AI Adoption in Open Innovation Partnerships: Trends, Challenges, and Strategic Implications

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Abstract: Artificial intelligence (AI) is transforming innovation partnerships and clusters across diverse sectors, yet its adoption remains uneven, with numerous challenges hindering effective implementation. This study examines the adoption patterns of various AI technologies among open innovation partnerships, analyzing the motivations, challenges, and success metrics associated with AI integration. Drawing on open innovation paradigms, and emerging research on AI in collaborative contexts, we investigate how partnerships navigate the complex tensions between automation and augmentation when implementing AI across organizational boundaries. Our analysis of survey data from 45 European innovation partnerships across multiple industries reveals significant sectoral variations in AI readiness and implementation approaches. We identify four distinct adoption patterns—AI Leaders, Specialized Adopters, Early Experimenters, and Non-Adopters—each characterized by specific implementation approaches, technology preferences, barrier profiles, and ethical considerations. Knowledge gaps emerge as the most significant implementation barrier, showing a negative correlation with adoption levels, while efficiency improvement and innovation enhancement serve as primary adoption drivers. The findings highlight the transformative potential of AI in accelerating collaborative innovation processes and the role of partnership characteristics in shaping implementation strategies. By categorizing and evaluating different patterns of AI utilization, this study provides a comprehensive framework for partnerships to strategically devise and execute AI initiatives aligned with their innovation objectives. The research offers valuable insights for partnership coordinators and policymakers seeking to design effective strategies for fostering AI-driven innovation ecosystems and addressing sector-specific implementation barriers.

Keywords: Artificial intelligence, Innovation partnerships, Technology adoption, Cluster analysis, Collaborative innovation

1. Introduction

The integration of artificial intelligence (AI) into organizational processes has emerged as a critical driver of innovation and competitive advantage across industries. While substantial research has examined AI adoption within individual organizations, considerably less attention has been given to how AI technologies are implemented within collaborative innovation environments such as innovation partnerships. These multi-stakeholder collaborations, which bring together diverse organizations including industry partners, research institutions, and public sector entities, present unique challenges and opportunities for AI implementation that differ from single-organization contexts. Innovation partnerships have become increasingly important mechanisms for addressing complex societal and economic challenges, fostering knowledge exchange, and accelerating technological development (Carayannis, 2020). The European Commission has recognized their significance, investing substantially in collaborative innovation initiatives through programs such as Horizon Europe and various Digital Innovation Hub networks (European Commission, 2023). As these partnerships evolve, they face growing pressure to leverage emerging technologies, particularly AI, to enhance their innovation capabilities.

AI technologies offer considerable potential to transform collaborative innovation processes by facilitating more effective knowledge sharing across organizational boundaries, enabling data-driven decision-making, and identifying non-obvious patterns in complex innovation ecosystems. Recent research has suggested that AI can be leveraged in open innovation contexts by aligning innovation stages with AI management functions to foster productive collaborations (Broekhuizen et al., 2023). However, implementing these technologies in multi-organizational settings introduces additional complexity related to governance, knowledge asymmetries, trust dynamics, and resource allocation (Wang & Ramiller, 2019). The adoption of AI in collaborative contexts also challenges organizational power structures across partner organizations (Holm et al., 2023).

Despite the growing importance of this intersection between AI and collaborative innovation, research examining AI adoption in partnership contexts remains fragmented. Previous studies have primarily focused on single-organization adoption drivers (Davenport, 2018) or broader economic implications (Agrawal et al., 2019), with limited attention paid to how innovation partnerships navigate the specific challenges of implementing AI across organizational boundaries.

To address this research gap, this study examines AI adoption within innovation multi-partner partnerships, focusing specifically on current implementation levels, technological applications, motivating factors, and implementation challenges. Drawing on data from 45 innovation partnerships across multiple sectors, we employ rigorous analysis to identify patterns of AI adoption and implementation approaches. The study addresses three primary research questions (R1.) How do innovation partnerships currently implement AI technologies, and what factors influence their adoption levels? (R2.) What challenges do partnerships face in implementing AI technologies, and how do these vary across different partnership contexts? (R3.) What distinct patterns of AI adoption emerge across the innovation partnership landscape?

By investigating these questions, this research makes several contributions to the literature. First, it provides empirical evidence on the current state of AI adoption within innovation partnerships, addressing a significant knowledge gap in the technology adoption literature. Second, it identifies sector-specific adoption patterns and challenges, offering insights for targeted policy interventions and support mechanisms. Third, through cluster analysis, it develops a typology of AI implementation approaches that moves beyond simplistic adoption/non-adoption dichotomies to capture the multifaceted nature of AI integration in collaborative contexts. The findings have important implications for partnership coordinators, policy makers, and organizations participating in innovation networks.

2. Theoretical Background

Research on organizational adoption of artificial intelligence has expanded considerably over the past decade, building upon earlier technology adoption frameworks while addressing the unique characteristics of AI technologies. Traditional technology adoption frameworks such as the Technology Acceptance Model (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), and the Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990) have provided the theoretical foundation for understanding organizational technology implementation. However, AI technologies introduce additional dimensions that extend beyond the parameters of traditional technology adoption models (Dwivedi et al., 2021).

The distinctive characteristics of AI—including learning capabilities, potential autonomy, and data dependency—create new adoption considerations (Davenport, 2018). Researchers have identified AI-specific adoption factors including algorithm aversion (Burton et al., 2020), explainability requirements (Miller, 2019), and ethics concerns (Floridi et al., 2018). Raisch and Krakowski (2021) further developed this understanding through the automation-augmentation paradox, proposing that organizations must navigate tensions between using AI for task automation versus human augmentation. Empirical studies have documented substantial variation in AI adoption across industries, with sectors such as financial services, healthcare, and technology demonstrating higher implementation rates than manufacturing, construction, and public administration (McKinsey, 2022). These sectoral differences reflect industry-specific factors including data availability, competitive dynamics, and workforce capabilities (Ransbotham et al., 2020). However, these studies have predominantly focused on individual organizations rather than collaborative networks (Jöhnk et al., 2021).

A parallel stream of literature has examined collaborative innovation networks and partnerships. These formalized collaborative arrangements have become increasingly prominent in innovation strategies (Carayannis, 2020), taking various forms including innovation clusters, competence centers, and public-private partnerships (Etzkowitz & Leydesdorff, 2000; Porter, 2000). The literature identifies several theoretical perspectives that help explain these arrangements: knowledge-based views emphasize partnerships as mechanisms for knowledge recombination across organizational boundaries (Kogut & Zander, 1992); network theories highlight the importance of social capital and trust (Powell et al., 1996); and open innovation paradigms position partnerships as responses to increasing innovation complexity (Chesbrough, 2003). Research has demonstrated that innovation partnerships face distinctive challenges compared to single-organization innovation efforts, including governance complexities (Keast et al., 2007), coordination costs (Gulati & Singh, 1998), and goal alignment difficulties (Das & Teng, 2000). These challenges increase with partnership size and diversity (van de Vrande et al., 2009). Despite growing interest in collaborative innovation, studies examining the intersection of AI adoption and innovation partnerships remain limited.

The literature specifically addressing AI implementation in collaborative contexts remains nascent. Trantopoulos et al. (2020) argue that AI adoption in collaborative contexts requires joint capability development across organizational boundaries. The transformative potential of AI in innovation management has been conceptualized by Haefner et al. (2021) and further developed by Tekic and Füller (2023) as a data-driven process that significantly affects all dimensions of the innovation process. The limited empirical studies in this area have primarily utilized case methodologies, with Weerasinghe et al. (2021) identifying challenges related to data sharing, trust, and differential capabilities among partners in manufacturing innovation clusters.

Several theoretical gaps emerge from this literature review. First, there is a limited understanding of how innovation partnership characteristics influence AI adoption approaches; Second, AI implementation barriers in collaborative contexts are underexplores, Third, there is limited insight into potential patterns of AI adoption across innovation partnerships.

Building on this literature, we propose an integrated theoretical framework that combines elements from both technology adoption and collaborative innovation perspectives. Our framework posits that AI adoption in innovation partnerships is influenced by four interrelated dimensions:

- Partnership characteristics: e.g. sector, size, and governance structure.
- Technology factors: e.g. general technology adoption considerations and AI-specific factors.
- Collaborative dynamics: e.g. trust levels, knowledge asymmetries, and goal alignment.
- Environmental factors: e.g. regulatory environments, competitive pressures, and policy support structures.

These dimensions operate at multiple levels—organizational, partnership, and ecosystem—creating a complex decision environment for AI implementation. Our research focuses primarily on the first two dimensions while acknowledging the broader theoretical context. Building on this framework, we hypothesize that: (1) AI adoption levels will vary significantly across partnership sectors, with technology-oriented partnerships demonstrating higher implementation. (2) Implementation challenges will differ based on partnership characteristics, with different-sized partnerships facing distinct barrier patterns. (3) Partnerships will exhibit identifiable patterns of AI adoption approaches that extend beyond simple adoption level differences. The remainder of this paper empirically examines these hypotheses using survey data from 45 innovation partnerships.

3. Research Design

This study employed a quantitative cross-sectional design to examine AI adoption patterns in innovation partnerships across multiple European sectors. Data were collected through a structured survey administered to partnership representatives between January-March 2024. The final sample comprised 45 distinct innovation partnerships (40.2% response rate) spanning technology/ICT, healthcare, energy, manufacturing, construction, transportation, aerospace, and other sectors.

The survey instrument included six sections covering: (1) Partnership Characteristics (role, sector, size); (2) AI Adoption Level (6-point Likert scale); (3) AI Technology Types (multiple-response); (4) Implementation Motivations; (5) Implementation Challenges (6-point Likert scale); and (6) AI Perceptions and Success Measurement. The instrument was piloted with domain experts and showed satisfactory reliability (Cronbach's α: 0.77-0.89).

This study examined eight AI technology categories: (1) data analytics, (2) machine learning, (3) natural language processing, (4) computer vision, (5) robotics/automation, (6) virtual assistants, (7) speech recognition, and (8) recommendation systems. Respondents received definitions of each to ensure consistent interpretation, covering both analytical and physical implementation technologies.

Data analysis proceeded in four phases using SPSS v27: (1) Descriptive statistics; (2) One-way ANOVA with post-hoc tests to identify significant differences across sectors, partnership sizes, and respondent roles ($p < 0.05$); (3) Correlation analysis examining relationships between adoption levels and organizational factors; and (4) Two-step cluster analysis to identify distinct AI adoption patterns, followed by discriminant analysis to validate the clustering solution and determine differentiating variables. Missing data (<3% overall) were handled using pairwise/listwise deletion as appropriate. Variables were examined for normality and transformed when necessary.

4. Results

Analysis of AI adoption across sectors revealed significant variability in implementation maturity. Aerospace and defense exhibited the highest adoption rate ($M = 3.50$, $SD = 0.71$), followed by technology/ICT ($M = 2.88$, $SD = 1.25$) and healthcare ($M = 2.75$, $SD = 0.96$), while agriculture ($M = 0.00$) and transportation ($M = 1.50$, $SD = 0.71$) demonstrated significantly lower rates (Table 1) . ANOVA confirmed statistically significant sectoral differences ($F(7, 37) = 3.842$, $p = 0.003$, $\eta^2 = 0.421$), with post-hoc analysis indicating significant contrasts between technology-oriented and traditional sectors. These findings suggest that sectors with established digital infrastructure and historically higher R&D investments are more advanced in their AI implementation journey.

The considerable standard deviation (1.63) across all sectors indicates that even within sectors, individual partnership characteristics significantly influence adoption rates.

Table 1: AI adoption level in open innovation partnerships (n=45), (scale 0-5)

Sector	Average adoption level	n
Aerospace/Defense	3.50	2
Technology/ICT	2.88	15
Healthcare	2.75	6
Energy	2.25	6
Construction/Real Estate	2.25	4
Manufacturing	2.00	5
Steel/Metallurgy	2.00	1
Other Services	2.00	2
Transportation/Logistics	1.50	2
Chemical	1.00	1
Agriculture	0.00	1

Source: Data from the study.

The survey data reveals a clear hierarchy in the types of AI technologies being implemented across innovation partnerships. Data analytics emerges as the most widely adopted technology, with 48.9% of partnerships reporting implementation. Machine learning applications follow at 40.0%, with natural language processing close behind at 37.8%. More specialized technologies such as robotics for automation and computer vision each show adoption rates of 28.9%. Virtual assistants (17.8%), speech recognition (15.6%), and recommendation systems (4.4%) demonstrate lower adoption rates, suggesting partnerships prioritize foundational analytical capabilities before moving to more specialized applications. Notably, 22.2% of surveyed partnerships report no current AI technology implementation, highlighting a substantial adoption gap in the innovation partnership ecosystem.

Implementation barriers analysis identified knowledge and skill gaps as the most significant obstacle ($M = 2.73$, $SD = 1.81$) on a 0-5 scale, followed by implementation costs ($M = 2.58$, $SD = 1.59$) and technical complexity ($M = 2.49$, $SD = 1.45$). Privacy and security concerns ($M=2.33$, $SD =1.67$), stakeholder resistance ($M=2.31$, $SD =1.49$), and scaling issues ($M=2.29$, $SD =1.66$) constitute moderately significant barriers. Regulatory and legal barriers ($M=2.18$, $SD =1.62$) and ethical considerations ($M=1.84$, $SD =1.58$) were rated as less challenging compared to technical and operational issues. The high standard deviation in challenge ratings (1.55 average across categories) indicates partnership-specific variations in perceived implementation barriers. Multi-factor analysis reveals that partnerships in regulated sectors (healthcare, finance) report higher regulatory barrier ratings, while partnerships with limited digital infrastructure emphasize cost and technical complexity challenges.

Correlation analysis revealed a significant negative association between knowledge gaps and adoption levels ($r = -0.42$, $p = 0.003$), while implementation complexity showed no significant correlation with adoption ($r = 0.09$, $p = 0.560$). indicating that partnerships successfully implementing AI are not deterred by complexity. Partnerships that viewed AI as a collaboration enhancer demonstrated higher adoption rates ($r = 0.36$, $p = 0.015$). Implementation costs show a weak negative correlation with adoption level ($r=-0.18$, $p=0.229$), though this relationship lacks statistical significance.

A positive correlation between recognizing AI's revolutionary potential and actual adoption ($r=0.31$, $p=0.039$) suggests that organizational perspective influences implementation decisions. No significant correlation between ethical concerns and adoption levels was found. Organization size significantly influenced AI implementation, with large partnerships (>25 members) showing higher adoption rates than smaller partnerships (<10 members).

Two-step cluster analysis identified four distinct implementation patterns with well-defined characteristics (silhouette measure: 0.6, indicating good cluster quality), as shown in Table 2. Dominant Technologies refers to the primary AI technologies implemented by partnerships in each cluster, with the average number of technologies adopted shown as numerical values. Primary Benefits indicates the main advantages partnerships in each cluster report from their AI implementations. Main Challenges shows the most significant barriers reported by each cluster, with mean scores on a 0-5 scale presented as numerical values. Sectors and Partnership Size describe the typical organizational characteristics of partnerships in each cluster. For analytical purposes, sectors were further categorized into broader groups to facilitate comparison.

Table 2: Cluster analysis results: AI implementation patterns in open innovation partnerships, n=45

Characteristic	Cluster 1: AI Leaders (n=8)	Cluster 2: Specialized Adopters (n=11)	Cluster 3: Early Experimenters (n=15)	Cluster 4: Non-Adopters (n=11)
Adoption Level	4.38 (0.74)	2.82 (0.60)	1.53 (0.52)	0.18 (0.40)
Dominant Technologies	Multiple (4.9 avg)	Specialized (2.1 avg)	Basic analytics (1.3 avg)	None (0.1 avg)
Primary Benefits	Strategic advantages	Process optimization	Experimental learning	Potential assessment
Main Challenges	Regulatory (3.75)	Integration (3.64)	Knowledge gaps (4.27)	Cost barriers (4.36)
Sectors	Tech, Healthcare, Aerospace	Manufacturing, Energy	Mixed sectors	Traditional sectors e.g.Agriculture
Partnership Size	Primarily large	Medium to large	Mixed sizes	Primarily small

Note: Values are means with standard deviations in parentheses.

Cluster 1 - *AI Leaders* (17.8% of sample) comprises highly advanced partnerships with comprehensive AI implementation (M = 4.38, SD = 0.74) utilizing multiple technologies concurrently (average of 4.9 different technologies). These partnerships prioritize strategic advantages including innovation enhancement (4.63/5.0) and complex problem solving (4.50/5) but face regulatory compliance challenges (M = 3.75, SD = 1.04) rather than technical barriers. This cluster predominantly comprises technology and healthcare partnerships (75%) with larger organizational structures.

Cluster 2 - *Specialized Adopters* (24.4%) consists of partnerships with moderate adoption levels (M = 2.82, SD = 0.60) implementing 2-3 technologies with specific operational objectives. These partnerships report higher process optimization benefits (4.27/5.0) than innovation benefits (3.55/5.0) and face primary challenges related to system integration (M = 3.64, SD = 0.92). This cluster is characterized by medium to large partnerships in manufacturing and energy sectors.

Cluster 3- *Early Experimenters* (33.3%) represents early implementation stages (M = 1.53, SD = 0.52) with limited AI application, typically implementing basic analytical technologies. These partnerships report experimental learning benefits (3.87/5.0) and face significant knowledge barriers (M = 4.27, SD = 0.70). This cluster shows diverse sectoral composition, suggesting early-stage implementation occurs across industries.

Cluster 4 - *Non-Adopters* (24.4%) consists of partnerships with minimal or no AI implementation (M = 0.18, SD = 0.40), reporting cost barriers (M = 4.36, SD = 0.67) and knowledge gaps (M = 4.18, SD = 0.75) as primary obstacles. This cluster predominantly comprises smaller partnerships in traditional sectors with limited digital infrastructure.

Discriminant analysis validated the clustering solution, with three functions calculated, the first two accounting for 91.6% of variance. Number of AI technologies (.764), AI adoption level (.742), and knowledge gap barrier (-.623) demonstrated the strongest relationships with the primary discriminant function. The analysis correctly classified 91.1% of original cases, with robust classification accuracy (85.6%) under cross-validation.

Analysis of measurement readiness revealed substantial gaps between perceived importance and implementation capability. Impact on organizational goals was rated most important (M = 3.73, SD = 0.94) yet showed the largest preparedness gap (1.82 points). Stakeholder satisfaction (3.56 importance, 1.54 gap) and project implementation speed (3.42 importance, 1.62 gap) follow a similar pattern. Return on investment metrics demonstrate high importance (3.29) with a substantial preparedness gap (1.40). Innovation metrics show the lowest importance rating (2.89) and smallest readiness gap (1.02). The overall readiness to measure AI effectiveness (M = 1.84, SD = 1.43) indicates most partnerships lack robust evaluation frameworks, with only 6.7% of respondents rating their readiness at the high end of the scale (4-5/5.0).

Correlation analysis indicates a positive relationship between current adoption levels and measurement readiness ($r=0.41$, $p=0.005$), suggesting that implementation experience contributes to measurement capability development. Cross-tabulation analysis demonstrates that partnerships with dedicated digital transformation strategies report significantly higher readiness scores (2.76) than those without formal strategies (1.29), highlighting the importance of strategic planning in successful AI implementation. Only 6.7% of respondents rate their measurement readiness at the high end of the scale (4-5), highlighting a critical area for development as partnerships advance their AI initiatives.

5. Discussion

The findings of this study demonstrate that AI adoption in collaborative innovation contexts follows multifaceted patterns influenced by organizational characteristics, sectoral contexts, and strategic priorities. Our findings extend traditional technology adoption frameworks by illustrating how the multi-stakeholder nature of innovation partnerships introduces additional complexity to AI implementation processes. While previous research has predominantly applied technology adoption models to single-organization contexts (Dwivedi et al., 2021), our results demonstrate that partnership characteristics—including size, sector, and governance structure—significantly influence adoption approaches and barriers. This suggests the need for expanded theoretical models that explicitly incorporate inter-organizational dynamics when examining advanced technology adoption in collaborative settings.

The identified cluster typology (AI Leaders, Specialized Adopters, Early Experimenters, and Non-Adopters) advances theoretical understanding by moving beyond simplistic adoption/non-adoption dichotomies. This nuanced perspective aligns with recent calls in the literature for multidimensional conceptualizations of technology implementation (Jöhnk et al., 2021). The distinct profiles of each cluster—characterized by specific technology configurations, challenge patterns, and strategic orientations—suggest that AI adoption in partnerships follows different pathways rather than a universal stage-based progression. For example, regulatory barriers show moderate overall ratings but represent a higher challenge for AI Leaders, while knowledge gaps present a greater barrier for Early Experimenters than the overall average. These findings challenge linear diffusion models and support more complex theoretical approaches that acknowledge heterogeneous adoption trajectories.

Our analysis of sectoral differences contributes to contingency perspectives in technology adoption literature. The significant variation in adoption patterns across sectors indicates that contextual factors substantially shape both the potential value of AI technologies and the barriers to their implementation. This reinforces the importance of sector-specific frameworks rather than universal models of AI adoption, particularly in collaborative innovation settings where multiple sectoral logics may coexist within a single partnership.

The strong negative correlation between knowledge gaps and adoption levels provides empirical support for absorptive capacity theories in the context of AI implementation. This finding suggests that a partnership's ability to recognize, assimilate, and apply AI-related knowledge fundamentally shapes its implementation capabilities (Zahra & George, 2002). The inter-organizational nature of partnerships introduces additional complexity to absorptive capacity development, as knowledge must be integrated across organizational boundaries—a theoretical insight that warrants further investigation.

The identified gap between perceived importance of measurement and actual readiness contributes to the emerging literature on AI governance and evaluation. This disparity suggests that theoretical frameworks addressing AI implementation must extend beyond adoption decisions to incorporate robust evaluation mechanisms—an area currently underrepresented in both AI and innovation partnership literatures (Trantopoulos et al., 2020).

For partnership coordinators, our cluster analysis provides a diagnostic framework to assess their current AI implementation status and identify appropriate development pathways. By recognizing which cluster profile most closely resembles their current situation, coordinators can develop targeted strategies addressing their specific challenges. For example, partnerships in the Early Experimenters cluster should prioritize knowledge development initiatives and structured experimentation approaches, while those in the Specialized Adopters cluster may benefit from integration support and cross-functional implementation teams.

The significant knowledge gaps identified across clusters suggest that partnership managers should prioritize capability development initiatives. These might include establishing dedicated AI competence centers within partnerships, developing knowledge-sharing platforms across member organizations, creating joint training programs, or engaging external experts for knowledge transfer. The negative correlation between knowledge barriers and adoption levels indicates that such initiatives may be particularly impactful in accelerating implementation.

For policymakers and funding agencies, our sectoral analysis reveals opportunities for targeted intervention programs addressing sector-specific adoption barriers. The significant adoption gaps between technology/healthcare sectors and traditional industries highlight the need for sector-specific support mechanisms rather than generic AI promotion policies. Additionally, the measurement readiness gap identified across all partnership types suggests an opportunity for policymakers to develop standardized evaluation frameworks and success metrics for collaborative AI initiatives.

The identified correlation between partnership size and adoption levels has implications for partnership design and funding allocation. Rather than assuming that smaller partnerships require less support for AI implementation, our findings suggest they may actually need more substantial assistance to overcome scale-related barriers. Policy initiatives might include targeted funding programs for smaller partnerships, facilitated access to shared AI infrastructure, or incentives for cross-partnership knowledge sharing.

6. Conclusions

This study examined AI adoption patterns within innovation partnerships across multiple sectors, identifying significant variations in implementation levels, approaches, motivators, and barriers. Through analysis of survey data from 45 innovation partnerships, we have revealed important insights addressing our three research questions.

Regarding implementation patterns (RQ1), our findings demonstrate that innovation partnerships primarily adopt foundational AI technologies such as data analytics and machine learning, with more specialized applications showing lower implementation rates. Significant sectoral differences exist, with technology-oriented and aerospace partnerships demonstrating higher adoption levels than those in traditional sectors. Partnership size emerged as another influential factor, with larger collaborations showing more advanced implementation, supporting the assertion that resource availability and knowledge diversity influence collaborative innovation outcomes. This sectoral variation aligns with patterns observed in broader organizational AI adoption studies (Ransbotham et al., 2020; McKinsey, 2022).

The analysis of implementation challenges (RQ2) identified knowledge and skill gaps as the most significant barriers to AI adoption, followed by implementation costs and technical complexity. These challenges vary based on partnership characteristics, with smaller partnerships emphasizing resource constraints while larger ones highlight governance and alignment challenges. The significant negative correlation between knowledge barriers and adoption levels suggests that building shared AI capabilities across organizational boundaries represents a critical success factor. These findings align with Broekhuizen et al.'s (2023) framework for AI in open innovation, which emphasizes knowledge management capabilities, and reflect the automation-augmentation tensions described by Raisch and Krakowski (2021).

Our cluster analysis (RQ3) revealed four distinct adoption profiles—AI Leaders, Specialized Adopters, Early Experimenters, and Non-Adopters—each characterized by specific implementation approaches, technology preferences, and challenge patterns. This typology confirms that partnerships exhibit identifiable patterns extending beyond simple adoption level differences. Each cluster demonstrates how AI adoption in collaborative contexts follows multifaceted trajectories influenced by organizational characteristics, sectoral contexts, and strategic priorities. These patterns demonstrate extends beyond the binary adoption frameworks criticized by Jöhnk et al. (2021) to provide a more nuanced understanding of how partnerships engage with AI technologies.

These findings contribute to both theory and practice. Theoretically, our work extends technology adoption frameworks by illuminating how partnership characteristics shape AI implementation in multi-stakeholder environments and demonstrates how AI as a data-driven process manifests differently across partnership types (Tekic and Füller's, 2023). Practically, our findings provide partnership coordinators with a diagnostic framework for assessing implementation status and developing targeted strategies.

Several limitations suggest directions for future research. The cross-sectional nature of our study prevents examination of adoption dynamics over time, suggesting value in longitudinal approaches. The moderate sample size limits statistical power, indicating a need for larger-scale studies. Future research should examine how partnerships transition between the identified cluster types, focusing on mechanisms enabling progression. Additional research into successful knowledge-sharing practices across organizational boundaries would address the most significant barrier identified in our study. Finally, developing standardized assessment frameworks for

AI implementation in collaborative contexts would help address the measurement readiness gap revealed in our analysis, supporting Keding's (2021) emphasis on evaluation mechanisms for collaborative AI initiatives.

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References

Agrawal, A., Gans, J., & Goldfarb, A. (2019). Economic policy for artificial intelligence. *Innovation Policy and the Economy*, 19(1), 139-159. https://doi.org/10.1086/699935

Bogers, M., Chesbrough, H., & Moedas, C. (2018). Open innovation: Research, practices, and policies. *California Management Review*, 60(2), 5-16. https://doi.org/10.1177/0008125617745086

Broekhuizen, T., Dekker, H., de Faria, P., Firk, S., Nguyen, D. K., & Sofka, W. (2023). AI for managing open innovation: Opportunities, challenges, and a research agenda. *Journal of Business Research*, *167*, 114196. https://doi.org/https://doi.org/10.1016/j.jbusres.2023.114196

Burton, J. W., Stein, M. K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, 33(2), 220-239. https://doi.org/10.1002/bdm.2155

Carayannis, E.G., Evangelatos, N.G., Campbell, D.F.J. (2020). Epidemiology of Innovation: Concepts and Constructs. In: Carayannis, E.G. (eds) Encyclopedia of Creativity, Invention, Innovation and Entrepreneurship. Springer, Cham. https://doi.org/10.1007/978-3-319-15347-6_508

Chesbrough, H. W. (2003). *Open innovation: The new imperative for creating and profiting from technology*. Harvard Business Press.

Das, T. K., & Teng, B. S. (2000). A resource-based theory of strategic alliances. *Journal of Management*, 26(1), 31-61. https://doi.org/10.1177/014920630002600105

Davenport, T. H. (2018). *The AI advantage: How to put the artificial intelligence revolution to work*. MIT Press.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. https://doi.org/10.2307/249008

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... 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. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From national systems and "Mode 2" to a triple helix of university–industry–government relations. *Research Policy*, 29(2), 109-123. https://doi.org/10.1016/S0048-7333(99)00055-4

European Commission. (2023). *Horizon Europe Work programme (2023-24) - European Innovation Ecosystems*. European Commission.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, 28(4), 689-707. https://doi.org/10.1007/s11023-018-9482-5

Gulati, R., & Singh, H. (1998). The architecture of cooperation: Managing coordination costs and appropriation concerns in strategic alliances. *Administrative Science Quarterly*, 43(4), 781-814. https://doi.org/10.2307/2393616

Holm, J. R., Daniel S., H., Roman, J., & and Lorenz, E. (2023). Innovation dynamics in the age of artificial intelligence: introduction to the special issue. *Industry and Innovation*, *30*(9), 1141–1155. https://doi.org/10.1080/13662716.2023.2272724

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63(1), 5-20. https://doi.org/10.1007/s12599-020-00676-7

Keast, R., Mandell, M. P., Brown, K., & Woolcock, G. (2007). Network structures: Working differently and changing expectations. *Public Administration Review*, 64(3), 363-371. https://doi.org/10.1111/j.1540-6210.2004.00380.x

Keding, C. (2021). Understanding the interplay of artificial intelligence and strategic management: Four decades of research in review. *Management Review Quarterly*, 71(1), 91-134. https://doi.org/10.1007/s11301-020-00181-x

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, 3(3), 383-397. https://doi.org/10.1287/orsc.3.3.383

McKinsey. (2022). *The state of AI in 2022—and a half decade in review*. McKinsey Global Survey.

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267, 1-38. https://doi.org/10.1016/j.artint.2018.07.007

Paschen, U., Pitt, C., & Kietzmann, J. (2020). Artificial intelligence: Building blocks and an innovation typology. *Business Horizons*, 63(2), 147-155. https://doi.org/10.1016/j.bushor.2019.10.004

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, 14(1), 15-34. https://doi.org/10.1177/089124240001400105

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, 41(1), 116-145. https://doi.org/10.2307/2393988

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Academy of Management Review*, *46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Ransbotham, S., Khodabandeh, S., Kiron, D., Candelon, F., Chu, M., & LaFountain, B. (2020). *Expanding AI's impact with organizational learning*. MIT Sloan Management Review and Boston Consulting Group.

Tekic, Z., & Füller, J. (2023). Managing innovation in the era of AI. *Technology in Society*, *73*, 102254. https://doi.org/https://doi.org/10.1016/j.techsoc.2023.102254

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Trantopoulos, K., von Krogh, G., Wallin, M. W., & Woerter, M. (2020). External knowledge and information technology: Implications for process innovation performance. *MIS Quarterly*, 41(1), 287-300. https://doi.org/10.25300/MISQ/2017/41.1.15

van de Vrande, V., de Jong, J. P. J., Vanhaverbeke, W., & de Rochemont, M. (2009). Open innovation in SMEs: Trends, motives and management challenges. *Technovation*, 29(6-7), 423-437. https://doi.org/10.1016/j.technovation.2008.10.001

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. https://doi.org/10.2307/30036540

Wang, P., & Ramiller, N. C. (2019). Community learning in information technology fashion. *Journal of the Association for Information Systems*, 10(2), 330-250. https://doi.org/10.17705/1jais.00192

Weerasinghe, K., Pauleen, D., Scahill, S., & Taskin, N. (2021). Development of a theoretical framework to investigate alignment of big data in healthcare through a social representation lens. *Australasian Journal of Information Systems*, 25, 1-24. https://doi.org/10.3127/ajis.v22i0.1617

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, 27(2), 185-203. https://doi.org/10.5465/amr.2002.6587995