8. Somayajula, P. P. (2024). AI-Augmented Strategic Decision-Making in Business Organizations. *International Journal of Global Tech Management*, *1*(1), 63-74.
9. Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational research methods*, *16*(1), 15-31.
10. Bérubé, M., Giannelia, T., & Vial, G. (2021). Barriers to the Implementation of AI in Organizations: Findings from a Delphi Study.
11. Merhi, M. I., & Harfouche, A. (2024). Enablers of artificial intelligence adoption and implementation in production systems. *International journal of production research*, *62*(15), 5457-5471.
12. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. International journal of information management, 57, 101994.
13. Ansari, I., Barati, M., Sadeghi Moghadam, M. R., & Ghobakhloo, M. (2023). An Industry 4.0 readiness model for new technology exploitation. International Journal of Quality & Reliability *Management*, *40*(10), 2519-2538.
14. Shea, C. M., Jacobs, S. R., Esserman, D. A., Bruce, K., & Weiner, B. J. (2014). Organizational readiness for implementing change: a psychometric assessment of a new measure. *Implementation science*, *9*(1), 7.
15. Gulzar, M., Naqvi, B., & Smolander, K. (2024, November). Technology Change Adoption in Organizations: Drivers, Challenges, and Success Enablers. In *International Conference on Software Business* (pp. 407-422). Cham: Springer Nature Switzerland.

LUT Group Confidential - Other information (3Y)