Integrating HI × AI to Improve Problem Identification and Innovation Practice in Organizations

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Author's Note

Portions of this annotated bibliography were developed with assistance from generative AI tools (ChatGPT) and writing-support software (Grammarly). These tools were used to help summarize articles, clarify concepts, refine wording, and correct minor grammatical issues. All ideas, analyses, and conclusions are my own, and all citations were reviewed for accuracy by the author. This use of digital tools reflects the HI × AI approach, in which human insights guide, evaluate, and validate AI-supported tasks.

Problem of Practice

Research across innovation, organizational learning, and design thinking shows that organizations often struggle with innovation because they lack consistent, scalable, and repeatable processes for identifying problems and creating solutions (Christensen, 1997; Liedtka, 2015; Van de Ven et al., 1995). Innovation scholarship emphasizes that progress occurs through iterative cycles of inquiry, prototyping, implementation, measurement, and refinement (Brown, 2009; Argyris & Schön, 1978; Damschroder et al., 2009). These models show that successful innovation arises from repeated cycles of experimentation rather than linear planning. Despite this evidence, many organizations continue to rely on fragmented methods or prematurely adopt data-driven or intelligence tools without a clear understanding of the underlying problem (Brown, 2009; Pisano, 2019). As a result, they often produce solutions that are misaligned, difficult to implement within existing systems, or unsustainable over time (Senge, 1990; Leonard-Barton, 1992).

The HI × AI framework described in *AMPLIFIED! How to identify the right problem and create the right solution with Human Insights × Artificial Intelligence* (forthcoming, CRC Press, 2026) addresses this gap by amplifying Human Insights with Artificial Intelligence to strengthen both problem identification and solution creation. AMPLIFIED! is an emerging practice-based framework developed by the author that positions Human Insights as the foundation and Artificial Intelligence as the multiplier that accelerates meaning-making, creativity, and implementation. Early practitioner work, including *Why Human Insights Matter More Than Intelligence*, *AI Will Not Kill Your Critical Thinking, Unless You Let It*, and *HI × AI: The Leadership Framework for a New Era of Innovation*, introduces this model by emphasizing that insight must precede intelligence for innovation to be effective. HI provides the context, empathy, and meaning needed to define why a problem matters, while AI contributes acceleration, pattern recognition, and generative capability once direction is clear. Together, HI × AI supports an innovation process that is teachable, scalable, and repeatable, with knowledge compounding as organizations revisit and refine their understanding of the problem.

This problem of practice investigates how organizations can improve innovation performance by applying the HI × AI framework across the innovation cycle. It examines the internal and external factors that influence problem identification and innovation adoption, as well as the human and organizational dynamics that shape implementation and iterative refinement. Supported by case stories, workshop applications, and emerging research, this work seeks to understand how HI × AI can help organizations identify the right problem, create the right solution, and sustain innovation with clarity, purpose, and long-term impact.

Peer-Reviewed Research on Innovation Adoption and Implementation

The peer-reviewed research that follows offers the empirical foundation for understanding how organizations adopt and implement innovation in complex environments. These studies examine the internal and external factors that shape adoption decisions and the human and organizational dynamics that influence implementation outcomes, aligning directly with Course Learning Outcome 1 (which focuses on evaluating the internal and external factors influencing innovation adoption within organizations). Drawing on leadership, organizational behavior, design, and implementation science, this section clarifies the conditions that support effective innovation practice. It also provides the evidence needed to evaluate how the HI × AI framework described in *AMPLIFIED!* can strengthen both problem identification and solution creation. Together, these findings support a deeper investigation into how organizations can build a scalable, repeatable innovation process that delivers clarity, alignment, and sustained impact.

1. Internal Factors Influencing Innovation Adoption

Internal factors shape how organizations interpret problems, decide what is worth solving, and adopt innovation with clarity and alignment. Research shows that internal factors such as leadership behavior, organizational culture, communication patterns, readiness for change, and structural capacity influence whether innovation moves forward or stalls (Armenakis & Harris, 2009; Damschroder et al., 2009; Jung et al., 2003; Lewis & Seibold, 1998; Schein, 1990). These internal conditions shape the insight work required to identify the right problem and determine how effectively teams can align around a shared direction. Human-centered practices such as sensemaking, reflection, and collaborative leadership enable organizations to frame problems more accurately and create the conditions for AI-enabled tools to accelerate the work once the direction is set. Together, these internal factors form the foundation of adoption and directly support the HI × AI model by ensuring that insight precedes intelligence and that technological capability amplifies, rather than replaces, human understanding.

1.1 Schein, E. H. (1990). Organizational culture.

Citation: Schein, E. H. (1990). Organizational culture. *American Psychologist, 45*(2), 109–119. https://doi.org/10.1037/0003-066X.45.2.109

Annotation: Schein explains organizational culture as the shared assumptions that guide how people interpret problems, evaluate information, and respond to change. Culture shapes whether employees see innovation as relevant, necessary, or risky. These underlying assumptions influence internal communication patterns, psychological safety, and openness to new ideas. Schein argues that leaders often underestimate the power of these shared beliefs when promoting innovation, resulting in adoption efforts that fail due to cultural misalignment rather than technical flaws. Within the HI × AI framework, the article underscores the importance of Human Insights preceding Artificial Intelligence. Insight work reveals the cultural context in which innovation decisions occur and clarifies how people make meaning and interpret the need for change. Adoption depends on whether cultural norms support exploration, questioning, and learning. Schein's analysis provides a foundational lens for understanding how internal cultural dynamics influence an organization's ability to identify the right problem and commit to new solutions with clarity and trust.

1.2 Jung, D. I., Chow, C., & Wu, A. (2003). Transformational leadership.

Citation: Jung, D. I., Chow, C., & Wu, A. (2003). The role of transformational leadership in enhancing organizational innovation: Hypotheses and some preliminary findings. *The Leadership Quarterly, 14*(4–5), 525–544. https://doi.org/10.1016/S1048-9843(03)00050-X

Annotation: Jung and colleagues investigate how transformational leadership creates internal conditions that support innovation adoption. Their empirical study shows that leaders who provide vision, encourage intellectual stimulation, and demonstrate individualized consideration increase employees' openness to new ideas and commitment to change initiatives. Transformational leadership strengthens communication quality, trust, and shared meaning, all of which support the insight work needed to frame problems accurately. The authors find that leadership indirectly influences adoption by shaping team climate and collective efficacy. Within the HI × AI framework, this research highlights how leadership behaviors shape the internal readiness needed for AI-enabled tools to accelerate solution creation. Leaders who foster psychological safety and curiosity enable teams to engage deeply with problem identification rather than rushing to premature technical answers. This article provides strong evidence that transformational leadership is a key internal factor because it influences how people interpret challenges, align around priorities, and support new approaches.

1.3 Armenakis, A. A., & Harris, S. G. (2009). Organizational readiness.

Citation: Armenakis, A. A., & Harris, S. G. (2009). Reflections: Our journey in organizational change research and practice. *Journal of Change Management, 9*(2), 127–142. https://doi.org/10.1080/14697010902879079

Annotation: Armenakis and Harris identify organizational readiness for change as a central determinant of innovation adoption. They explain that readiness is shaped by five core beliefs: the need for change, the appropriateness of the proposed innovation, confidence in the organization’s capability, support from leadership, and personal relevance. These beliefs determine whether employees interpret change as meaningful and feasible, making readiness a psychological and relational condition rather than a procedural one. The authors argue that readiness must be cultivated before implementation begins. This aligns closely with the HI × AI framework, which positions insight work ahead of intelligence work. People must understand why a problem matters before evaluating how AI or other tools might accelerate solutions. The readiness model reinforces the importance of communication, involvement, and sensemaking in the early stages of adoption. This article offers a foundational perspective on how internal belief structures influence an organization's ability to commit to innovation with clarity, confidence, and alignment.

1.4 Holt, D. T., Armenakis, A. A., Feild, H. S., & Harris, S. G. (2007). Change readiness measurement.

Citation: Holt, D. T., Armenakis, A. A., Feild, H. S., & Harris, S. G. (2007). Readiness for organizational change: The systematic development of a scale. *Journal of Applied Behavioral Science, 43*(2), 232–255. https://doi.org/10.1177/0021886306295295

Annotation: Holt and colleagues present one of the most widely used instruments for measuring organizational readiness for change. Their work extends the Armenakis and Harris model by developing and validating a reliable scale that assesses employees' beliefs about discrepancy, appropriateness, efficacy, principal support, and personal valence. The authors provide evidence that readiness is a measurable internal condition that directly influences whether innovation is adopted. Organizations with higher readiness scores demonstrate stronger engagement, more transparent communication, and more constructive attitudes toward change. This article is particularly relevant to the HI × AI framework because it operationalizes the human insights required for problem identification and early adoption decisions. Readiness functions as a diagnostic tool that helps organizations determine whether teams are prepared to engage in the insight work that precedes solution development. By making readiness measurable, the authors offer a practical method for assessing adoption potential and identifying internal barriers. This scale remains a valuable instrument for organizations seeking to implement innovation with greater accuracy, alignment, and sustainability.

1.5 Norman, D. A., & Stappers, P. J. (2015). DesignX.

Citation: Norman, D. A., & Stappers, P. J. (2015). DesignX: Complex sociotechnical systems. *She Ji: The Journal of Design, Economics, and Innovation, 1*(2), 83–106. https://doi.org/10.1016/j.sheji.2016.01.002

Annotation: Norman and Stappers introduce the DesignX framework to address problem identification and design within complex sociotechnical systems. They argue that traditional design approaches are insufficient for large-scale, interconnected challenges and emphasize the need for iterative learning, interdisciplinary collaboration, and contextual understanding. DesignX begins with deep insight work to understand the system, stakeholders, and underlying causes of the problem. The authors highlight that innovation adoption improves when organizations build internal structures that support reflection, framing, and feedback before moving into solution development. This aligns directly with the HI × AI model, which positions Human Insights as the foundation for defining direction and Artificial Intelligence as the accelerator once clarity is established. DesignX reinforces the principle that insight must precede intelligence and demonstrates how insight practices influence the quality of adoption. The article provides a strong conceptual foundation for understanding how teams frame the right problem and align around meaningful innovation goals within complex organizational environments.

2. External Factors Influencing Innovation Adoption

External factors shape the environment in which organizations evaluate innovation and determine whether adoption is feasible, necessary, or urgent. Research consistently shows that market pressures, institutional forces, technological acceleration, competitive dynamics, and regulatory requirements influence how organizations perceive innovation opportunities and how quickly they commit to new solutions. These external conditions also shape expectations from customers, partners, and stakeholders, creating both constraints and opportunities for innovation. Understanding external factors is essential to the HI × AI framework, as Human Insights enable organizations to interpret environmental signals with clarity and relevance. At the same time, Artificial Intelligence supports faster scanning, modeling, and analysis of complex external conditions. Together, these capabilities inform more intentional and strategically aligned adoption decisions. The following peer-reviewed studies illustrate how external forces shape the landscape of innovation adoption and influence the context in which organizations identify problems and evaluate potential solutions.

2.1 DiMaggio, P. J., & Powell, W. W. (1983). Institutional isomorphism.

Citation: DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160. https://doi.org/10.2307/2095101

Annotation: DiMaggio and Powell explain how institutional pressures drive organizations to adopt similar innovations regardless of internal needs or strategic priorities. They identify three forms of isomorphism: coercive pressures from regulation, mimetic pressures from uncertainty, and normative pressures from professional standards. These forces shape organizational decisions by establishing expectations about what "legitimate" or "modern" organizations should do. Adoption often becomes a response to conformity rather than a reflection of internal insight. This study is foundational for understanding how external environments influence innovation, particularly in sectors where regulatory and competitive forces exert intense alignment pressure. In the HI × AI framework, this work underscores the importance of insight work to accurately interpret external forces before committing to innovation. AI-enabled tools may accelerate scanning or benchmarking, but Human Insights determine whether external pressures align with actual organizational needs and context. The article reinforces the need to balance environmental legitimacy with internal clarity to avoid adopting innovations that lack strategic or human relevance.

2.2 Oliveira, T., & Martins, M. F. (2011). The TOE model review.

Citation: Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at the firm level. Information & Management, 49(5), 294–307. https://academic-publishing.org/index.php/ejise/article/view/389

Annotation: Oliveira and Martins review firm-level technology adoption models, focusing on the Technology–Organization–Environment (TOE) framework. Their synthesis shows that environmental conditions such as competitive intensity, external support, industry structure, and regulatory context significantly influence adoption decisions. The authors highlight that organizations often adopt innovation in response to competitive pressure or opportunities for differentiation. They also note that external readiness factors, including vendor maturity and technological infrastructure, shape the timing and feasibility of adoption. The review provides strong empirical support for viewing adoption as a function of both internal capability and external opportunity. Within the HI × AI framework, this study illustrates how AI can accelerate environmental scanning and pattern detection, while Human Insights remain essential for interpreting contextual signals and determining strategic fit. The TOE framework reinforces that adoption depends on an organization's ability to navigate environmental uncertainty with clarity. This article provides a rigorous foundation for understanding how external pressures shape adoption and why insight work is necessary before applying AI-enabled tools.

2.3 Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). UTAUT.

Citation: 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

Annotation: Venkatesh and colleagues integrate eight major technology adoption models into the Unified Theory of Acceptance and Use of Technology (UTAUT), offering one of the most influential frameworks in information systems research. Their empirical analysis shows that performance expectancy, effort expectancy, social influence, and facilitating conditions are the strongest predictors of technology adoption. Social influence represents a key external factor because peer expectations, industry norms, and stakeholder pressures shape perceptions of legitimacy and usefulness. The study demonstrates that adoption is not solely a technical decision but also a social and environmental one influenced by expectations beyond the organization's boundaries. Within the HI × AI framework, UTAUT illustrates how AI can support modeling, forecasting, and analyzing adoption patterns, while Human Insights remain essential for interpreting social signals and aligning technology decisions with organizational purpose. The authors emphasize that human attitudes, trust, and interpretation moderate the influence of external factors. This article provides a foundational understanding of how external pressures shape adoption behavior and why internal clarity is necessary to respond effectively.

2.4 Zhu, K., Kraemer, K., & Xu, S. (2006). Institutional environments and diffusion.

Citation: Zhu, K., Kraemer, K. L., & Xu, S. (2006). The process of innovation assimilation by firms in different countries: A technology diffusion perspective. Management Science, 52(10), 1557–1576. https://doi.org/10.1287/mnsc.1050.0487

Annotation: Zhu, Kraemer, and Xu examine how institutional environments influence the process of innovation assimilation across countries. Using survey data from more than 1,000 organizations, they show that environmental factors such as national policy, market sophistication, and technological infrastructure significantly affect the timing, pace, and depth of adoption. Firms operating in supportive institutional environments exhibit higher adoption rates and stronger assimilation of innovation capabilities. The authors also find that external pressures, including global competition and customer expectations, accelerate the adoption of new technologies. This article strengthens the external factors section by demonstrating how macro-level conditions shape organizational decisions and motivate adoption. Within the HI × AI framework, the study highlights the need for insight work to interpret institutional signals and determine whether an innovation aligns with organizational purpose. AI-enabled tools can support environmental scanning and analysis, but Human Insights determine meaning, relevance, and direction. This article provides robust evidence that institutional environments play a critical role in shaping adoption behavior across diverse contexts.

2.5 Bharadwaj, El Sawy, Pavlou, & Venkatraman (2013): Digital Business Strategy and External Pressures

Citation: Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, 37(2), 471–482. https://doi.org/10.25300/MISQ/2013/37:2.3

Annotation: External pressures not only shape technology adoption—they reshape strategy itself. Bharadwaj et al. (2013) argue that digital business strategy emerges in response to accelerating environmental forces such as market turbulence, competitive intensity, technological volatility, and rapidly changing customer expectations. These pressures create conditions in which organizations must continuously sense shifts in their environment, re-evaluate strategic priorities, and realign resources to remain competitive. Their work demonstrates that external forces do more than influence adoption decisions; they drive the need for new organizational capabilities, faster learning cycles, and clearer insight into what problems truly matter. This supports the HI × AI model by showing that environmental pressure is often the trigger for insight work. When organizations face uncertainty or disruption, they must first interpret these external signals with clarity (HI) before using AI-enabled tools to accelerate exploration and execution. In this way, external pressures are catalysts that push organizations toward innovation while reinforcing the need for insight-led interpretation before intelligent action.

3. Human Dynamics Influencing Innovation Implementation

Human dynamics play a central role in determining whether innovation is implemented with fidelity and sustained over time. Research shows that psychological safety, sensemaking, motivation, resistance, and learning behaviors directly influence whether individuals engage with new practices, interpret change constructively, and support implementation efforts. These human factors shape how people understand the purpose behind innovation and whether they trust the process enough to participate fully. Within the HI × AI framework, Human Insights represent the core of implementation because people choose how to interpret problems, adopt solutions, and respond to uncertainty. AI tools can accelerate analysis, generate insights, or streamline tasks, but implementation succeeds only when individuals feel safe, supported, informed, and aligned. The following peer-reviewed studies illustrate the human conditions that enable or hinder effective implementation and highlight why insight-driven engagement is essential before intelligence-driven acceleration.

3.1 Edmondson, A. (1999). Psychological safety.

Citation: Edmondson, A. (1999). Psychological safety and learning behavior in work teams. Administrative Science Quarterly, 44(2), 350–383. https://doi.org/10.2307/2666999

Annotation: Edmondson's study on psychological safety is foundational for understanding how human behavior influences the implementation of innovation. Through mixed-method research in manufacturing and healthcare teams, she shows that psychological safety enables open communication, experimentation, and error reporting. These behaviors are essential for implementing new practices because they require individuals to navigate uncertainty and learn through iteration. Edmondson finds that teams with higher levels of psychological safety are more willing to test new approaches, surface concerns, and contribute ideas, which improves implementation fidelity and accelerates improvement. Within the HI × AI framework, psychological safety reinforces the importance of Human Insights by enabling people to interpret new solutions with curiosity rather than fear. AI tools may support analysis or problem-solving, but implementation depends on whether individuals feel safe enough to ask questions, identify issues, and participate actively in refinement. Edmondson's work provides strong evidence that human dynamics shape whether innovation becomes embedded in daily practice and contributes to sustained organizational improvement.

3.2 Oreg, S. (2006). Resistance to change.

Citation: Oreg, S. (2006). Personality, context, and resistance to organizational change. Personnel Psychology, 59(4), 913–946. https://doi.org/10.1080/13594320500451247

Annotation: Oreg examines how personality traits and contextual factors influence resistance to change, a key barrier to the implementation of innovation. Through a series of empirical studies, he identifies dispositional resistance, perceived control, and communication quality as major predictors of how individuals respond to organizational change. The research shows that people resist change not only because of the change itself but because of how they interpret its purpose, fairness, and impact. These findings align with the HI × AI framework by highlighting the centrality of human interpretation in implementation. Human Insights reveal how individuals make meaning of change and what concerns must be addressed to promote engagement. AI can support communication and decision-making, but it cannot overcome resistance rooted in fear, uncertainty, or lack of ownership. Oreg's study underscores that successful implementation requires understanding individual differences, building trust, and involving employees early in the process. This work provides a strong foundation for examining human barriers and enablers of innovation adoption and sustained implementation.

3.3 Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Sensemaking.

Citation: Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. Organization Science, 16(4), 409–421. https://doi.org/10.1287/orsc.1050.0133

Annotation: Weick and colleagues provide a theoretical explanation of sensemaking as the process through which individuals interpret events, construct meaning, and guide action. Sensemaking is critical during innovation implementation because people must understand what the change is, why it matters, and how it affects their work. The authors argue that implementation becomes more effective when organizations create opportunities for ongoing interpretation and dialogue. Sensemaking supports alignment, reduces ambiguity, and helps teams navigate unexpected challenges. Within the HI × AI framework, sensemaking represents a core Human Insight mechanism that gives purpose to technological tools. AI can generate information, insights, and predictions, but humans determine relevance, meaning, and action. Implementation succeeds when individuals actively engage in interpretation rather than passively receiving directives. Weick's work offers a powerful lens for understanding how human cognition and shared meaning shape implementation success and provides the interpretive foundation for iterative learning within complex systems.

3.4 Ford, J. D., Ford, L. W., & D'Amelio, A. (2008). Resistance reconsidered.

Citation: Ford, J. D., Ford, L. W., & D'Amelio, A. (2008). Resistance to change: The rest of the story. Academy of Management Review, 33(2), 362–377. https://doi.org/10.5465/amr.2008.31193235

Annotation: Ford and colleagues challenge traditional views of resistance by reframing it as engagement rather than an obstacle. They argue that resistance provides valuable feedback about concerns, misalignments, or unmet needs in the change process. Through conceptual analysis, they show that resistance often arises from gaps in communication, lack of clarity, or perceived misalignment between proposed changes and existing work systems. This perspective aligns with the HI × AI framework by emphasizing that Human Insights are essential for interpreting resistance as information rather than opposition. AI tools may support monitoring or feedback analysis, but only human interpretation can uncover the underlying meaning behind responses to change. The authors highlight that when organizations treat resistance as a resource, they can adapt implementation strategies, strengthen alignment, and improve adoption. This reframing explains why implementation succeeds when organizations foster dialogue, address concerns directly, and incorporate diverse perspectives. Ford's work offers a sophisticated understanding of human dynamics in change, demonstrating that resistance can play a constructive role in shaping successful innovation.

3.5 Van de Ven, A. H., & Poole, M. S. (1995). Human dynamics in change processes.

Citation: Van de Ven, A. H., & Poole, M. S. (1995). Explaining development and change in organizations. Academy of Management Review, 20(3), 510–540. https://doi.org/10.5465/amr.1995.9508080329

Annotation: Van de Ven and Poole present a comprehensive framework for understanding the human and organizational dynamics that shape change processes. They identify four motors of change: life-cycle, teleological, dialectical, and evolutionary. Each represents a different pattern of human behavior, interaction, and coordination. Their model shows that implementation is not linear but shaped by competing perspectives, negotiation, conflict, adaptation, and ongoing learning. These dynamics influence how individuals interpret change and how collective action develops within organizations. This aligns with the HI × AI framework by emphasizing that Human Insights guide interpretation, negotiation, and adjustments throughout implementation. AI tools may support scenario modeling, analysis, or pattern recognition, but change requires human judgment, meaning-making, and collaborative alignment. This article provides a strong theoretical foundation for understanding why implementation depends on human engagement and how diverse viewpoints contribute to adaptive and sustained innovation. It reinforces the idea that implementation succeeds when individuals participate actively in shaping solutions rather than receiving them passively.

4. Organizational Dynamics Influencing Innovation Implementation

Organizational dynamics determine whether innovations move beyond early adoption and become embedded in daily practice. Systems, structures, workflows, and feedback mechanisms shape how effectively new solutions are implemented, refined, and sustained. Research shows that implementation quality depends on alignment among organizational processes, learning systems, and improvement routines, as well as the ability to balance exploration with operational demands. These dynamics influence how people interact with solutions, interpret their purpose, and integrate new practices into their work. Within the HI × AI framework, organizational dynamics provide the structures that allow Human Insights to circulate and enable Artificial Intelligence to accelerate learning and optimization. The following studies illustrate how organizational environments support or constrain the implementation and long-term sustainability of innovation and why effective implementation requires coherent systems that amplify both insight and intelligence.

4.1 Damschroder et al. (2009). The CFIR model.

Citation: Damschroder, L. J., Aron, D. C., Keith, R. E., Kirsh, S. R., Alexander, J. A., & Lowery, J. C. (2009). Fostering implementation of health services research findings into practice: A consolidated framework for advancing implementation science. Implementation Science, 4, 50. https://doi.org/10.1186/1748-5908-4-50

Annotation: Damschroder and colleagues present the Consolidated Framework for Implementation Research (CFIR), one of the most comprehensive and widely used frameworks for understanding organizational determinants of implementation. CFIR identifies five domains that influence implementation outcomes: intervention characteristics, inner setting, outer setting, individual characteristics, and implementation processes. The framework shows that successful implementation depends on how well innovations align with organizational culture, workflows, leadership engagement, and communication structures. CFIR also highlights the importance of continuous evaluation and iterative refinement, which reinforces the idea that implementation is a dynamic cycle rather than a single event. Within the HI × AI framework, CFIR offers a structure for integrating insight and intelligence by showing how human interpretation and system-level factors interact throughout implementation. Human Insights shape how teams understand and adapt an innovation to their context, while AI can support measurement, monitoring, and optimization. This article provides essential conceptual grounding for analyzing organizational determinants of implementation and supports the iterative learning cycles emphasized in AMPLIFIED!.

4.2 March, J. G. (1991). Exploration and exploitation.

Citation: March, J. G. (1991). Exploration and exploitation in organizational learning. Organization Science, 2(1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Annotation: March's seminal work explains how organizations must balance exploration of new ideas with exploitation of existing capabilities to sustain innovation. Exploration involves experimentation, variation, and discovery, while exploitation involves refinement, efficiency, and execution. March argues that organizations that invest too heavily in exploitation risk stagnation, while those that overemphasize exploration lack the stability needed to integrate new practices. Implementation depends on maintaining this balance because new solutions must be tested, adapted, and integrated into existing systems without disrupting performance. This framework aligns with HI × AI because Human Insights support exploration through interpretation and problem framing, while Artificial Intelligence can accelerate exploitation through optimization and analytical efficiency. Effective implementation requires organizations to cycle between insight-driven exploration and intelligence-driven refinement, mirroring the iterative structure described in AMPLIFIED! March's theory provides a foundational understanding of organizational learning dynamics and helps explain why some innovations fail to scale or endure.

4.3 Bessant, J., & Caffyn, S. (1997). High-involvement innovation.

Citation: Bessant, J., & Caffyn, S. (1997). High-involvement innovation through continuous improvement. International Journal of Technology Management, 14(1), 7–28. https://doi.org/10.1504/IJTM.1997.001705

Annotation: Bessant and Caffyn introduce the concept of high-involvement innovation, where continuous improvement and innovation become part of everyday organizational routines. Their study shows that organizations with distributed participation, robust suggestion systems, and learning-oriented processes achieve stronger implementation outcomes. High-involvement innovation depends on structures that enable employees at all levels to contribute insights, identify problems, and refine solutions. This approach aligns closely with the HI × AI framework because it emphasizes human-driven insight generation and collective problem solving, while allowing AI tools to support analysis, feedback, and pattern detection. Implementation improves when organizations create mechanisms that encourage ongoing input, foster psychological safety, and institutionalize learning. The article provides practical guidance for embedding innovation into daily work and shows why implementation requires both human engagement and system-level support.

4.4 Leonard-Barton, D. (1992). Core capabilities and rigidities.

Citation: Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in new product development. Strategic Management Journal, 13(S1), 111–125. https://doi.org/10.1002/smj.4250131009

Annotation: Leonard-Barton analyzes how organizational capabilities that support performance can also become rigidities that hinder the implementation of innovation. She identifies four dimensions of core capabilities: skills, systems, managerial processes, and values. Each can evolve into a barrier when organizations rely too heavily on established routines or resist necessary change. This paradox explains why innovations that require new behaviors or perspectives often encounter resistance, even when they align with strategic goals. Implementation is shaped by whether existing systems and values support learning, experimentation, and adaptation. This framework aligns with HI × AI by illustrating that Human Insights are needed to recognize when established practices no longer serve organizational objectives and when new approaches are required. AI tools may help reveal inefficiencies or opportunities, but overcoming rigidities requires insight into cultural and systemic constraints. Leonard-Barton’s work provides a critical perspective on how organizational strengths can obstruct innovation and why implementation requires both structural flexibility and reflective practice.

4.5 Adler, P. S., Goldoftas, B., & Levine, D. I. (1999). Lean production and learning.

Citation: Adler, P. S., Goldoftas, B., & Levine, D. I. (1999). Flexibility versus efficiency? A case study of model changeovers in the Toyota Production System. Organization Science, 10(1), 43–68. https://doi.org/10.1287/orsc.10.1.43

Annotation: Adler and colleagues examine how the Toyota Production System balances flexibility and efficiency during model changeovers, offering insights into organizational dynamics that support effective implementation. Their case study shows that successful implementation depends on structured routines, continuous learning, employee involvement, and strong communication channels. The authors demonstrate that organizations can achieve both reliability and adaptability when systems are designed to support iterative problem-solving and collective responsibility. This balance mirrors the HI × AI framework, in which Human Insights guide interpretation, learning, and problem identification. At the same time, Artificial Intelligence enhances efficiency, optimization, and feedback analysis. The Toyota example illustrates how implementation improves when organizations integrate disciplined processes with opportunities for reflection and improvement. This study provides evidence that system design, learning architecture, and team-level engagement shape implementation quality and help innovations become embedded in daily operations.

5. ROI and Value Realization in Innovation Implementation

Return on investment is a central indicator of whether innovation delivers meaningful value and can be sustained over time. Implementation science shows that financial outcomes, performance improvements, user experience gains, and operational efficiencies influence whether organizations continue to invest in and support new practices. ROI also serves as a feedback mechanism, linking adoption efforts to measurable impact and informing decisions about scale, sustainability, and further iteration. Within the HI × AI framework, Human Insights define what value should look like and why it matters, while Artificial Intelligence accelerates measurement, forecasting, and evaluation. Together, HI and AI strengthen an organization's ability to determine whether innovations achieve their intended outcomes and whether refinement is needed to improve effectiveness. The following studies examine how organizations evaluate the value of innovation and how ROI shapes long-term implementation and continuous improvement.

5.1 Goldzweig et al. (2009). Costs and benefits of innovation implementation.

Citation: Goldzweig, C. L., Towfigh, A. A., Paige, N. M., & Shekelle, P. G. (2009). Costs and benefits of health information technology: New trends from the literature. Health Affairs, 28(2), w282–w293. https://doi.org/10.1377/hlthaff.28.2.w282

Annotation: Goldzweig and colleagues review empirical evidence on the costs and benefits of large-scale innovation implementation in the context of health information technology. Their analysis shows that return on investment varies widely based on implementation quality, workflow alignment, user engagement, and leadership support. Organizations that integrate technology into existing processes and involve employees early in the transition achieve stronger performance outcomes. Those who implement technology without addressing human or organizational factors often fail to realize value. The authors note that ROI is influenced by both direct financial results and indirect benefits, such as improved quality, reduced errors, and better coordination. This aligns with the HI × AI framework by emphasizing that value emerges when Human Insights guide the design, adaptation, and adoption of AI-enabled tools. AI can accelerate performance measurement and analysis, but humans must define meaningful outcomes and interpret results. This article provides strong evidence that ROI should be treated as a multidimensional measure that reflects the interaction of human, organizational, and technological factors during implementation.

5.2 Melville, Kraemer, & Gurbaxani (2004). IT business value and performance.

Citation: Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Information technology and organizational performance: An integrative model of IT business value. MIS Quarterly, 28(2), 283–322. https://doi.org/10.2307/25148636

Annotation: Melville and colleagues present an integrative model explaining how information technology investments create organizational value. Drawing from empirical studies across industries, they show that IT generates performance gains only when supported by human capital, organizational processes, and complementary assets. The authors argue that value realization depends on alignment between technology and organizational context. This supports the HI × AI framework by demonstrating that Artificial Intelligence alone cannot produce measurable value. It must be paired with insight-driven design, user engagement, and strategic clarity. The study concludes that return on investment arises from the interaction between technical and organizational capabilities. Their model provides a strong foundation for understanding how innovation creates value and why implementation requires both human understanding and structural alignment. This article helps explain why some organizations achieve strong returns from new technologies while others do not, making it highly relevant to innovation implementation.

5.3 Devaraj & Kohli (2003). Usage as the link to performance impact.

Citation: Devaraj, S., & Kohli, R. (2003). Performance impacts of information technology: Is actual usage the missing link? Management Science, 49(3), 273–289. https://doi.org/10.1287/mnsc.49.3.273.12736

Annotation: Devaraj and Kohli investigate the relationship between IT investment and organizational performance, emphasizing that actual usage mediates the link between adoption and value realization. Their study demonstrates that organizations generate positive return on investment only when employees meaningfully engage with new tools and integrate them into daily workflows. Adoption alone does not guarantee value. Usage quality and implementation fidelity are stronger predictors of performance outcomes. This aligns with the HI × AI framework by showing that Human Insights, reflected in how people interpret and apply technology, determine whether AI-enabled solutions generate measurable impact. AI may offer powerful analytical and automated capabilities, but value emerges only when humans use those capabilities effectively and with purpose. The study reinforces the need for insight-driven implementation strategies that support user engagement, training, and contextual adaptation. This article provides strong empirical evidence that return on investment is not a technical outcome but a human and organizational one.

5.4 Tallon (2010). Process alignment and IT value realization.

Citation: Tallon, P. P. (2010). A process-oriented perspective on the alignment of information technology and business strategy. Journal of Management Information Systems, 26(2), 227–268. https://doi.org/10.2753/MIS0742-1222240308

Annotation: Tallon examines how organizations create value from IT investments by aligning technology initiatives with business processes and strategic priorities. His findings show that value realization is strongest when organizations integrate technology into well-designed processes supported by training, communication, and continuous improvement. Misalignment between IT and organizational needs results in poor performance outcomes and limited return on investment. This connects directly to the HI × AI framework because insight work determines whether technology aligns with actual user needs and organizational goals. AI can enhance workflow optimization and data-driven decision-making, but technology produces value only when shaped by human understanding and embedded within supportive structures. Tallon's process-oriented perspective reinforces the importance of coherence between strategy, people, and systems during implementation. The article provides a valuable lens for analyzing how organizations convert IT investments into measurable performance gains, making it directly relevant to innovation implementation and return-on-investment analysis.

5.5 Nwankpa & Roumani (2016). IT capability, digital transformation, and firm performance

Citation: Nwankpa, J. K., & Roumani, Y. (2016). *IT capability and digital transformation: A firm performance perspective* [Conference paper]. **Thirty Seventh International Conference on Information Systems (ICIS)**, Dublin, Ireland.

Annotation: Nwankpa and Roumani examine how IT capability influences firm performance through the mediating role of digital transformation. Drawing on the resource-based view, they use survey data from 167 CIOs across U.S. firms and demonstrate that IT capability positively influences digital transformation, which in turn drives innovation and performance outcomes. Their model (shown in Figure 2 of the paper) confirms that the effect of IT capability on firm performance is partially mediated by the organization's ability to use digital technologies to reshape business processes, enhance customer engagement, and improve operational efficiency. This aligns strongly with the HI × AI framework because it shows that technological capability alone does not generate value; instead, value emerges when organizations pair technological resources with human-centered interpretation, redesign, and strategic integration. Digital transformation functions as the mechanism through which IT capability becomes meaningful, reinforcing the insight-first, intelligence-amplified structure at the core of the HI × AI model.

6. Integrating Human Insights and Artificial Intelligence in Innovation Practice

Integrating Human Insights with artificial intelligence is becoming increasingly important as organizations seek to enhance decision-making, creativity, and innovation performance. Research in hybrid intelligence, human–AI collaboration, and augmented decision systems shows that innovation improves when human interpretation, contextual understanding, and ethical reasoning are combined with the computational power of AI. Human Insights provide the sensemaking, meaning, and strategic framing needed to guide innovation efforts, while AI accelerates exploration, analysis, and solution generation. This convergence aligns directly with the HI × AI framework in *AMPLIFIED!*, where insight precedes intelligence and AI amplifies human capability rather than replacing it. Together, these complementary strengths support innovation across the full cycle of problem identification, solution creation, implementation, and iteration. The following peer-reviewed studies illustrate how human and artificial intelligence can be integrated to strengthen innovation practice and improve outcomes at scale.

6.1 Shrestha, Ben-Menahem, & von Krogh (2019). AI and organizational decision-making.

Citation: Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. California Management Review, 61(4), 66–83. https://doi.org/10.1177/0008125619862257

Annotation: Shrestha and colleagues examine how artificial intelligence reshapes organizational decision-making structures. Their study shows that AI expands analytical capacity and increases the speed of information processing, but effective use depends on human involvement in framing, interpretation, and judgment. The authors argue that AI shifts decision-making toward more distributed models in which humans collaborate with algorithms to evaluate alternatives and anticipate outcomes. This aligns directly with the HI × AI framework by emphasizing that insight work must guide algorithmic output. AI can generate options, detect patterns, or simulate scenarios, but humans determine meaning and direction. The authors highlight the importance of organizational structures that support transparency, explainability, and cross-functional collaboration. This article provides strong evidence for hybrid decision systems that combine human judgment with artificial intelligence and reinforces the need for processes that integrate insight and intelligence throughout innovation cycles.

6.2 Dellermann et al. (2019). Hybrid intelligence for innovation.

Citation: Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. Business & Information Systems Engineering, 61(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2

Annotation: Dellermann and colleagues introduce the concept of hybrid intelligence, which describes collaborative systems in which humans and artificial intelligence work together to solve complex problems. Their study argues that hybrid intelligence outperforms either humans or machines acting alone because it combines human creativity, empathy, and contextual reasoning with the computational power of AI. The authors highlight key design principles, including complementary roles, shared control, transparency, and iterative learning. This article strongly reinforces the HI × AI framework by demonstrating that innovation improves when insight and intelligence are integrated rather than treated as competing approaches. AI can explore large solution spaces and generate alternatives, while humans evaluate relevance, interpret context, and guide ethical considerations. Hybrid intelligence supports innovation by strengthening both problem identification and solution creation. This research provides a conceptual foundation for organizations seeking to use AI to enhance human capability rather than replace it.

6.3 Raisch & Krakowski (2021). The automation–augmentation paradox.

Citation: 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

Annotation: Raisch and Krakowski analyze the tension between automation and augmentation in organizational use of artificial intelligence. They argue that AI can either replace human tasks or amplify human capability, depending on how organizations design work systems. The authors show that augmentation produces stronger innovation outcomes because humans contribute contextual understanding, ethical reasoning, and interpretive insight. Automation may improve efficiency, but it limits organizational learning and reduces adaptability. This aligns with the HI × AI framework because Human Insights define purpose and meaning, while Artificial Intelligence accelerates execution once direction is established. The authors identify leadership, culture, and role design as key determinants of whether organizations pursue augmentation or automation. Their work supports viewing AI as a tool that enhances human creativity and problem-solving rather than replacing it. This article provides a strong theoretical foundation for implementing AI to support innovation and sustain human involvement in complex decision-making.

6.4 von Krogh (2018). AI-enabled innovation opportunities.

Citation: von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. Business Horizons, 61(6), 825–832. https://doi.org/10.5465/amd.2018.0084

Annotation: von Krogh explores the potential for artificial intelligence to expand organizational innovation capability. He argues that AI accelerates the generation and evaluation of ideas by analyzing large datasets, identifying patterns, and enabling rapid prototyping. The author emphasizes that meaningful innovation emerges only when AI is integrated with human creativity, empathy, and contextual understanding. AI can widen the range of possibilities, but humans determine relevance, value, and direction. This aligns directly with the HI × AI framework by showing that insight is required before intelligence can be effectively applied. von Krogh highlights the importance of organizational conditions such as learning culture, openness, and interdisciplinary collaboration in supporting successful AI-driven innovation. This article provides a contemporary perspective on how organizations can use AI to complement human capability and strengthen the innovation process.

6.5 Seeber et al. (2020). Human–AI collaboration in problem-solving.

Citation: Seeber, I., Bittner, E., Briggs, R. O., De Vreede, G. J., & Söllner, M. (2018). Machines as teammates: A collaboration research agenda. Information & Management, 57(2), 103213. https://doi.org/10.24251/HICSS.2018.055

Annotation: Seeber and colleagues examine how artificial intelligence can function as a teammate in collective problem-solving environments. Their conceptual work shows that effective collaboration with AI requires trust, transparency, role clarity, and shared mental models. The authors argue that when humans and AI work together, teams can explore more alternatives, process information faster, and reach more informed decisions. However, collaboration succeeds only when humans remain actively engaged in interpreting insights, framing challenges, and evaluating solutions. This supports the HI × AI framework by demonstrating that human involvement is essential throughout the innovation cycle. AI can enhance creativity and accelerate analysis, but innovation requires human understanding of context, relationships, and meaning. The authors call for organizational structures that enable seamless interaction between humans and intelligent systems, reinforcing the idea that innovation improves when insight and intelligence are integrated. This article provides strong justification for incorporating human AI collaboration models into innovation practice.

6.6 Drucker, P. F. (1967). Human judgment and intelligent tools.

Citation: Drucker, P. F. (1967). The manager and the moron. *The Atlantic Monthly, 220*(6), 63–67.

Annotation: Drucker's essay anticipates many of the challenges associated with modern artificial intelligence. He argues that technology cannot replace human judgment, observation, or insight. Drucker warns that managers often hide behind data and automation rather than engaging in direct observation and critical thinking. He maintains that the value of technology depends on the intelligence and clarity of the person using it. This idea aligns closely with the HI × AI framework, which asserts that Human Insights must guide the definition of problems and the interpretation of information before Artificial Intelligence can amplify performance. Drucker's perspective reinforces the need for human-centered decision-making and highlights that innovation fails when leaders delegate thinking to tools. His early analysis provides historical grounding for understanding why organizations must invest in insight work before leveraging AI-enabled methods.

Synthesis and Implications for Practice

The peer-reviewed studies reveal that innovation success depends on a set of interconnected conditions that shape how organizations adopt and implement new ideas. Internal factors such as leadership behavior, organizational culture, communication patterns, and readiness determine whether teams can engage in the insight work required to frame problems accurately and make aligned decisions about adoption. External factors, including market pressures, technological acceleration, competitive demands, and institutional expectations, influence when and why organizations commit to new solutions. Human dynamics such as psychological safety, sensemaking, motivation, and learning determine whether individuals engage with innovation activities and contribute to implementation with fidelity. Organizational dynamics, including system design, feedback structures, improvement routines, and learning architecture, influence whether innovations become embedded in long-term practice and evolve through iterative cycles.

The literature also highlights the role of value realization in sustaining innovation. ROI and related measures serve as feedback mechanisms that help organizations determine whether solutions are producing the intended outcomes. When implementation processes align human behavior, workflow design, and technological capability, organizations are more likely to achieve measurable improvements in performance, efficiency, and experience. These value signals reinforce learning and inform continued cycles of problem identification and solution development.

Together, these findings confirm that innovation is both a human and a systems process. It requires clarity of purpose, alignment across teams, and the capability to learn and adapt over time. The HI × AI framework strengthens this process by ensuring that Human Insights guide the definition of the problem and that Artificial Intelligence accelerates the creation, testing, and refinement of solutions. When organizations pair human understanding with technological capability, they develop a scalable, repeatable approach to innovation that compounds in value, like a fractal that grows in complexity and insight with each iteration. This integrated perspective supports the broader aim of *AMPLIFIED!*: helping organizations identify the right problem, create the right solution, and build the conditions for continuous improvement.

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