

When Knowing Outpaces Doing: Knowledge Management and AI Implementation gap in Innovation Partnerships

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Abstract: Innovation partnerships (research consortia, digital innovation hubs, public-private collaborations) are increasingly expected to implement artificial intelligence technologies such as machine learning, computer vision, natural language processing, robotics, and data analytics. Yet many partnerships exhibit a persistent disconnect between AI knowledge and AI implementation. This knowing-doing gap (Pfeffer and Sutton, 2000) is well documented within individual firms, but its antecedents and consequences in multi-partner settings, where knowledge asymmetries, distributed governance, and heterogeneous absorptive capacities complicate knowledge transfer (Cohen and Levinthal, 1990), remain poorly understood. This study draws on survey data from 45 European innovation partnerships across 15 countries and employs a two-stage analytical design. First, OLS regression examines the knowledge management antecedents of the knowing-doing gap. Results ($R^2 = .31$, $p = .01$) indicate that measurement readiness significantly narrows the gap ($B = -0.67$, $p = .015$), while technology diversity ($B = 0.41$, $p = .002$) widens it. Second, hierarchical OLS regression examines whether the gap predicts innovation performance beyond baseline knowledge management variables. Adding the knowing-doing gap significantly improves the model ($\Delta R^2 = .10$, $F\text{-change} = 10.05$, $p = .003$), with both the gap ($B = 0.46$, $p = .003$) and measurement readiness ($B = 1.10$, $p < .001$) independently predicting innovation performance. We introduce the concept of *productive knowledge disequilibrium* to theorise this finding: in rapidly evolving technological domains, the misalignment between action and measurement can function as a generative force, enabling learning-by-doing that complements formal knowledge management practices.

Keywords: Knowledge management, Knowing-doing gap, AI implementation, Innovation partnerships, Productive knowledge disequilibrium

1. Introduction

Artificial intelligence technologies are transforming how organisations manage knowledge. Innovation partnerships are increasingly expected to serve as vehicles for AI adoption (Broekhuizen et al., 2023; McPhillips, 2025), yet many demonstrate sophisticated AI understanding while struggling to implement it (Füller et al., 2022). This disconnect represents the knowing-doing gap (Pfeffer and Sutton, 2000).

The knowing-doing gap is well documented at firm level (Pfeffer and Sutton, 2000; Szulanski, 1996; Rogers, 2003), but partnerships introduce structural complications: absorptive capacity varies across members (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998), governance distributes decision-making, and knowledge asymmetries create divergent perceptions of readiness.

Knowledge management research has not examined how multi-partner dynamics shape the knowing-doing gap. The gap in partnerships emerges from distributed knowledge stocks and collective action problems structurally distinct from intra-organisational barriers (Easterby-Smith, Lyles and Tsang, 2008; van Wijk, Jansen and Lyles, 2008; Dyer and Singh, 1998). Many societal challenges depend on AI-enabled collaborative solutions that individual firms cannot deliver alone.

This study asks two research questions. *RQ1: What knowledge management characteristics predict the magnitude of the AI knowing-doing gap in innovation partnerships?* *RQ2: Does the knowing-doing gap predict innovation performance beyond its constituent knowledge management components?* Using survey data from 45 European innovation partnerships across 15 countries, we find that both the knowing-doing gap and measurement readiness independently predict innovation performance. We introduce the concept of *productive knowledge disequilibrium* to account for this finding, arguing that in rapidly evolving technological domains, a degree of misalignment between action and measurement capacity can function as a generative force for collaborative innovation.

2. Theoretical Framework

2.1 The Knowing-doing gap in Knowledge Management

The knowing-doing gap, the systematic failure to convert knowledge into action, is a pervasive feature of organisational life (Pfeffer and Sutton, 2000). In inter-organisational settings, this gap is compounded by the complexity of knowledge boundaries across partners (Carlile, 2004), the stickiness of tacit knowledge (Szulanski, 1996; Nonaka, 1994), and the tendency for analysis to substitute for implementation (Mintzberg, 1994). AI

technologies amplify these challenges because they are generative, opaque, and evolving (Berente et al., 2021), and their introduction reconfigures knowledge practices across organisations (Kellogg et al., 2020).

Competitive advantage rests on combinative capabilities across domains (Kogut and Zander 1992). Gama and Magistretti (2023) note the paucity of empirical research on how organisations move from recognising AI's potential to deploying it, suggesting that readiness frameworks may substitute preparation for implementation.

2.2 Absorptive Capacity and Knowledge Transfer in Partnerships

Absorptive capacity provides a complementary lens (Cohen and Levinthal, 1990). Zahra and George (2002) distinguished potential absorptive capacity (acquiring knowledge) from realised absorptive capacity (exploiting it), a distinction mapping onto the knowing-doing gap. Raisch and Krakowski (2021) identified a further tension between automation and augmentation logics in AI adoption. In partnerships, these challenges are amplified by heterogeneous engagement strategies across partners (Lebovitz et al., 2022) and the need for relation-specific knowledge-sharing routines (Dyer and Singh, 1998; Lane and Lubatkin, 1998; van Wijk, Jansen and Lyles, 2008). Transfer is further shaped by trust and cognitive distance (Easterby-Smith, Lyles and Tsang, 2008; Nooteboom et al., 2007).

We propose that the knowing-doing gap can reflect action-oriented learning outpacing formal systematisation. Organisations learn about AI through iterative deployment (Von Krogh, 2018). Kemp (2024) extended this through the concept of situated AI: competitive advantage comes from grounding and recasting AI in specific contexts, activities that in partnerships are distributed and experiential. Mikalef and Gupta (2021) confirmed that AI capability develops through accumulated implementation experience. Sensemaking is retrospective, suggesting the gap may be a necessary condition for enactive learning in multi-partner settings (Weick, 1995).

The dominant knowledge management paradigm assumes knowledge acquisition precedes action (Huber, 1991; Davenport and Prusak, 1998), yet knowledge can emerge from action (Crossan, Lane and White, 1999), and excessive reliance on accumulated knowledge produces learning myopia (Levinthal and March, 1993). This leads to our hypotheses:

H1: *Measurement readiness is negatively associated with the AI knowing-doing gap, such that partnerships with more developed measurement systems exhibit smaller gaps between knowledge and action.*

H2: *Technology diversity is positively associated with the AI knowing-doing gap, such that partnerships deploying AI across a broader range of application domains exhibit larger gaps.*

H3: *The knowing-doing gap positively predicts innovation performance, controlling for baseline knowledge management characteristics, indicating that the gap captures productive variance beyond its constituent components.*

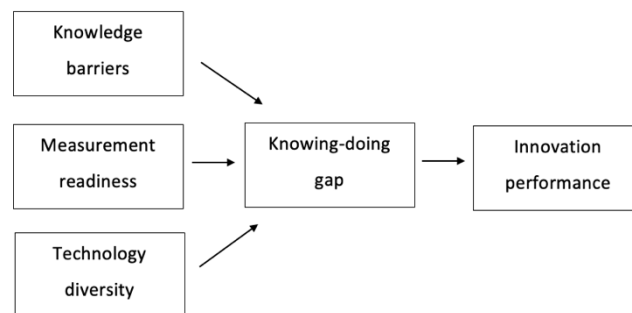


Figure 1: A conceptual model

3. Method

3.1 Research Design

Data were collected through a structured online questionnaire administered to representatives of 112 innovation partnerships between January and March 2024. Partnership coordinators were targeted as key

informants. The study focuses on 45 innovation partnerships across 15 European countries, capturing a diverse institutional landscape and cross-border knowledge asymmetries.

The final sample (40.2% response rate; Baruch and Holtom, 2008) spans several sectors: Technology/ICT (33%), Healthcare (13%), Energy (13%), Manufacturing (11%), Construction (9%), and other sectors (20%). Non-response bias assessment revealed no significant differences.

The knowing-doing gap serves as the dependent variable in Stage 1 and independent variable in Stage 2. It is operationalized as the arithmetic difference between AI adoption level and measurement readiness. To ensure mathematical comparability between the six- adoption scale and four-point measurement scale, both variables were mean centered and standardized before the subtraction.

Positive values indicate that usage outpaces measurement capacity ($M = 1.13$, $SD = 1.25$). Knowledge barriers were measured on a six-point scale (0 to 5) capturing the intensity of knowledge-related obstacles to AI implementation ($M = 2.13$, $SD = 1.80$). Measurement readiness was assessed as a composite indicator of evaluation capacity (0 to 3, $M = 1.02$, $SD = 0.84$). Technology diversity is a count of distinct AI technology types implemented by the partnership, ranging from 0 to 7 ($M = 2.02$, $SD = 1.76$). Innovation performance, the dependent variable in Stage 2, was measured on a six-point scale (0 to 5) capturing the extent to which the partnership generates measurable innovation outcomes through AI activities ($M = 2.87$, $SD = 1.52$). Sector controls were included as binary variables for technology/ICT and healthcare sectors.

The analysis proceeds in two stages. In Stage 1, OLS regression models the knowing-doing gap as a continuous dependent variable, with knowledge barriers, measurement readiness, technology diversity, and sector controls as predictors.

In Stage 2, hierarchical OLS regression models innovation performance as a continuous dependent variable. Model 1 includes the baseline knowledge management variables. Model 2 adds the knowing-doing gap to test whether it provides incremental predictive power beyond its constituent components. Variance inflation factors were calculated for all models and all values fell below 2.0, indicating no multicollinearity concerns.

4. Results

4.1 Descriptive Statistics and Bivariate Correlations

Table 1 presents the descriptive statistics and bivariate correlations for all study variables.

Table 1: Descriptive statistics and bivariate correlations (N = 45)

Variable	M	SD	1	2	3	4	5	6
1. Knowing-doing gap	1.13	1.25	-					
2. Knowledge barriers	2.13	1.80	-.27	-				
3. Measurement readiness	1.02	0.84	-.13	-.08	-			
4. Technology diversity	2.02	1.76	.34*	-.15	.52**	-		
5. AI adoption level	2.16	1.41	.81**	-.29	.48**	.61**	-	
6. Innovation performance	2.87	1.52	.37*	-.43**	.57**	.48**	.67**	-

Note: * $p < .05$, ** $p < .01$ (two-tailed). N = 45.

The knowing-doing gap is positively correlated with technology diversity ($r = .34$, $p < .05$) and innovation performance ($r = .37$, $p < .05$). Innovation performance shows the strongest correlations with AI adoption level ($r = .67$, $p < .01$) and measurement readiness ($r = .57$, $p < .01$), and a negative correlation with knowledge barriers ($r = -.43$, $p < .01$). Knowledge barriers and measurement readiness are not significantly correlated ($r = -.08$), suggesting they capture distinct dimensions of the knowledge management environment.

4.2 Knowledge Management Antecedents of the Knowing-doing gap

Table 2 presents the OLS regression results for Stage 1.

Table 2: OLS regression: Antecedents of the knowing-doing gap (N = 45)

Variable	B	SE	t	p	
Constant	1.373	0.376	3.65	<.001	***
Knowledge barriers	-0.141	0.095	-1.49	.144	
Measurement readiness	-0.667	0.262	-2.54	.015	*
Technology diversity	0.407	0.120	3.39	.002	**
Technology sector	-0.297	0.375	-0.79	.433	
Healthcare sector	0.197	0.575	0.34	.734	

Note: $R^2 = .31$, Adjusted $R^2 = .22$, $F(5, 39) = 3.52$, $p = .01$. * $p < .05$, ** $p < .01$, *** $p < .001$.

The overall model was significant ($R^2 = .31$, $F(5, 39) = 3.52$, $p = .01$), explaining 31 per cent of variance in the knowing-doing gap. Supporting H1, measurement readiness was significantly and negatively associated with the gap ($B = -0.667$, $p = .015$), indicating that each unit increase in measurement readiness reduces the gap by approximately two-thirds of a point. Supporting H2, technology diversity was significantly and positively associated with the gap ($B = 0.407$, $p = .002$). Knowledge barriers were not significantly associated with the gap ($B = -0.141$, $p = .144$), nor were sector controls.

4.3 The Knowing-doing gap as Predictor of Innovation Performance

Table 3 presents the hierarchical OLS regression results for Stage 2.

Table 3: Hierarchical OLS regression: Predicting innovation performance (N = 45)

	Model 1			Model 2			
Variable	B	SE	p	B	SE	p	
Constant	2.362	0.363	<.001	1.744	0.382	<.001	
Knowledge barriers	-0.305	0.094	.002	-0.234	0.088	.011	*
Measurement readiness	0.809	0.234	.001	1.097	0.230	<.001	***
Technology diversity	0.162	0.112	.156	-0.008	0.115	.947	
Knowing-doing gap	-	-	-	0.455	0.144	.003	**

Model 1: $R^2 = .50$, Adjusted $R^2 = .46$, $F(3, 41) = 13.74$, $p < .001$

Model 2: $R^2 = .60$, Adjusted $R^2 = .56$, $F(4, 40) = 15.04$, $p < .001$

$\Delta R^2 = .10$, $F\text{-change}(1, 40) = 10.05$, $p = .003$. * $p < .05$, ** $p < .01$, *** $p < .001$.

Model 1, containing the baseline knowledge management variables, was significant ($R^2 = .50$, $F(3, 41) = 13.74$, $p < .001$) and explained 50 per cent of variance in innovation performance. Knowledge barriers were negatively associated with performance ($B = -0.305$, $p = .002$) and measurement readiness was positively associated ($B = 0.809$, $p = .001$). Technology diversity was not significant ($B = 0.162$, $p = .156$).

Model 2, adding the knowing-doing gap, significantly improved model fit ($\Delta R^2 = .10$, $F\text{-change} = 10.05$, $p = .003$), explaining 60 per cent of variance. Supporting H3, the knowing-doing gap was a significant positive predictor of innovation performance ($B = 0.455$, $p = .003$). Crucially, measurement readiness strengthened in Model 2 (from $B = 0.809$ to $B = 1.097$, $p < .001$), indicating that after accounting for the gap, the independent contribution of measurement readiness becomes even more pronounced. Knowledge barriers remained significant ($B = -0.234$, $p = .011$), while technology diversity was fully absorbed by the gap variable ($B = -0.008$, $p = .947$).

5. Discussion

5.1 Productive Knowledge Disequilibrium

The central finding is that the knowing-doing gap positively predicts innovation performance beyond its constituent components, challenging the assumption (Pfeffer and Sutton, 2000; Szulanski, 1996) that gaps between knowledge and action are inherently problematic. We propose the concept of productive knowledge disequilibrium to account for this pattern.

Productive knowledge disequilibrium describes a state in which a partnership's implementation activity outpaces its formal capacity to measure and evaluate outcomes. Rather than reflecting a deficiency, this state captures the experiential learning (Kolb, 1984) that arises when organisations act under conditions of uncertainty. In the context of AI adoption, where technologies evolve rapidly and implementation knowledge is largely tacit (Nonaka, 1994), partnerships that wait for measurement systems to mature before acting may forfeit the first-mover advantages in learning that early implementation provides. Alavi et al. (2024), revisiting foundational knowledge management theory in light of generative AI, caution that AI-driven knowledge processes carry risks of bias, reduced socialisation, and knowledge misapplication, suggesting that not all disequilibrium is productive. Our concept specifies the conditions under which it is: when the gap reflects action-oriented learning rather than uninformed experimentation. The concept connects to Crossan, Lane and White's (1999) 4I framework of organisational learning, in which intuiting and interpreting (action-oriented, experiential processes) precede and enable institutionalising (the formalisation of knowledge into measurement and evaluation systems). While this disequilibrium is generative in the short term, failing to eventually codify implementation experience into formal measurement systems risks institutionalizing a permanent state of unmanaged experimentation.

The concept connects to the dynamic capabilities' framework (Teece, 2007). Mikalef and Gupta (2021) demonstrated that AI capability develops through the interplay of experience accumulation and deliberate codification, suggesting that partnerships actively deploying AI are building experiential repertoires that will enable reconfiguration of their collaborative processes. Argyris and Schön (1978) proposed a related distinction between single-loop learning, which adjusts actions within existing frameworks, and double-loop learning, which questions and revises the frameworks themselves. The productive disequilibrium we observe may reflect a transition phase in which implementation experience (single-loop learning through direct engagement with AI technologies) gradually creates the conditions for double-loop learning, a fundamental reappraisal of the partnership's knowledge management assumptions. Murray et al. (2021) theorised that humans and technologies form conjoined agency through iterative interaction, suggesting that the productive tension between the gap and measurement readiness represents a co-evolutionary process: implementation experience reshapes what partners understand about AI, which transforms their evaluation practices.

The data support this interpretation. Partnerships with larger knowing-doing gaps, those where AI deployment has outpaced measurement infrastructure, achieve higher innovation performance not despite this misalignment but, we argue, partly because of it. The act of implementation generates tacit knowledge about organisational readiness, user acceptance, and integration challenges that cannot be obtained through measurement system design alone (Leonard-Barton, 1995). In this sense, the gap is not an obstacle to be closed but a productive tension to be managed.

5.2 The Dual Pathway to Innovation Performance

A particularly noteworthy finding is that both the knowing-doing gap and measurement readiness independently predict innovation performance in Model 2. This suggests two complementary pathways rather than a single mechanism. The action pathway, captured by the knowing-doing gap, generates innovation performance through experiential learning and the accumulation of implementation knowledge. The reflection pathway, captured by measurement readiness, generates performance through the systematic codification and evaluation of outcomes. Neither pathway alone is sufficient; the strongest innovation performance emerges when partnerships engage in both action and reflection. This finding resonates with Olan et al.'s (2022) demonstration that AI implementation alone does not reliably improve organisational performance; only configurations that combine AI deployment with robust knowledge-sharing practices yield performance benefits. Jia et al. (2024) provided complementary evidence at the individual level, demonstrating that AI augments employee creativity only when organisational conditions support the integration of AI-generated insights into human decision-making, reinforcing our finding that the benefits of AI deployment depend on parallel investments in knowledge management infrastructure. AI creates opportunities for phenomenon-based

theorising precisely because existing frameworks struggle to accommodate the way AI-related knowledge is generated and applied in practice. Our dual-pathway finding illustrates this point: conventional models that prescribe either action or measurement as the primary driver of performance cannot account for the complementary relationship between the two that our data reveal.

This dual-pathway interpretation aligns with the organisational learning literature's emphasis on the complementarity of exploration and exploitation (March, 1991). Zimmermann et al. (2023) demonstrated that organisations manage persistent tensions between exploration and exploitation through configurational approaches rather than by resolving them definitively. Our findings suggest that innovation partnerships achieving the highest performance are those that manage a form of collaborative ambidexterity: exploring AI applications through implementation (generating the gap) while simultaneously exploiting measurement infrastructure to codify and evaluate learning. Action without reflection risks directionless experimentation; reflection without action risks the paralysis that Pfeffer and Sutton (2000) identified as the core of the knowing-doing problem. The finding that measurement readiness strengthens as a predictor when the gap is included (from $B = 0.809$ to $B = 1.097$) further supports this interpretation: once the variance attributable to action-oriented learning is accounted for, the unique contribution of reflective, measurement-oriented knowledge management becomes clearer.

This finding also challenges the standard prescriptive model of sequential knowledge management: acquire, codify, measure, then implement. Our data suggest successful partnerships pursue these in parallel. This is consistent with Crossan, Lane and White's (1999) observation that organisational learning involves concurrent feed-forward and feedback processes.

5.3 Knowledge Barriers as Constraints on Innovation Performance

Knowledge barriers negatively predicted innovation performance in both models but did not significantly predict the knowing-doing gap itself. This suggests that knowledge barriers operate primarily as a constraint on the conversion of learning into outcomes rather than as a determinant of the knowing-doing gap's magnitude. Partnerships facing high knowledge barriers (lack of AI expertise, insufficient training, poor knowledge sharing across partners) may engage in AI implementation (thereby exhibiting a gap) but fail to convert that implementation experience into innovation performance. This interpretation is consistent with research on the stickiness of knowledge transfer in inter-organisational settings (Easterby-Smith, Lyles and Tsang, 2008) and suggests that knowledge barriers moderate rather than mediate the relationship between action and outcomes. Viewed through Carlile's (2004) boundary framework, knowledge barriers represent the persistence of pragmatic boundaries that have not been adequately addressed: partners may share the same AI technologies but lack the transformative capacity to reshape their domain-specific practices in response to shared implementation experience. Lebovitz et al. (2022) showed that professionals confronted with opaque AI systems develop heterogeneous engagement strategies, ranging from full reliance to selective contestation, depending on their organisational context and professional identity. In partnership settings, this heterogeneity of engagement strategies may compound knowledge barriers, as different partners develop incompatible approaches to integrating AI into their workflows. Kellogg et al. (2020) further noted that algorithmic systems reconfigure the very knowledge hierarchies through which organisations coordinate action. Our finding that knowledge barriers constrain performance independently of the gap's magnitude underscores the importance of addressing these relational and structural barriers: without dedicated investment in shared AI literacy and cross-partner knowledge integration mechanisms, even partnerships with high levels of experiential learning from AI deployment may fail to distribute and capitalise on the knowledge generated.

5.4 Practical Implications

For partnership managers, these findings yield several actionable insights. First, they should resist the temptation to delay AI implementation until measurement systems are fully developed. The preparatory trap, investing in assessment infrastructure at the expense of experimentation, narrows the knowing-doing gap without advancing innovation performance. Small-scale pilots and iterative experimentation generate implementation knowledge that formal evaluation frameworks cannot substitute. Second, they should invest in measurement readiness in parallel with, rather than as a prerequisite for, implementation. The dual-pathway finding indicates that measurement and action are complementary: partnerships that both act and reflect outperform those that pursue either strategy in isolation. Third, they should address knowledge barriers directly, as they constrain the conversion of implementation experience into innovation outcomes regardless of the gap's magnitude. Targeted investments in AI expertise, cross-partner training programmes, and knowledge-sharing mechanisms are necessary conditions for productive disequilibrium to generate performance benefits.

For policymakers, evaluation frameworks for AI adoption should incorporate process indicators alongside outcome indicators. Partnerships showing high experimentation alongside developing measurement systems should be recognised as being in a productive phase, and funding should support measurement development alongside implementation rather than requiring it as a precondition.

5.5 Limitations and Future Research

Several limitations warrant acknowledgment. The cross-sectional design precludes causal inferences; longitudinal research is needed to examine how productive knowledge disequilibrium evolves. The sample of 45 partnerships constrains statistical power for complex interaction models. The difference score operationalisation (Edwards, 2001) is partially addressed by the hierarchical design entering component variables first. Single key informants may not capture within-partnership heterogeneity.

6. Conclusion

This study examined the AI knowing-doing gap in innovation partnerships. The gap is widened by technology diversity and narrowed by measurement readiness. Both the gap and measurement readiness independently predict innovation performance, revealing complementary pathways to effective AI adoption.

We introduced the concept of productive knowledge disequilibrium to account for the counter-intuitive finding that the misalignment between action and measurement can serve a generative function in contexts of rapid technological change. This study makes three contributions to knowledge management theory. First, it extends the knowing-doing gap (Pfeffer and Sutton, 2000) from its original firm-level formulation to inter-organisational innovation partnerships, demonstrating that the gap operates differently when knowledge asymmetries, distributed governance, and heterogeneous absorptive capacities are present. Second, it challenges the assumption that knowledge-action misalignment is uniformly detrimental by identifying the conditions under which it functions as a generative force for collaborative innovation, connecting the knowing-doing gap literature to dynamic capabilities theory (Teece, 2007) and the concept of situated AI (Kemp, 2024). Third, it reveals a dual-pathway mechanism through which partnerships achieve innovation performance, integrating action-oriented experiential learning with reflection-oriented measurement, and thereby contributing to ongoing debates about ambidexterity and the sequencing of exploration and exploitation in organisational learning (Zimmermann et al., 2023). Successful partnerships manage the productive tension between experiential learning and systematic evaluation, pursuing action and reflection in parallel rather than in sequence.

Ethics declaration: This research involved the collection of organisational-level data from partnership representatives via an anonymised online survey. No personally identifiable data were collected. Ethical clearance was obtained from the author's institution prior to data collection.

AI declaration: AI tools were used to assist with statistical code verification and language editing during the preparation of this manuscript. All analytical decisions, theoretical development, interpretation, and writing were conducted by the author.

References

- Alavi, M., Leidner, D. and Mousavi, R. (2024) "Knowledge management perspective of generative artificial intelligence", *Journal of the Association for Information Systems*, Vol 25, No. 3, pp 1-15. <https://doi.org/10.17705/1jais.00859>
- Argyris, C. and Schön, D.A. (1978) *Organizational Learning: A Theory of Action Perspective*, Addison-Wesley, Reading, MA.
- Baruch, Y. and Holtom, B.C. (2008) "Survey response rate levels and trends in organizational research", *Human Relations*, Vol 61, No. 8, pp 1139-1160. <https://doi.org/10.1177/0018726708094863>
- Berente, N., Gu, B., Recker, J. and Santhanam, R. (2021) "Managing artificial intelligence", *MIS Quarterly*, Vol 45, No. 3, pp 1433-1450. <https://doi.org/10.25300/MISQ/2021/16274>
- Broekhuizen, T., Dekker, H., De Faria, P., Firk, S., Nguyen, D. and Sofka, W. (2023) "AI for managing open innovation: Opportunities, challenges, and a research agenda", *Journal of Business Research*, Vol 167, 114196. <https://doi.org/10.1016/j.jbusres.2023.114196>
- Carlile, P.R. (2004) "Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries", *Organization Science*, Vol 15, No. 5, pp 555-568. <https://doi.org/10.1287/orsc.1040.0094>
- Cohen, W.M. and Levinthal, D.A. (1990) "Absorptive capacity: A new perspective on learning and innovation", *Administrative Science Quarterly*, Vol 35, No. 1, pp 128-152. <https://doi.org/10.2307/2393553>
- Crossan, M.M., Lane, H.W. and White, R.E. (1999) "An organizational learning framework: From intuition to institution", *Academy of Management Review*, Vol 24, No. 3, pp 522-537. <https://doi.org/10.5465/amr.1999.2202135>
- Davenport, T.H. and Prusak, L. (1998) *Working Knowledge: How Organizations Manage What They Know*, Harvard Business School Press, Boston.

- Dyer, J.H. and Singh, H. (1998) "The relational view: Cooperative strategy and sources of interorganizational competitive advantage", *Academy of Management Review*, Vol 23, No. 4, pp 660-679. <https://doi.org/10.5465/amr.1998.1255632>
- Easterby-Smith, M., Lyles, M.A. and Tsang, E.W.K. (2008) "Inter-organizational knowledge transfer: Current themes and future prospects", *Journal of Management Studies*, Vol 45, No. 4, pp 677-690. <https://doi.org/10.1111/j.1467-6486.2008.00773.x>
- Edwards, J.R. (2001) "Ten difference score myths", *Organizational Research Methods*, Vol 4, No. 3, pp 265-287. <https://doi.org/10.1177/109442810143005>
- Füller, J., Hutter, K., Wahl, J., Bilgram, V. and Tekic, Z. (2022) "How AI revolutionizes innovation management: Perceptions and implementation preferences of AI-based innovators", *Technological Forecasting and Social Change*, Vol 178, 121598. <https://doi.org/10.1016/j.techfore.2022.121598>
- Gama, F. and Magistretti, S. (2023) "Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications", *Journal of Product Innovation Management*, Vol 40, No. 4, pp 515-542. <https://doi.org/10.1111/jpim.12698>
- Huber, G.P. (1991) "Organizational learning: The contributing processes and the literatures", *Organization Science*, Vol 2, No. 1, pp 88-115. <https://doi.org/10.1287/orsc.2.1.88>
- Jia, N., Luo, X., Fang, Z. and Liao, C. (2024) "When and how artificial intelligence augments employee creativity", *Academy of Management Journal*, Vol 67, No. 1, pp 5-32. <https://doi.org/10.5465/amj.2022.0426>
- Kellogg, K.C., Valentine, M.A. and Christin, A. (2020) "Algorithms at work: The new contested terrain of control", *Academy of Management Annals*, Vol 14, No. 1, pp 366-410. <https://doi.org/10.5465/annals.2018.0174>
- Kemp, A. (2024) "Competitive advantage through artificial intelligence: Toward a theory of situated AI", *Academy of Management Review*, Vol 49, No. 3, pp 618-635. <https://doi.org/10.5465/amr.2020.0205>
- Kogut, B. and Zander, U. (1992) "Knowledge of the firm, combinative capabilities, and the replication of technology", *Organization Science*, Vol 3, No. 3, pp 383-397. <https://doi.org/10.1287/orsc.3.3.383>
- Kolb, D.A. (1984) *Experiential Learning: Experience as the Source of Learning and Development*, Prentice-Hall, Englewood Cliffs, NJ.
- Lane, P.J. and Lubatkin, M. (1998) "Relative absorptive capacity and interorganizational learning", *Strategic Management Journal*, Vol 19, No. 5, pp 461-477. [https://doi.org/10.1002/\(SICI\)1097-0266\(199805\)19:5<461::AID-SMJ953>3.0.CO;2-I](https://doi.org/10.1002/(SICI)1097-0266(199805)19:5<461::AID-SMJ953>3.0.CO;2-I)
- Lebovitz, S., Lifshitz-Assaf, H. and Levina, N. (2022) "To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis", *Organization Science*, Vol 33, No. 1, pp 126-148. <https://doi.org/10.1287/orsc.2021.1549>
- Leonard-Barton, D. (1995) *Wellsprings of Knowledge: Building and Sustaining the Sources of Innovation*, Harvard Business School Press, Boston.
- Levinthal, D.A. and March, J.G. (1993) "The myopia of learning", *Strategic Management Journal*, Vol 14, No. S2, pp 95-112. <https://doi.org/10.1002/smj.4250141009>
- March, J.G. (1991) "Exploration and exploitation in organizational learning", *Organization Science*, Vol 2, No. 1, pp 71-87. <https://doi.org/10.1287/orsc.2.1.71>
- McPhillips, M. (2025) "AI adoption in open innovation partnerships: Trends, challenges, and strategic implications", in *Proceedings of the 26th European Conference on Knowledge Management*, Academic Conferences International, Reading. <https://doi.org/10.34190/eckm.26.1.3590>
- Mikalef, P. and Gupta, M. (2021) "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance", *Information and Management*, Vol 58, No. 3, 103434. <https://doi.org/10.1016/j.im.2021.103434>
- Mintzberg, H. (1994) *The Rise and Fall of Strategic Planning*, Free Press, New York.
- Murray, A., Rhymer, J. and Sirmon, D.G. (2021) "Humans and technology: Forms of conjoined agency in organizations", *Academy of Management Review*, Vol 46, No. 3, pp 552-571. <https://doi.org/10.5465/amr.2019.0186>
- Nonaka, I. (1994) "A dynamic theory of organizational knowledge creation", *Organization Science*, Vol 5, No. 1, pp 14-37. <https://doi.org/10.1287/orsc.5.1.14>
- Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V. and van den Oord, A. (2007) "Optimal cognitive distance and absorptive capacity", *Research Policy*, Vol 36, No. 7, pp 1016-1034. <https://doi.org/10.1016/j.respol.2007.04.003>
- Olan, F., Arakpogun, E., Suklan, J., Nakpodia, F., Damij, N. and Jayawickrama, U. (2022) "Artificial intelligence and knowledge sharing: Contributing factors to organizational performance", *Journal of Business Research*, Vol 145, pp 605-615. <https://doi.org/10.1016/j.jbusres.2022.03.008>
- Pfeffer, J. and Sutton, R.I. (2000) *The Knowing-Doing Gap: How Smart Companies Turn Knowledge into Action*, Harvard Business School Press, Boston.
- Raisch, S. and Krakowski, S. (2021) "Artificial intelligence and management: The automation-augmentation paradox", *Academy of Management Review*, Vol 46, No. 1, pp 192-210. <https://doi.org/10.5465/amr.2018.0072>
- Rogers, E.M. (2003) *Diffusion of Innovations*, 5th edition, Free Press, New York.
- Szulanski, G. (1996) "Exploring internal stickiness: Impediments to the transfer of best practice within the firm", *Strategic Management Journal*, Vol 17, No. S2, pp 27-43. <https://doi.org/10.1002/smj.4250171105>
- Teece, D.J. (2007) "Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance", *Strategic Management Journal*, Vol 28, No. 13, pp 1319-1350. <https://doi.org/10.1002/smj.640>

- van Wijk, R., Jansen, J.J.P. and Lyles, M.A. (2008) "Inter- and intra-organizational knowledge transfer: A meta-analytic review and assessment of its antecedents and consequences", *Journal of Management Studies*, Vol 45, No. 4, pp 830-853. <https://doi.org/10.1111/j.1467-6486.2008.00771.x>
- Von Krogh, G. (2018) "Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing", *Academy of Management Discoveries*, Vol 4, No. 4, pp 404-409. <https://doi.org/10.5465/amd.2018.0084>
- Weick, K.E. (1995) *Sensemaking in Organizations*, Sage, Thousand Oaks, CA.
- Zahra, S.A. and George, G. (2002) "Absorptive capacity: A review, reconceptualization, and extension", *Academy of Management Review*, Vol 27, No. 2, pp 185-203. <https://doi.org/10.5465/amr.2002.6587995>
- Zimmermann, A., Raisch, S. and Cardinal, L.B. (2023) "Managing persistent tensions on the frontline: A configurational perspective on ambidexterity", *Journal of Management Studies*, Vol 60, No. 4, pp 951-985. <https://doi.org/10.1111/joms.12884>