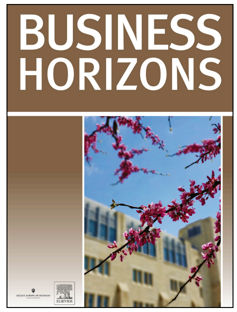

Managing the dual challenge of AI adoption: An integrative framework for employee and customer success

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PII: S0007-6813(26)00103-5

DOI: https://doi.org/10.1016/j.bushor.2026.06.010

Reference: BUSHOR 2162

To appear in: *Business Horizons*

Managing the dual challenge of AI adoption: An integrative framework for employee and customer success

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AI was used in this manuscript for language editing.

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Abstract

Despite massive investments in artificial intelligence, most pilots fail to achieve full business impact. We argue these failures stem from a critical oversight: Organizations treat employee and customer AI adoption as separate challenges rather than recognizing their interdependence. By analyzing past technology adoptions and interviewing employees and customers on current AI considerations, we identify consistent patterns where success hinges on simultaneously addressing both stakeholder groups' needs across different implementation stages. This paper introduces an integrative framework that maps management strategies to the intersection of the Gartner Hype Cycle's stages (Hype, Disillusionment, Enlightenment) and key stakeholders (Employees, Customers). Informed by theories of social contagion, socio-technical systems and the service-profit value chain, we distill our findings into a managerial toolkit. Our framework yields five recommendations: (1) set realistic expectations early to avoid credibility-damaging overhype; (2) invest in employee reskilling during disillusionment; (3) offer tangible customer benefits to maintain trust; (4) give employees agency in shaping AI applications; and (5) maintain competitive customer value. We demonstrate how organizations ignoring these principles experienced failures, while those applying them achieved sustainable integration. Our framework offers managers actionable guidance for navigating AI's unique challenges. Unlike previous specialized technologies, AI broadly touches customer interactions and employee workflows simultaneously, meaning failures in one group rapidly cascade to the other. Organizations recognizing and managing these interdependencies from the outset can overcome daunting failure statistics and realize AI's transformative potential.

KEYWORDS: Artificial intelligence adoption; Employee engagement; Customer experience; Technology implementation; Organizational change management

> *"If we feel good about using it [AI], then it seems like the customer also feels comfortable with us using it too. And they feel confident that we know what we're doing with it rather than just using it as an easy shortcut."* Interviewed[1] web developer at a software company (E4)

> *"It's better always to educate customers on how to use AI and how AI is used in our platform because that gives them more clarity [...] it increases the transparency of the company as well and it just builds trust."* Data scientist at a healthcare company (E5)

1. Introduction

The adoption of artificial intelligence (AI) in business shows high expectations but mixed results. Recent studies reveal alarming trends in AI implementation success rates. MIT's 2025 NANDA report found that approximately 95% of generative AI pilot programs fail to achieve measurable impact on profits and losses (Challapally et al., 2025). The RAND Corporation's 2024 study confirmed that over 80% of AI projects fail—twice the failure rate of non-AI technology projects (Ryseff et al., 2024). Moreover, abandonment rates are accelerating: S&P Global's 2025 survey found that 42% of companies abandoned most AI initiatives in 2025, up sharply from just 17% in 2024 (Johnston, 2025). Gartner reports that only 48% of AI projects make it past the pilot stage, with at least 30% of generative AI projects expected to be abandoned after proof of concept by the end of 2025 (Kumar, 2025).

A critical factor contributing to these failures is that AI adoption projects typically operate in silos, managed exclusively by technical teams with limited input from a small subset of employees (WRITER & Workplace Intelligence, 2025). However, full adoption requires addressing both technological and human factors, while most organizations focus disproportionately on technology while underinvesting in people strategies (Tursunbayeva & Chalutz-Ben Gal, 2024). In particular, successful AI adoption requires comprehensive involvement from both employees and customers throughout the implementation process (De Cremer, 2024). When employees across all levels actively participate in AI adoption, they develop the necessary *capabilities* to leverage these technologies effectively. Similarly, when customers are meaningfully engaged, they provide valuable *feedback* that shapes implementation in ways that enhance value creation.

The existing literature on AI adoption, however, tends to examine employee and customer management independently. Marketing literature focuses primarily on customer acceptance of AI technologies, exploring factors like perceived usefulness, ease of use, and trust (Davenport et al., 2020; Huang & Rust, 2021). Meanwhile, organizational behavior literature emphasizes employee readiness, resistance, and adaptation to AI systems (Bailey et al., 2022; Bankins et al., 2024).

[1] In April 2026, we interviewed 5 employees and 5 customers about AI adoption. See Appendix A for sample specifics and interview transcripts. Unless otherwise specified, all quotes in this manuscript are from these interviews.

Thus, silos in practice are reflected in silos in academia. This isolated approach fails to capture the intricate interdependencies between these stakeholder groups. Therefore, the time is ripe for a conceptual synthesis, applying academic insights on organizational transformation to this urgent practical problem in an integrative framework.

[Insert Figure 1 About Here]

As visualized in Figure 1, the connection between employees' and customers' acceptance and use of technology influences business transformation success. For instance, when employees are effectively equipped to integrate AI into their workflows, they can provide enhanced customer service, which in turn improves customer willingness to engage with technological transformations (as expressed by employee E4 in our opening quote). This positive feedback loop ultimately drives overall efficiency improvements throughout the organization. Conversely, when either stakeholder group disengages from the process, it triggers a negative spiral that undermines implementation efforts. As an interviewed customer noted of their experience with AI technologies: when *"employees admit they don't know how to use a newly introduced* [AI] *system, it affects customer confidence."* (C3). Among previous technologies, Meta's Horizon Worlds is a great case in point. The virtual reality platform struggled to gain traction with customers, which subsequently undermined employee enthusiasm and commitment to the project. This lack of customer adoption led to diminished employee engagement, creating a cyclical pattern that hindered the platform's development and refinement (Horwitz et al., 2022). Likewise in 2026 for AI, both employees and customers need to trust the process and the output: an interviewee noted a case where a company AI chatbot would frequently hallucinate, leading customers to push back and request solely human support. To remedy this connection failure, we address the following research question: "What are the main sensitivities of employees and customers, and how do they interact?" To answer this question, we first detail our methodology and foundations in theory.

2. Methodology

This paper presents a conceptual synthesis[2] to structure emergent phenomena into an organizing framework that practitioners and future researchers can build upon (Jaakkola, 2020; MacInnis, 2011). The synthesis draws on four evidence bases: (1) a literature review of relevant theories and frameworks on technology adoption, (2) interviews with employees and customers on AI adoption, (3) a structured review of AI adoption outcomes from published case evidence; and (4) the authors' combined research and consulting experience across multiple AI implementations, which provides contextual grounding for the framework's practical recommendations.

The framework was developed through an iterative process across two phases. In the first phase, the authors independently reviewed the available evidence on AI adoption outcomes in organizational settings, from academic literature to practitioner testimonials of failures and

[2] We acknowledge this is not a primary data study. At the current stage of enterprise AI adoption, characterized by rapidly evolving practices and high variance in implementation maturity, a conceptual synthesis is well-positioned to distill observable patterns into actionable guidance and generate propositions that future empirical work can test (Gregor, 2006). Each of the five lessons is grounded in this evidence base.

successes. At the same time, two authors reviewed more than 15 prior technological innovations that experienced significant hype in their early stages, which was eventually narrowed to a focused set including enterprise resource planning systems, blockchain, virtual reality, and electric vehicles[3]. These cross-technology patterns form the evidential backbone of the framework, allowing the five lessons to be grounded in documented historical precedent rather than derived solely from the still-evolving AI adoption landscape. The second phase involved structured collaborative iteration, in which the authors brought their independently developed observations together, identified convergent patterns, and refined the framework through repeated cycles of discussion and revision until a stable structure emerged.

3. Relevant theories on human interaction with technology

Throughout the 20th century, two complementary theories have guided modern intersection of technical systems and human processes. First, Sociotechnical Systems Theory (Bostrom & Heinen, 1977; Trist & Bamforth, 1951) posits that technical and social systems within organizations are fundamentally interdependent and must be designed jointly rather than sequentially. In the seminal 1950s case study of British coal miners, productivity fell when management redesigned the technical systems (with the goal of optimizing workflows), because the redesign disrupted the social system (team norms, structures, and work habits) that workers had developed around the old technology. Sounds familiar? Indeed, organizations that invest heavily in AI technology while ignoring the human systems existing around it (workflows, team norms, customer interaction patterns) face the same failure dynamics (De Cremer, 2024).

Second, social contagion is 'the spread of behavior from one person to another or to a whole group' (Redl, 1949, p. 315). This theory spread from epidemiology (Bartlett, 1960) to marketing, where Bass (Bass, 1969) and following papers demonstrated that the major driver of new product adoption is imitation, i.e. consumers seeing the new product in use by another consumer. Later expanded to 'emotional' contagion (Schoenewolf, 1990, p. 50), organizational studies have shown that emotions and attitudes can also be 'caught' from coworkers (Barsade et al., 2018). We posit that both AI adoption and disadoption behavior, both excitement about, and aversion to the technology, can be transmitted within and across employees and customers. As an interviewed systems engineer at a major tech company noted: *"[The company] strongly believes that if their employees like the product, then their customers are going to like the product."* (E2)

More recently, two frameworks detail such transmission. First, the service-profit chain (Heskett et al., 1994) links firms' profitability to customer loyalty and satisfaction as well as employees' loyalty, satisfaction, and performance. The framework suggests that employee satisfaction drives employee retention and productivity, which in turn boosts external service quality, which then promotes customer satisfaction and thereby loyalty, ultimately leading to greater profitability. Applied to AI adoption, this framework implies that investments in AI must support both

[3] Cases were selected on three grounds: documentation quality (sufficient detail existed in published sources to assess how stakeholder management shaped outcomes), outcome variation (the set includes both failed and successful adoptions to enable pattern identification rather than confirmation bias), and stage coverage (cases were chosen to illustrate dynamics across the various stages). Prior technology cases were included alongside AI-specific examples on the same selection grounds.

employees and customers: If AI undermines employee satisfaction or capability, service quality will suffer, and if AI-enabled services fail to create value for customers, gains in employee productivity will not translate into improved firm performance.

Finally, service-dominant logic (Vargo & Lusch, 2004) conceptualizes value as co-creation by multiple actors engaging in a service-for-service exchange. Moreover, value emerges in use through the integration of resources across actors, rather than being embedded in the technology itself. As a result, the effectiveness of AI adoption in firms depends not only on whether employees adopt it, but also on whether customers are able and willing to integrate AI-enabled outputs into their own activities. This implies that mismatches in AI adoption or capability across employees and customers can disrupt value co-creation, limiting or even undermining the realized benefits of AI.

In sum, prior theories and frameworks suggest that both employees and customers learn from each other regarding technology adoption attitude and behavior. But how do they apply to more recent technologies, and specifically to the fast changing technology of AI?

4. Employee Dimensions in AI Adoption

Employees exhibit several key sensitivities that influence their receptiveness to AI adoption. First, job security concerns frequently emerge, as many perceive AI as a potential threat to their employment status. Second, professional identity considerations shape employee responses, particularly among knowledge workers whose expertise and judgment constitute core components of their self-concept (De Cremer, 2024). When AI systems appear to encroach on these domains, resistance often intensifies.

The training gap is substantial: nearly half of employees want formal AI training and believe it is essential for adoption, yet only 29% feel fully supported for capability building, while 22% report receiving minimal or no organizational support (Mayer et al., 2025). 31% of employees (41% of Gen Z) admit to sabotaging their company's AI strategy by refusing to use AI tools or circumventing official systems (WRITER & Workplace Intelligence, 2025).

Employee habits also significantly impact adoption outcomes. Established workflows represent time investments in learning and efficiency, creating natural resistance to changes that disrupt these patterns. The cognitive load associated with learning new AI systems while maintaining current performance levels can overwhelm employees, leading to avoidance behaviors or superficial engagement with new technologies (Bedard et al., 2026).

Attitudinally, employees vary in their technological self-efficacy—their belief in their ability to successfully use new technologies. Employees with higher AI self-efficacy demonstrate greater readiness and actual adoption of AI tools, whereas lower self-efficacy is associated with reduced engagement and use(Akben & Dong, 2025). Similarly, general attitudes toward change—whether employees view organizational changes as opportunities for growth or threats to stability—strongly predict their responses to AI initiatives.

Behaviorally, employees engage in various adaptation strategies when confronted with AI implementation. Some actively explore new capabilities, seeking to integrate AI into their work processes innovatively. Others engage in passive resistance, nominally complying while avoiding meaningful engagement. Still others may actively undermine implementation through criticism, non-participation, or even sabotage of systems.

5. Customer Dimensions in AI Adoption

Customers bring their own set of sensitivities to AI interactions. While Deloitte's 2025 Connected Consumer Survey found that 53% of consumers are now experimenting with or regularly using generative AI, trust issues persist (Fineberg et al., 2025). Attest's 2025 Consumer Adoption report found that only 33% of consumers trust companies with data collected through AI technology, though this represents a 4-percentage-point improvement from 2024 (Booker, 2025). Meanwhile, 82% of consumers view AI data loss-of-control as a serious personal threat, with 43% considering it "very serious" (Relyance AI, 2025).

Still, growing familiarity breeds trust: Among consumers who currently use generative AI tools, 68% trust the information provided, compared to only 43% among all consumers (Booker, 2025). Bain & Company's 2025 research found that while 72% of US consumers have used AI in some form, only 24% feel comfortable using it to make purchases—highlighting the gap between experimentation and full adoption (Zhu & Boyd, 2025). Control preferences also shape customer reactions, with many expressing discomfort when AI systems make decisions without human oversight or the ability to override recommendations.

Customer habits in digital interaction significantly influence their receptivity to AI implementations. Those with established patterns of using digital services demonstrate greater willingness to engage with AI features (Flavián et al., 2022), while those with less developed digital habits tend to rely more on intentional evaluation processes, implying that explicit value propositions become particularly important in shaping adoption decisions (Venkatesh et al., 2012). The effort required to learn new interaction models represents a barrier that many customers are unwilling to overcome without clear benefits.

Attitudinally, customers vary in their trust of AI systems, on perceived competence (whether the AI can perform as expected), perceived benevolence (whether the AI acts in the customer's interest), and perceived integrity (whether the AI adheres to acceptable principles). Additionally, customers differ in their preference for human interaction versus automated services, with substantial segments expressing strong preferences for human contact in complex or emotionally significant transactions.

Behaviorally, customers demonstrate varying levels of usage of AI-enabled features. Some eagerly experiment with new capabilities, providing valuable feedback that guides refinement. Others engage selectively, using AI features for certain tasks while avoiding them for others. The majority of our interviewed customers noted distrusting AI use in "*high-stakes*" situations whether it was human health (C1), finances (C4), or confidential personal information (C2, C3). Following the loyalty-exit-voice framework (Hirschman, 1970), unhappy customers will either leave or express their complaints in online reviews and offline word-of-mouth, which directly threaten business results (Fay et al., 2019; Pauwels et al., 2016).

6. Interdependencies Between Employee and Customer Dimensions

The sensitivities, habits, attitudes, and behaviors of employees and customers are not merely parallel concerns but are deeply interconnected in ways that can create either virtuous or vicious cycles during AI adoption. When employees develop positive attitudes toward AI systems and effectively integrate them into their workflows, they convey confidence and competence to customers, enhancing the customer experience. Conversely, employee resistance or confusion manifests in customer interactions, undermining trust and acceptance.

Similarly, customer reactions to AI implementations provide essential feedback that shapes employee perceptions. As shown in our interviews, positive customer responses reinforce employee confidence and willingness to engage, while negative customer reactions can validate employee concerns and intensify resistance. Beyond their paycheck, many employees also take pleasure in satisfying customers and are more likely to engage in costly behavior if they see it as improving customer interactions (Brown et al., 2002). Organizations must recognize these interdependencies when designing adoption strategies, ensuring that interventions address both stakeholder groups in coordinated ways.

To address these challenges, we propose an integrative framework that simultaneously considers both customers and employees throughout the AI adoption journey. Our framework leverages the Gartner Hype Cycle as a temporal model to understand the evolution of expectations and experiences as new technologies are introduced and integrated into organizational processes (Gartner, n.d.). By examining employee and customer management across the three key phases of the hype cycle—innovation trigger, trough of disillusionment, and plateau of productivity—we develop a 2×3 framework that yields five essential lessons for successful AI implementation. Such a structured approach enables organizations to anticipate challenges, align stakeholder expectations, and develop targeted interventions that enhance adoption outcomes.

7. The Hype Cycle as a Lens

We use the Gartner Hype Cycle as an interpretive lens, not a predictive tool nor explanatory theory. Its pattern of early over-enthusiasm (Hype), a period of disappointment (Trough of Disillusionment), and eventual stabilization (Slope of Enlightenment), gives managers a useful framework for anticipating the human challenges that accompany each stage. Scholarly review has confirmed that this pattern reflects patterns in the economics and sociology of technology diffusion (Dedehayir & Steinert, 2016). These dynamics have been observed across generations of technologies: hype creates real market commitments and organizational investments that can be difficult to reverse even when results disappoint (Geiger & Gross, 2017); organizations facing uncertain adoption environments often engage in herd behavior, following peers rather than their own organizational context, which amplifies both the peak and the trough (Li et al., 2014); and firms that treat adoption as a mindful, context-specific process consistently achieve better outcomes than those that do not (Swanson & Ramiller, 2004).

AI follows this general pattern, as evident in the interviews we discuss next, though with important differences from earlier technology waves. Within two years of ChatGPT's launch, adoption already exceeded that of personal computers and the internet at comparable points in their product cycles (Bick et al., 2026). Additionally, and crucially for our framework, AI simultaneously reshapes both internal workflows and external customer interactions: this is a dual exposure that creates the interdependencies at the heart of our framework (Brynjolfsson et al., 2025; Huang & Rust, 2021), compressing a cycle that took technologies like enterprise resource planning systems or blockchain years to traverse into months. This means that both the hype-driven over-commitment and the disillusionment-driven backlash propagate across both stakeholder groups simultaneously. Sociotechnical Systems Theory explains why: when the technical subsystem is disrupted, misalignment cascades through the entire social system, reaching not just employees but all stakeholders those employees interact with (Bostrom & Heinen, 1977; Trist & Bamforth, 1951). Emotional contagion theory explains how: employee anxiety, frustration, or enthusiasm during adoption transmits directly to customer experiences through service interactions (Hatfield et al., 1993; Pugh, 2001), meaning the internal emotional climate of an organization under AI disruption becomes visible to customers whether leaders intend it or not. Managing these interdependencies simultaneously is therefore not optional but structurally necessary, which is precisely what our framework is designed to do.

8. Interviews with employees and customers

We conducted in-depth semi-structured interviews with 5 employees in the tech sector and 5 tech savvy customers (see Appendix A for interview guide, interviewee information, and key themes). Every interviewee described some form of attitude shift, consistent with the dynamic patterns and challenges in this paper. The patterns cluster into four types:

1. **Skepticism to full adoption:** Employee 2 (E2) described the most dramatic shift. Employees who doubted AI just months ago now don't write a single line of code manually. The driver was rapid model improvement, not organizational pressure.

2. **Excitement to normalization:** E3 described excitement fading into routine. E5's team started with high expectations, found the output wasn't immediately usable, adjusted their setup, and reached a productive steady state.

3. **Frustration to gradual trust:** Customer 1 (C1) was initially frustrated by AI chatbot layers but now appreciates the speed. C2 watched Rufus (Amazon's chatbot) improve from poor to good over two years. C3 described Spotify improving from poor to a 90% hit rate. C5 left ChatGPT entirely due to freezing issues but continues using other AI tools.

4. **Resistance leading to departure:** E4's company saw content writers leave rather than accept AI tools that stripped their creative voice.

As to the core argument of our paper, employee-customer interdependence in AI adoption, surfaced in the majority of both employee and customer interviews. The different contexts illustrate the multiple pathways through which the interdependence operates.

- **E1 (Fintech Startup): Direct product feedback loop.** The team built AI-powered products, customers liked them, and that positive feedback motivated the employees.

- **E2 (Major Tech Company): Employees as proxy customers.** The company beta-tests products with employees before releasing to customers. Employee satisfaction predicts customer satisfaction.

- **E3 (Major Technology Company): Confidence reinforcement loop.** Positive customer feedback on AI products increases employee confidence and motivation to continue investing in the product.

- **E4 (Freelance/Web Development): Bidirectional signal.** When employees feel confident with AI, customers sense that competence. When customers pushed back on AI chatbots, it made employees reconsider whether human interaction was better for certain tasks.

- **E5 (Health Tech): Indirect quality loop.** AI-written code powers customer-facing products. Improved customer KPIs (notification click-through rates) validated the adoption. Leadership emphasized that educating customers about AI builds trust.

- **C1 (Healthcare/Customer): Trust dependency.** A clinician must understand how the AI system works before communicating a diagnosis to a patient. Employee incompetence directly erodes patient trust.

- **C2 (Data Science Student): Indirect evidence.** Described colleagues who visibly distrust their own internal AI tools and constantly seek verification from others.

- **C3 (Data Science Student): Competence visibility.** Customers notice when employees are comfortable versus confused with AI tools. Employee proficiency translates directly into better and faster service. Key statements include: "*Employees sometimes admit they don't know how to use a newly introduced system, which affects confidence*" and "*when employees are comfortable with AI and know how to use it fully, they make the customer's life easier.*"

- **C4 (Consulting Background): Product knowledge cycle.** Employees who know their AI product deeply can communicate its value to customers. Customer needs flow back to employees who improve the product: "*employees need to be well-versed with their own product so they can communicate its value to customers"*

- **C5 (Biomedical Engineering Student): Dissenting view.** The only participant to directly state they see no connection between employee and customer AI experiences: "*it comes down to the quality of the experience, not who or what is delivering it.*"

Thus, mechanisms vary from direct feedback loops to organizational design to trust dependencies to competence visibility. The dissenting view from C5 is informative about boundary conditions: it suggests the connection may be less visible to customers who interact primarily through automated systems and have limited exposure to the employees behind them.

9. The Integrative Framework: Five Lessons

We propose an integrative framework that maps specific management strategies to the intersection of adoption stages (Hype, Disillusionment, Enlightenment) and stakeholder groups (Employees, Customers). We provide evidence for our 2×3 framework in our analysis of how past transformative technologies (based on the examples of Metaverse, blockchain and electric vehicles) succeeded or failed based on their approach to managing these stakeholder groups.

The framework reveals five critical lessons: One universal lesson during the Hype stage that applies to both groups, and four stage-specific lessons that recognize the distinct challenges employees and customers face during Disillusionment and Enlightenment phases. Table 1 summarizes these five lessons and their strategic applications. The framework's structure reflects a key insight from past technology adoptions: While initial hype affects employees and customers similarly (requiring unified expectation management), the subsequent stages demand differentiated approaches that acknowledge each group's distinct needs while maintaining their interconnected relationship.

[Insert Table 1 About Here]

These five lessons are grounded in our systematic analysis of how organizations successfully navigated employee-customer dynamics during previous technology transformations. Each lesson addresses specific failure patterns: Lesson 1 prevents the credibility collapse seen with Meta's Metaverse overhype; Lessons 2 and 3 address the dual challenges organizations face during disillusionment (employee disengagement and customer trust erosion); and Lessons 4 and 5 capitalize on the enlightenment stage's opportunities for sustainable adoption through employee empowerment and demonstrated customer value.

The employment of this integrative approach—through our 2×3 framework—allows us to address three critical gaps in existing AI adoption guidance:

- Gap 1 - Stakeholder Interdependence: Unlike single-focus frameworks, our approach recognizes that employee AI competence directly impacts customer experience, while customer acceptance influences employee motivation to embrace AI tools.

- Gap 2 - Stage-Specific Strategies: Rather than generic "best practices," our framework provides targeted interventions for each adoption stage, reflecting the distinct challenges organizations face as AI moves from hype through disillusionment to practical implementation.

- Gap 3 - Evidence-Based Patterns: Each lesson is supported by documented cases from past technology adoptions, providing leaders with proven strategies rather than theoretical recommendations.

Table 2 maps the interviewee responses to our Framework's lessons. For lessons that are primarily employee-focused, the customer column captures the cross-cutting impact, showing how employee-side interventions create ripple effects on the customer side. This reflects our paper's core argument that the two groups should not be managed in isolation.

The following sections examine each lesson in detail, demonstrating how organizations can apply these insights to navigate AI adoption successfully. We show how companies that ignored these principles experienced costly failures, while those that applied similar strategies achieved sustainable technological integration that benefited both their workforce and customers.

9.1. Hype Stage: A Lesson for Both Employees and Customers

In the first stage of hype, when AI excitement is high, and the technology is just beginning to be brought into the business, employees and customers will bring their own preconceptions of the technology. While younger, more tech-savvy employees and customers might already be AI savvy, others will not. In the Hype stage, it is critical for business leaders to set realistic expectations early to avoid overhype.

As a company adopts AI, business leaders will need to think critically and openly about how AI may change current processes. Surveys have found that AI buy-in and support from top-level management is critical to the success of AI adoption, as it drives employee perceptions of the technology and in turn, willingness and ease of adoption itself. Managers who overpromise the abilities of AI without realizing the nuance and time it can take for a business to find the right processes will be disappointed when early AI returns are low. Similarly, employees of such leaders will face frustration and fear when the adoption process of the technology is less successful than planned for. AI is still a new technology, and for many companies, adoption must move through disillusionment stages before a company can get to eventual AI enlightenment. The same concept can be applied to customers of companies promising strong results from AI. Customers who do not see immediate positive impacts will be disappointed by companies that overpromised on AI's ability to make their experience better.

The importance of framing expectations in the hype stage of technology adoption can be seen in previous examples such as Facebook's Metaverse. When the company, formerly known as Facebook, first moved to rebrand to Meta and become a Virtual Reality (VR) and Metaverse-forward company, the leaders overhyped the technology beyond its limitations. Employees were encouraged by senior leadership to "fall in love" with VR and the company's new Metaverse platform in hopes that it would translate to consumer excitement; even though the reality was that the platform was relatively untested for public adoption. Instead of falling in love with the technology, employees were dissatisfied with the platform, which translated further to low customer adoption levels. A technology that had been highly praised by leadership as groundbreaking failed to excite consumers.

A similar example is found with Alexa, Amazon's first smart speaker and at-home virtual assistant tool. Since its launch in 2014, Amazon thought the product would drive a new wave of at-home voice assistants. Jeff Bezos told shareholders the devices would be sold at breakeven because "we want to make money when people use our devices—not when they buy our devices" (Yarow, 2012). Amazon Alexa achieved widespread adoption, with hundreds of millions of Alexa devices in households around the world. However, the nature of that adoption diverged from Amazon's original intention: Rather than functioning primarily as a voice-powered assistant to drive faster purchases from Amazon's website, the device has, for many customers, served mainly as a platform for free app extensions. "We worried we've hired 10,000 people and we've built a smart timer," said a former employee to the WSJ as the company faced billion-dollar losses. The initial promises for Alexa's use as a profit driver as well as a game-changing technology were unrealistic. Instead, most customers use the devices for a very small number of simple tasks. Early expectations for the technology were untested in actual consumer markets, and as such failed to meet expectations for both employees and customers.

AI-forward leaders can learn from the missteps of Meta and Amazon's leadership in overhyping new technologies. When lofty promises are made too early, it sets emerging technology solutions up for high expectations and leaves less room for gradual improvement and testing within consumer markets. Leaders should aim to instead give realistic expectations and address the potential limitations of the technology instead of saying things like "This will be a whole new way of interacting with people." Overpromising seamlessness of adopting AI leaves little room for nuance with the actual adoption rates and use cases for the technology. In the hype stage, framing expectations realistically is the first step toward sustainable adoption.

9.2. Disillusionment Stage: A Lesson for Employees

In the next stage of AI adoption, disillusionment, employee outcomes often drive consumer outcomes. Employees often express fear and distrust, as they were told AI would wipe out industries and take jobs. Many employees have also heard contrasting claims of when and where AI should be used in their jobs, while lacking the proper resources to be trained (Mayer et al., 2025). Despite this current lack of readiness, AI reskilling is critically tied to positive outcomes. For example, an experiment conducted by the Boston Consulting Group and Harvard Business School found that consultants using AI were more productive and produced higher-quality results (40% higher) compared to a control group (Dell'Acqua et al., 2026). What the World Economic Forum has dubbed the "Reskilling Revolution" is the beginning of companies and employees globally moving to reskill employees to be AI literate.

The importance of reskilling employees can be seen in technology adoption as far back as early Enterprise Resource Planning (ERP) systems of the 1990s. At the time, Enterprise Resource Planning (ERP) systems were a relatively new class of enterprise technology, designed to integrate finance, supply chain, and customer data into a single system. Companies rushed to adopt ERP as a cutting-edge solution, but the novelty of the technology meant steep learning curves for employees. Hershey was one of those early drivers of technology adoption and sought to implement a massive ERP/CRM/SCM rollout in just 30 months (instead of the recommended 48) to beat the Y2K deadline. To save time, the company skipped key system tests and provided insufficient training to employees. The system went live in July 1999—just before Hershey's busiest Halloween and Christmas sales season.

Unfortunately, their quick push for employee adoption failed, as employees were both undertrained and underprepared to use the technology and struggled to operate the new system. Hershey could not process about $100 million in orders, profits dropped 19%, and its stock price fell 8%. Analysts noted the failure was not due to the technology itself, but to the lack of adequate training and readiness among employees. Because ERP was an emerging technology, employees needed extensive reskilling to adapt to its new workflows. Without investing in training, even powerful technologies collapse in practice. Companies must treat employee readiness as central—not optional—for navigating the disillusionment stage of adoption.

We can look to companies like Ikea as prime examples of companies that have invested deeply in the reskilling of their employees for AI-powered tools and solutions. When the company first introduced Billie, their AI customer service voicebot, it became clear the tool could successfully outperform current human solutions. Despite its immense ability to automate roles, they chose to reskill employees for the use of the tool, and in turn were able to generate 1.3 billion euros in revenue from the tool in 2022. Since then, they have set the goal to train more than 70,000 employees in AI within the next year. Ikea representatives shared: "Instead of standardising learning into a single track, IKEA is adapting to different roles, backgrounds, and comfort levels. The message isn't 'get with the program', it's 'let's shape this together.'" Their policy is to keep their AI developments people-focused and meet people where they are at in their AI literacy journey.

Ikea's prioritization of employee reskilling in AI adoption highlights the benefits of leadership that plan for AI adoption in a people-centric way, choosing to support employees in succeeding for the future. Positive, successful AI outcomes center around prioritizing people—both employees and customers.

9.3. Disillusionment Stage: Lessons for Customers

Like employees, customers are likely to experience various issues as they adjust to changes arising from the firms' adoption of AI. These issues, big and small, will lead customers to realize that the benefits of AI are not all that they were hyped up to be. For example, a customer might call a company's support line only to be greeted by an AI chatbot that gives generic or even misleading answers, making it harder to resolve a problem than if they had spoken directly to a human. Online shoppers may encounter recommendation systems that repeatedly push irrelevant products, despite promises of "personalization." Travelers might be frustrated when an airline's AI-driven booking system auto-cancels or reroutes flights without clear explanation. Even something as mundane as trying to correct a mistaken food delivery can become more aggravating if AI systems block or delay access to a human representative.

As disillusionment about AI sets in for customers, firms need to address customers' disappointment and skepticism by providing tangible benefits that restore their trust and confidence. Two examples from past technologies demonstrate this lesson: Louis Vuitton's Aura Blockchain Consortium and Hilton's VR hotel tours.

The Aura Blockchain Consortium is a nonprofit association to promote "transparency, traceability, and trust in the luxury goods industry" through blockchain technology. Initiated by Louis Vuitton, the system works by assigning each product a digital code at the time of manufacturing, which is permanently stored on the Aura ledger. When purchasing an item, customers gain access to a platform that details the product's history and includes its origin, materials, environmental and ethical attributes, proof of ownership, warranty, and care instructions (Paton, 2021). While customers may not understand the technical workings of blockchain, they can use the system in simple, familiar ways. After purchasing an item, they receive secure access—typically through the brand's mobile app or a web portal—where they can log in to view the digital certificate tied to their product. By scanning a QR code or entering product details, customers can open a personalized dashboard that displays the item's full history and confirmation of its authenticity. The platform also stores practical information such as warranty coverage, care instructions, and proof of ownership, which can be transferred if the item is resold. In this way, Aura turns blockchain into an easy-to-use digital passport. Rather than relying on abstract claims about blockchain innovation, customers can see concrete proof of the authenticity of their products, which reassures them that the new technology is working in their interest.

Another example of tangible benefits is Hilton's VR hotel tours. By offering prospective guests the ability to virtually walk through hotel rooms before making a reservation, Hilton reduced the uncertainty that often comes with booking travel online. Customers could preview the size, layout, and amenities of a room in advance, which increased their confidence that what they saw on the website would match their actual experience. In this case, VR was not promoted as a revolutionary technology in itself but was used to solve a concrete customer problem—helping travelers make more informed choices. By delivering a clear and practical benefit, Hilton was able to strengthen trust and encourage adoption, showing that new technologies gain traction when they make the customer journey simpler and more reliable.

The lesson for the disillusionment stage regarding customers is straightforward: When customers face disappointment following the initial hype about firms' adoption of AI, firms can remedy the situation and sustain customer adoption by providing tangible benefits to customers and delivering meaningful improvements to their experience.

9.4. Enlightenment Stage: A Lesson for Employees

> *"[They] have full independence in deciding how much to rely on AI. Nobody forces [them] … AI products receive positive customer feedback, and hearing that increases internal confidence in the product and motivation to keep improving it."* Product manager at a major tech company (E3)

Once AI technology has demonstrated its usefulness through the Hype and Disillusionment stages, organizations must focus on enabling employees to shape how AI is applied to fully realize its benefits. Specifically, by allowing employees to provide input into how AI tools are used in their workflows, leaders can ensure not only a smooth transition into the final stage of AI adoption but also a more sustained integration of AI that improves employee productivity and organizations' performance. An example of such efforts can again be seen in Hilton's virtual reality program.

Hilton's Hotel Immersion VR training program allows employees to practice operational tasks such as checking in guests and cleaning hotel rooms. The program provided agency to employees by letting them follow a "choose-your-own-adventure" format, where they experience guest reactions when their service exceeds, meets, or falls short of expectations. Designed to make training more efficient, the VR program reduced classroom instruction from four hours to just 20 minutes, saving time for both employees and leadership. Moreover, 75% of surveyed participants reported improvements in their problem-solving and customer service skills. In this way, Hilton's adoption of an emerging technology illustrates how giving employees a sense of agency in learning through an emerging technology can enhance their productivity which would translate to improved organizational performance.

The value of employee agency in technology adoption is further underscored by experiences from industry leaders. Paul DeMott, CTO of Helium SEO, noted how his company invited employees' feedback when adopting a new project management solution. Specifically, he invited team leaders from different departments to test different options of software and provide feedback. He recalled, "Because they had input, the transition was much smoother, and people felt empowered to use the new system right away." Helium SEO's experience suggests that giving employees agency in adopting some new tool or technology can speed up the actual adoption by the employees. This insight aligns with Alan McNabb's observation as VP of Image Building Media, who cautioned that overlooking employee perspectives can lead to failed adoption: "I've always believed that employees are the ones who know what their day-to-day work requires, and if their needs aren't considered, adoption rates suffer…I remember one client who implemented new software without consulting their team, and it ended up being a mess—people just went back to their old ways, and the investment didn't pay off."

The importance of giving employees flexibility with technology also shows up in the enlightenment stage for analytics dashboards (Pauwels, 2014). Projects to improve effectiveness, efficiency, and measurement, often start top-down, and require standardization of metrics to be comparable across geographies, departments, and business units (Pauwels & Joshi, 2016). The resulting Key Performance Indicators reflect what management believes will be useful to make decisions and evaluate employees. Over time though, frequent dashboard users will notice that some metrics are no longer relevant, and propose others to take their place. Likewise, customer priorities shift with changes in technology, competition, and preferences, and the organization should evolve measurement to fit what customer (segments) value most (Pauwels & D'Aveni, 2016). As long as these objectives are served, executives should allow employees to innovate and show leadership in proposing, validating, and pruning dashboard metrics.

9.5. Enlightenment Stage: A Lesson for Customers

> *"Use your product, know the value of that product in and out for you to communicate the same to the customer."* AI customer studying data science (C4)

In the Enlightenment stage, companies should prioritize lowering the cost of AI use for customers, since affordability and ease of use become key. Tetra Pak is a case in point. In the 1950s and 1960s, Tetra Pak transformed the packaging industry by offering a radically cheaper alternative to heavy, fragile glass bottles. Its lightweight cartons reduced manufacturing, storage, and distribution costs. However, in the early 2000s, CEO Dennis Jönsson noted that Tetra Pak's main competition was increasingly coming from companies producing alternative types of packaging with lower costs (Froste, 2006). The company countered these threats with continuous innovation, adaptation to sustainability concerns, geographic expansion, and strategic acquisition. By keeping the cost of adoption low for its customers (dairies and food producers), Tetra Pak created a system that incentivized customers to scale usage, which in turn secured Tetra Pak's long-term growth. The success of Tetra Pak illustrates how low costs for consumers can accelerate widespread adoption and ultimately deliver stronger profits for the firm.

A similar dynamic has played out in the electric vehicle (EV) industry. Tesla generated much of the early excitement around EVs, but its premium pricing limited accessibility to wealthier customers. By contrast, Chinese manufacturer BYD built its strategy around affordability and scale. As a result, BYD overtook Tesla in Q4 of 2023 as the world's largest EV seller by volume (Hoskins & Sherman, 2024), and in April 2025 in the European market (Eddy, 2025).

Once organizations have demonstrated the usefulness of AI beyond the Hype and Disillusionment stages, the challenge in the Enlightenment stage becomes ensuring that everyday use of AI remains affordable for customers. Just as Tetra Pak's low-cost cartons enabled widespread adoption of its packaging and BYD offered lower-cost alternatives to Tesla's premium EVs to surpass its competitor in sales volume, lowering the cost of AI solutions makes it easier for customers to embrace the technology consistently over a long period of time and helps organizations translate this sustained AI adoption into lasting profitability.

10. Synthesis of the evidence from other tech for our Integrative Framework

Our above examples from ERP systems, electric vehicles, virtual reality, blockchain, and more reveal that organizations consistently stumble when they treat employee and customer adoption as separate challenges, yet thrive when they recognize these paths as interconnected.

The failure pattern is clear across multiple scenarios. When organizations neglect employee readiness (as seen in Hershey's ERP rush) customer experience inevitably suffers. Employees who do not see value in new systems or are underprepared often struggle to deliver the promised customer experience—becoming the bottleneck that prevents customers from realizing technology benefits, regardless of underlying technical capabilities. Conversely, prioritizing employee outcomes while ignoring customer needs leads to a lack of customer buy-in and erosion of trust that can doom projects despite strong organizational backing. Even when employees are supported, adoption stalls if customers do not trust or see value. The most notable failures, like Meta's Horizon Worlds or Amazon's overpromised Alexa capabilities, occur when organizations become enamored with technology possibilities without considering either stakeholder group's actual needs or motivations.

In contrast, the winning examples created distinct but complementary value for both employees and customers (Hilton's VR applications and Louis Vuitton's blockchain authentication). Employees gained tools that enhanced their capabilities, while customers received tangible benefits that justified their engagement with new technology. This synchronization isn't coincidental. When employees see personal value in technology, they become empowered and authentic advocates who help customers navigate adoption challenges. When customers experience genuine benefits, they provide the market validation that motivates continued employee investment in learning and optimization.

AI adoption amplifies this interdependence dynamic. Unlike previous technologies that typically focused on specific business functions, AI broadly touches customer interactions and employee workflows. This expansive reach means that adoption failures in one stakeholder group can quickly cascade to the other. Moreover, AI's "learning" nature requires ongoing input and refinement from both groups. Employees need to provide the contextual knowledge that makes AI useful, while customers generate the usage patterns that improve AI performance over time. Without both stakeholder groups actively engaged, AI systems can stagnate or, worse, produce results that satisfy neither. Table 2 summarizes the evidence for our five lessons from the interviews with employees and customers on AI adoption.

[Insert Table 2 About Here]

11. Implications for Leaders and Organizations for AI adoption

As adoption succeeds when both employees and customers are considered together, we have the following implications for leaders facing the current wave of AI adoption. In the Hype stage: Manage expectations. In contrast to most technologies where the lack of leadership advocacy is a significant obstacle to adoption, less than 4% of vice presidents and C-suite executives surveyed in mid 2023 reported it being an issue with GenAI (Harvard Business Review Analytic Services, 2024). This immense enthusiasm reflects the technology potential. At the same time, it has created obstacles to effective GenAI adoption. AI adoption is a complicated, expensive process, and expectations must be carefully managed both internally and externally.

Early on, leaders must resist overselling AI to customers in marketing or to employees in internal communications. Setting overly ambitious benchmarks for AI outcomes without recognizing potential obstacles and limitations can create distrust amongst employees when benchmarks are not met. Furthermore, inflated claims that AI will "revolutionize everything" create early credibility gaps. Instead, leaders should emphasize incremental improvements and explain clearly what AI can—and cannot—do. For employees, setting expectations means transparency in changes being made and outlining what resources will be made available for employees to equip themselves for these changes. For customers, this means emphasizing the value add AI will bring to their experience without overpromising what AI can do. This important first step sets the groundwork for AI adoption success in later stages, building trust and room for employees to take chances with the expectation that roadblocks are expected. Likewise, it sets up the company for external success and builds customer trust, setting realistic expectations for what value-add AI will bring. The disillusionment stage is to be expected, and leaders can better prepare for it by managing expectations appropriately.

In the Disillusionment stage: Address both internal and external challenges. For employees, this means leaders should heavily invest in reskilling so that employees can integrate AI into their daily roles. Without training, employees may resist, misuse, or disengage from AI. Proper educational resources and training ensure employees will feel confident and equipped with the right skills to succeed at using AI productively. Challenges may arise, but when employees have resources to turn to and are better prepared to face them, they will be able to overcome obstacles more effectively. For customers, addressing challenges means maintaining trust through transparency. Just as in the previous step of setting expectations, leaders should acknowledge AI's limitations and provide clear explanations. Additionally, they should ensure customer fallback options (such as access to human service representatives). This also means promptly recognizing and addressing when customers face obstacles, providing clarity on those obstacles, as well as resources and added support for utilizing new technology. Mistakes and customer frustrations will occur in the disillusionment phase. Just as leaders prepare employees by providing resources for managing challenges, they must also support customers as AI reshapes their experience. This includes acknowledging errors promptly and committing to do better. Finally, managing challenges effectively will mean that as AI solutions become more familiar and successful to both customers and employees, they will see the added value to their respective outcomes.

In the Enlightenment stage: Focus on empowerment and value. When the organization has navigated and overcome significant roadblocks in AI adoption, leaders can focus on showing employees and customers why strategic changes were made in the first place. For employees, leaders should design AI in ways that give workers a voice in how tools are implemented, ensuring AI augments rather than replaces their skills. With proper training and confidence in the skills, employees will likely find their own best practices for working with the tools. Leadership should emphasize the new value employees bring through their own willingness to use the tools to optimize their everyday jobs, bringing better outcomes across the organization. This similarly translates into customer success: When employees use and believe in the tools, customers will begin to see it in their own improved experiences. Leaders should further showcase tangible improvements (e.g., faster service, greater personalization, or higher reliability) to demonstrate that AI delivers tangible benefits.

The managerial toolkit (Appendix B) details the diagnostic checklist (which stage are we?), the stage-specific advice, key metrics and common mistakes to avoid. We visualize these practical takeaways in Table 3.

[Insert Table 3 About Here]

All in all, for successful AI adoption, leaders must apply stage-specific strategies that at the same time synchronize employee empowerment with customer value to avoid the pitfalls of past technologies while realizing AI's full potential. This is key to adoption that promotes long-term growth for both employee and customer outcomes.

[Insert Appendix A Here]

[Insert Appendix B Here]

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Figure 1. Interlocking employee and customer technology adoption

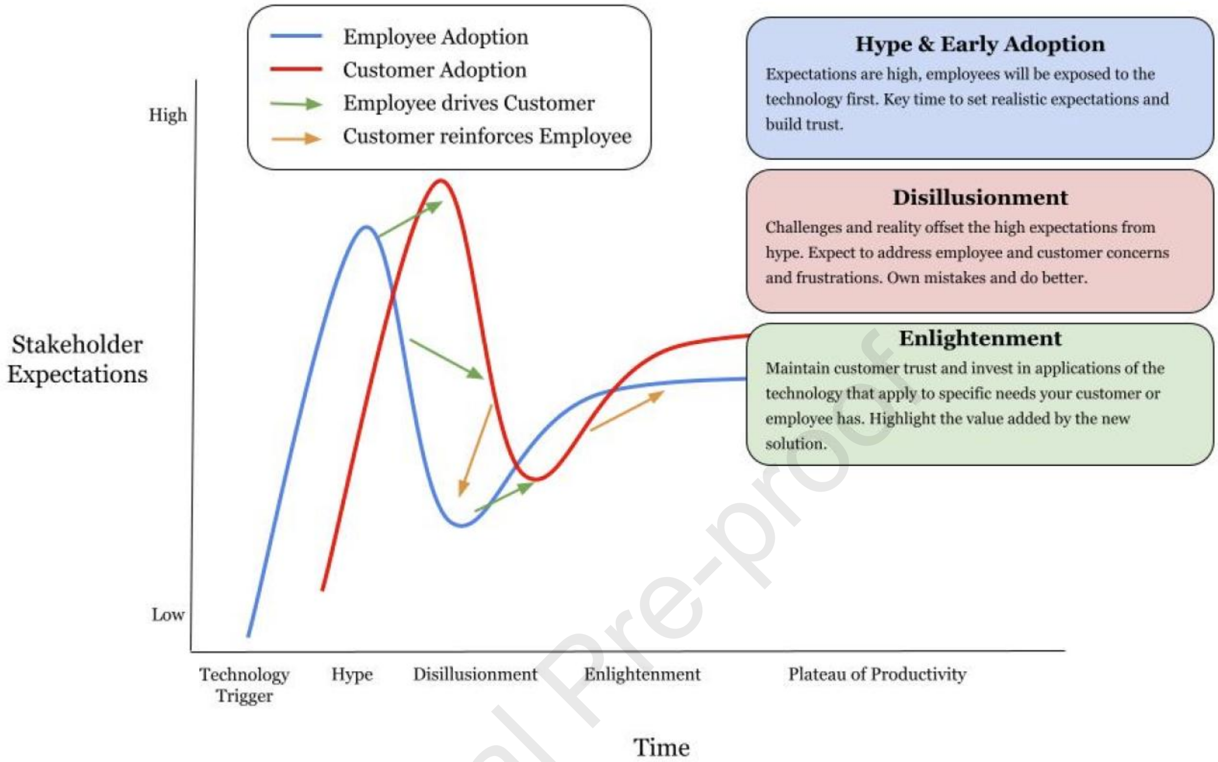

Table 1. How to manage employees and customers to the technology adoption stages

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">Technology Adoption Stages</td></tr>
<tr><td>Hype</td><td>Disillusionment</td><td>Enlightenment</td></tr>
<tr><td rowspan="2">Stakeholders</td><td>Employees</td><td rowspan="2">Lesson 1: Set realistic expectations early to avoid over-hype

For employees: provide transparency for changes to come and emphasize which resources will be made available.</td><td>Lesson 2: Invest in reskilling employees to prevent disengagement</td><td>Lesson 4: Give employees agency in shaping how AI is used</td></tr>
<tr><td>Customers</td><td>Lesson 3: Offer tangible benefits to customers to maintain trust</td><td>Lesson 5: Maintain competitive advantage also in value for money</td></tr>
</table>

Table 2. Mapping the interview responses into the framework lessons

Hype: Set realistic expectations (L1)	E1: Tool didn't fully meet expectations . E3: Early meeting tools invented action items. E4: AI introduced more bugs than it fixed. E5: Leadership expected immediate results but ground reality required more time.	C2: Rufus initially couldn't understand purchase themes. C3: Spotify recommendations initially poor. C4: AI convenience improving but UX has gaps. C5: AI voice bots can't handle accents; ChatGPT freezing led to abandonment.
Disillusionment: Reskill employees (L2)	E1: No formal training; relied on tech lead. E2: Iteratively simplified tools until training was unnecessary. E3: Extensive workshops; peer demos most effective. E4: No company training; self-taught prompting outside.	C1: Patient trust depends entirely on the clinician understanding the AI's internal workings before communicating a diagnosis. C3: Employees who don't know how to use newly introduced systems visibly affect customer confidence. E5: Leadership advocates educating customers on AI usage for transparency.
Disillusionment: Tangible customer benefits (L3)	E2: Human-in-loop protects customer experience. E4: Faster content output valued by clients. E5: AI-improved notifications increased customer click-through rates.	C1: Speed of AI bots is a benefit; explainability needed for trust. C2: Improved guardrails and contextual understanding over time. C4: Speed and accuracy clear benefits. C5: Instant price-match refund via Target chatbot. C5: Customer doesn't care how employees use AI; only quality of outcome matters.
Enlightenment: Employee agency (L4)	E2: Invisible feedback loop; teams experiment, company standardizes. E5: Collaborative decision through team standups; successfully pushed back on a tool that wasn't working.	C4: Employees empowered to know the product deeply communicate its value to customers. C3: Employee comfort with AI translates directly into better and faster customer service.
Enlightenment: Customer value (L5)	E2: Ensure product is easy to use before release. E3: Positive enterprise feedback reinforces investment. E5: Leadership advocates educating customers about AI for transparency and trust.	C1: Speed is primary value; explainability for trust. C2: Improving guardrails build long-term trust. C3: Convenience is the core value. C4: Customization and continuous improvement sustain value. C5: AI following company rules consistently is the value (Target example).

Table 3. Managerial matrix: Five lessons for AI adoption

Each lesson is mapped to four action dimensions for organizational leaders:

Lesson	What to communicate	What to invest in	What metrics to track	What mistakes to avoid
L1 **Act by stage, not by aspiration**	Which adoption stage the organization is in and why it matters What 'progress' looks like at this specific stage	Stage diagnostic as a recurring leadership exercise Stage-specific playbooks, not one-size-fits-all rollout	Stage-transition signals (rising complaints → disillusionment; repeatable use cases → productivity)	Applying Productivity-stage logic during the Hype stage Skipping the diagnostic and assuming you know where you are
L2 **Structure employee adoption; don't assume it**	Which tasks are appropriate for AI and which are not That learning curves and errors are expected, not failures	Structured onboarding and targeted reskilling Workflow redesign so AI reduces steps, not adds them Formal channels for employee feedback on AI tools	AI usage frequency and breadth of use AI reliance calibration (accept/revise / reject rates) Resistance indicators (workarounds, nonuse)	Treating AI rollout as a technology project, not a workflow change Measuring adoption by usage rate alone Denying employees authority to reject AI outputs
L3 **Earn customer trust; don't borrow against it**	The specific problem AI solves for the customer When AI is involved and what human backup exists AI errors and limitations directly and early	Low-risk, reversible AI touchpoints first Clear fallback options (human or hybrid channels) Customer feedback mechanisms at every touchpoint	Trust in AI-enabled services AI-related complaint rate over time Fallback demand (customers requesting a human) Repeat usage of AI-enabled service	Promising seamless AI experiences before reliability is proven Making AI the selling point instead of customer value Removing human support prematurely
L4 **Synchronize employee and customer readiness**	That employee and customer readiness will not move at the same speed How employee AI use affects what customers experience	Employee training on explaining AI to customers VoC sessions where employees share AI-related customer feedback Interdependence diagnosis before scaling	Employee–customer alignment (AI task use vs. customer comfort) Customer response to AI-assisted employees Escalation patterns and post-escalation satisfaction	Optimizing internal efficiency while ignoring customer experience Scaling AI before both sides are aligned Letting employee frustration become visible during customer interactions
L5 **Close feedback loops; AI adoption is never 'done'**	That employee AI feedback is diagnostic intelligence, not complaint Proven AI practices as new standard workflow	Formal employee channels to propose workflow and training updates Shared loops: customer usage data refines employee AI prompts	Service consistency across AI, human, and hybrid interactions Business outcomes by interaction type (conversion, retention) Output quality over time (error and revision rates)	Treating adoption as complete once the tool is live Running employee-side and customer-side metrics in silos Codifying early AI practices without updating them as the tool matures

Stage-transition indicators: (1) Hype → Disillusionment: rising complaints, stalled ROI, employee frustration. (2) Disillusionment → Productivity: stabilizing performance, improved trust, repeatable use cases.

Appendix A. Interview methodology and summaries

We conducted 10 semi-structured qualitative interviews (5 employee, 5 customer) to add primary data to the revision of “Managing the Dual Challenge of AI Adoption”.

1. Methodology

The Interviews followed below semi-structured guide. The questions started broad (general AI experiences) and moved toward specific themes from the paper. The employee -customer interdependence question was only asked directly if it did not come up on its own.

Employee Interview

1. Tell me a bit about your role, what do you do day to day, and where does technology fit into that?
2. Has Artificial Intelligence shown up in your work at all? What’s that been like?
3. What’s been good about it, and what hasn’t worked so well?
4. In some companies, use of AI is encouraged or even enforced by leadership, so employees show their AI use to managers. In some others, AI use is discouraged, but employees may use it anyway while not telling their managers. Where would you put your company on a scale from leadership encouragement vs discouragement of AI use?
5. When your company first brought in AI tools, how did you and your colleagues react? Has that changed over time? Why?
5. Did you feel like you had enough training or support to actually use these tools well?
6. Do you feel like you’ve had any say in how AI gets used in your work?
7. Does any of the AI your company uses touch customers directly or indirectly? Have you noticed how customers react to it? If you do not have such feedback from customers, what have you heard about it from colleagues or from leadership?
8. *[If interdependence hasn’t come up naturally:] One thing we’re exploring in this research is whether there’s a connection between how employees feel about AI and how customers experience it. From what you’ve seen, does one affect the other?*
9. If you could give one piece of advice to a company about to roll out AI, what would it be?
10. Anything else about your experience with AI at work that feels important and we haven’t touched on?

Customer Interview

1. When you hear “AI” or “artificial intelligence,” what comes to mind for you?
2. Have you had any experiences with AI as a customer, chatbots, recommendations, automated services, anything like that? Walk me through what that was like.
3. What’s worked well in those experiences, and what’s been frustrating?
4. How much do you trust AI when it’s part of a service you’re using? What makes you trust it more or less?
5. Are there situations where you’d strongly prefer a human over AI? What makes those different?
6. Has a company ever used AI in a way that actually made your experience noticeably better? What did that look like?
7. Do you ever notice whether the employees at a company seem comfortable or confident with their own AI tools? Does that matter to you?
8. *[If interdependence hasn’t come up naturally] We’re exploring whether there’s a link between how well employees use AI and how customers experience it. From your perspective, do you think one affects the other?*
9. If you could tell companies one thing about how they use AI with customers, what would it be?
10. Anything else about your experience with AI as a customer that we haven’t covered?

All interviews were audio-recorded with verbal consent and transcribed. Participant identities are anonymized throughout. The sample was recruited by two authors at a large US university. Interviews ranged from approximately 18 to 42 minutes.

2. Participants

ID	Type	Description	Industry / Context	Format
E1	Employee	AI engineer intern at a fintech analytics startup	Fintech / Predictive analytics	In-person

E2	Employee	Systems development engineer at a major tech company	Big tech / Cloud infrastructure	Virtual
E3	Employee	Product manager at a major technology company	Big tech / Software products	Virtual
E4	Employee	Freelance software engineer and web developer	Software / Web development	Virtual
E5	Employee	Data scientist at a health tech company	Healthcare / AI automation	Virtual
C1	Customer	PhD candidate in biomedical informatics	Healthcare / Academia	Virtual
C2	Customer	Graduate student in data science and research assistant	Academia / Data science	Virtual
C3	Customer	Data science student	Academia / Data science	Virtual
C4	Customer	Recent graduate with consulting background	Consulting / Business	Virtual
C5	Customer	Biomedical engineering graduate student	Healthcare / Academia	Virtual

3. Interview Summaries

Employee 1 (E1): AI Engineer Intern, Fintech Startup

E1 was an AI engineer intern at a fintech startup that used AI for stock forecasting and predictive analytics. He worked on two projects: a RAG system and an AI agentic forecasting system using the OpenAI API and Google's Agent Development Kit.

The company was fairly encouraging about AI use (E1 rated it 7 out of 10). There was no formal training program, but E1 had a supportive tech lead who would sit with him for hours when he got stuck, and the company ran a short 2 to 3 day orientation on AI usage guidelines. When the tech lead was busy with other projects, E1 relied on official documentation to figure things out on his own.

Management told E1 to use Google's Agent Development Kit because the company had credits for it, even though E1 would have preferred a different framework like CrewAI. The tool worked okay but had limitations for simulating a crew of financial analysts, which shows a gap between what employees want to use and what the company decides.

Customers responded well to the AI-powered products. Users liked how fast the system was and how it gave data-backed financial advice. Positive feedback from users motivated the team.

> *"It's a correlation between us employees creating something for the users and what the users use... it was a win-win for both of us."* - E1

Employee 2 (E2): Systems Development Engineer, Major Tech Company

E2 is a systems development engineer at a large tech company, working on firewall configurations for fulfillment centers globally. AI is built into every stage of their software development process, from writing code to reviewing, testing, and deploying. E2 said that the engineering role has basically become managing an AI agent rather than writing code yourself.

This company had the most structured approach to AI adoption of anyone we interviewed. Leadership pushes adoption in three ways: tracking AI usage metrics per employee, collecting feedback to improve tools, and continuously simplifying the interface. Over the past year, they went from a complex multi-step setup process (installing plugins, configuring AWS models, connecting workspaces) to a single web page where you just chat with an agent. E2 described how the company built its own IDE by taking all the feedback from employees who were struggling with the earlier setup, and by the time the new tool launched, it was easy enough that no documentation was needed.

Attitudes changed fast. Employees who were skeptical just a few months ago because of hallucination problems now use AI for everything. E2 noted that the concerns were almost entirely about hallucination and code quality, not about moral or job-loss fears. Those fears existed but nobody used them as a reason to resist.

E2 called the company's approach an "invisible feedback loop" where curious employees experiment with new tools, leadership watches what sticks, standardizes it, and rolls it out to everyone. When a tool doesn't work, they're quick to kill it and move on.

On interdependence, E2 initially said he didn't have direct exposure to customer feedback since he works on an internal team. But as he thought about it, he identified a clear pattern: the company beta-tests products with employees before releasing to customers.

> *"[The company] strongly believes that if their employees like the product, then their customers are going to like the product."* - E2

Employee 3 (E3): Product Manager, Major Technology Company
E3 is a product manager at a major technology company who uses AI extensively for reviewing documents, drafting communications, getting summaries of videos and meetings, and staying current on industry developments. As someone for whom English is a second language, she found AI especially helpful for smoothing and professionalizing her written communications.

AI use at her company is strongly encouraged, approaching mandatory. Employees are asked to use AI tools for customer meeting notes, career and performance activities, and document creation. There is no stigma around it. The company offers a large number of internal training workshops, classes, and contests to drive adoption.

E3 said what helped her most was not the formal training itself but seeing examples of how colleagues used AI in practice. Peer demonstrations gave her the confidence to try it herself. She also participated in an internal hackathon specifically for product managers, which gave her a low-stakes environment to experiment with a wider range of tools than she would have tried in her regular work.

When AI was first introduced, everyone was excited. Over time, the excitement faded into normalcy. E3 described the shift not as disillusionment, but as AI becoming an expected, routine part of the workflow. She recalled that early meeting summary tools sometimes hallucinated, inventing action items that were never discussed, but noted this was around two years ago and has since been resolved.

On agency, E3 said she has full independence in deciding how much to rely on AI. Nobody forces her. On customer impact, she noted that the company's enterprise AI products receive positive customer feedback, and hearing that increases internal confidence in the product and motivation to keep improving it.

Employee 4 (E4): Freelance Software Engineer/Web Developer
E4 is a freelance software engineer who previously worked at a company that rolled out AI tools across departments. He uses AI primarily for coding tasks (database migrations, debugging, security implementations) and for preparing for client conversations.

E4 described a clear learning curve. Early on, AI would introduce more bugs than it fixed because he didn't know how to prompt effectively. He had to seek training outside the company on his own because no internal training was provided. Once he learned to write better prompts, the experience improved significantly. He rated his overall experience around 7 out of 10.

At his previous company, leadership encouraged AI use but in a metrics-driven way. They tracked usage rates per employee and required a certain amount of AI use per week to justify the seat licenses, without giving employees much say in how to use it. There was no formal training, just an expectation to use the tools.

The most notable data point from this interview was what happened with the writing team. When AI writing tools were rolled out, several content writers resisted and eventually left the company. Their concern was that AI stripped away their creativity and personal voice, making everything feel cookie-cutter. Those who stayed accepted the tool. On customer impact, E4 said the writing team's customers appreciated the faster content turnaround. But he also described a case where AI chatbots were deployed to collect customer information, and customers pushed back because the chatbots would hallucinate, loop, or fail to properly capture and transmit the data. Some customers said they preferred human interaction for anything beyond simple tasks.

> *"If we feel good about using it, then it seems like the customer also feels comfortable with us using it too. And they feel confident that we know what we're doing with it rather than just using it as an easy shortcut."* - E4

Employee 5 (E5): Data Scientist, Health Tech Company
E5 is a data scientist with four years of experience who worked at a health tech firm using AI to streamline prior authorization in healthcare. This was the only interview where AI adoption was driven bottom-up: employees proposed the integration to leadership rather than the other way around. The team saw that external tools like GitHub Copilot were accelerating development cycles and made a case for adopting similar tools internally.

The company adopted AI through AWS SageMaker's native copilot for model building and later added CodeRabbit, a third-party AI agent on GitHub, for automating pull requests and code management. E5 described a clear increase in efficiency, estimating that AI reduced their overall development time by 60 to 70%.

Leadership was supportive once the tangible impact became visible. The company provided documentation and knowledge transfer sessions to help employees integrate AI into their workflows. However, E5 noted a misalignment between leadership expectations and ground reality: leadership expected immediate results, but the actual process of deploying models in healthcare required careful consideration of data integrity, geographic applicability, and regulatory constraints.

On the question of whether customers were informed about AI changes, E5 said directly: "I don't think any customer is informed about the changes we do in the company." This was the clearest example of internal-only AI communication across all interviews.

E5 described a turning point in the team's AI adoption. Initially, AI output was not usable out of the box because it lacked context about their specific healthcare domain. The team had to create custom markdown instruction files and predefined prompts to guide the AI toward the right kind of output. Once those were in place, productivity improved significantly and the team reached a point where they were satisfied with AI-generated results.

E5 also provided the only clear example of employee pushback that resulted in organizational change: the team was using AWS's AI tools for GitHub operations, but the tool couldn't handle the complexity of their repository structure. They identified the problem, proposed switching to CodeRabbit, and the company adopted it.

On customer impact, E5 noted that another department used AI to improve customer notifications, which led to a measurable increase in click-through rates. Positive customer feedback made the engineering team feel validated in their adoption decisions.

> *"It's better always to educate customers on how to use AI and how AI is used in our platform because that gives them more clarity, it increases the transparency of the company as well and it just builds trust."* - E5 (relaying leadership's position)

Customer 1 (C1): PhD Candidate, Biomedical Informatics

C1 is a PhD candidate who works on AI agents for biomedical discovery. As a customer, C1 had mixed feelings about AI-powered services. AI customer support bots like Amazon's Rufus were appreciated for speed and shorter wait times, but having to go through an AI layer before reaching a human agent was frustrating.

Trust was the biggest theme for C1. He said trust depends on explainability: being able to see citations, reasoning traces, and links that actually work. Broken or hallucinated citations immediately destroy trust. He described AI as something that "hallucinates very confidently" and then only corrects itself when challenged.

For high-stakes situations like healthcare diagnosis or therapy, C1 strongly prefers humans. AI lacks empathy and the hallucination risk is too high when the consequences involve patient safety. He described his own work on a cardiac risk stratification project where AI recommendations determine patient treatment categories, and emphasized that a pilot phase of human review is essential before trusting any AI system.

On the interdependence theme, C1 gave the strongest direct example of how employee competence with AI affects customer trust:

> *"It's very important for the clinician or for me to understand how the system is working internally before we tell a diagnosis to a patient because we do not want to lose a patient's trust."* - C1

Customer 2 (C2): Graduate Student in Data Science
C2 is a first-year graduate student in data science at a major university, also working as a research assistant. He had one of the most technically informed perspectives of any customer we interviewed, which shaped how he evaluates AI systems.

C2 described a clear trust hierarchy based on stakes. For research and factual questions, he trusts AI highly because it cites sources he can verify. For code generation, he cross-checks across multiple LLMs before accepting any output. For legal matters (he described filing taxes using a Sprintax chatbot), he did not trust the AI at all and emailed the human support team instead. For medical questions, he would not trust AI recommendations because the outcome could affect his health.

C2 gave a detailed account of how Amazon's Rufus improved over time. Early on, it could not understand the thematic context of his purchase history (recommending modern products when his home decor theme was antique). It also lacked guardrails, letting him write Python code through a shopping chatbot. By 2025-2026, both issues were fixed. This iterative improvement increased his trust.

On the question of whether he notices employee comfort with AI, C2 described his own workplace: colleagues who lack technical background don't trust their organization's internal LLM and constantly ask others to verify the output, especially for high-impact decisions. This suggests that employee confidence (or lack of it) is visible to those around them and affects the broader team's trust in the system.

C2 was one of two customers who did not surface the interdependence theme directly. When asked whether his AI work touches customers, he said his department doesn't interact with customers directly, and there are multiple layers between them. However, his observations about colleague behavior and trust provide indirect evidence.

Customer 3 (C3): Data Science Student
C3 is a data science student who uses AI daily, primarily Claude for email drafting and Spotify's recommendation algorithm as his go-to example of AI as a customer. He described a clear learning curve in the recommendation system: initially it was poor, but as he liked and listened to more songs, it reached what he estimated as a 90% hit rate.

C3's trust in AI sits at about 75%. He uses it as a drafting tool that saves time but always needs manual review. What builds trust for him is seeing improvement over time: when the AI produces fewer mistakes and better matches his style, trust increases incrementally. He specifically mentioned that release notes and transparency about what's been fixed help build confidence.

On human preference, C3 drew a clear line around data privacy. He would not share sensitive information like a Social Security number with an AI chatbot because he doesn't trust how securely the data is stored. With a human, he feels the information goes directly where it's supposed to, without sitting in a chatbot's database.

C3 gave a strong positive example of AI done right. His internet provider's app diagnosed a router problem automatically by connecting to the network, identified that the router wasn't delivering the subscribed speed, logged a support ticket, and scheduled a replacement, all without him having to speak to anyone.

On interdependence, C3 made a direct and clear connection. He said that when employees are comfortable with AI and know how to use it fully, they make the customer's life easier. He noted that generational differences play a role, and observed that employees sometimes admit they don't know how to use a newly introduced system, which affects customer confidence.

> *"If I myself am an employee and I'm comfortable and I know how to harness the full power of that AI system, I can make the customer's life easier."* - C3

Customer 4 (C4): Recent Graduate with Consulting Background
C4 is a recent graduate with five years of consulting experience. She uses Claude extensively for research, analysis, and productivity, and NotebookLM for synthesizing multiple resources into summaries and podcasts. She described AI as having fundamentally changed how she learns and works.

Her trust in AI has increased significantly over the past year. She used to verify outputs regularly but now trusts them at the surface level, only checking source links for very specific information. What builds trust for her is transparency (seeing where information comes from) and the continuous improvement she observes in model quality over time.

C4 draws a clear line around purchases and financial decisions. When real money is involved, she wants a human in the loop because of three things AI cannot provide: accountability (a face behind the answer), personal understanding (a human reads her expressions and context in real time), and consistency (the same question to an AI can produce different answers on different days).

On whether employee competence with AI matters, C4 made a clear connection. She said employees need to be well-versed with their own product so they can communicate its value to customers. She went further, saying employees should be "a step ahead" of the customer, knowing what's possible beyond basic use cases.

On interdependence, C4 described a feedback loop: when customers have unmet needs, employees who use the product extensively can identify those gaps and improve the tool. She sees the employee and customer experience as directly linked through this cycle.

> *"Use your product, know the value of that product in and out for you to communicate the same to the customer."* - C4

Customer 5 (C5): Biomedical Engineering Graduate Student
C5 is a first-year biomedical engineering master's student. He uses LLMs (ChatGPT, Gemini, Claude) for research and academics, and has interacted with AI chatbots in retail settings. His responses were generally shorter and less detailed than other participants, but provided a contrasting perspective on several key themes.

C5 trusts AI about 70% of the time. His frustration centers on prompting: when he doesn't provide enough context, the output is irrelevant. He also described leaving ChatGPT entirely because extended chat sessions would freeze and become unresponsive, which eroded his trust in the platform.

For high-stakes situations, C5 strongly prefers humans, particularly in healthcare and emergencies. He cited emotional intelligence and the ability to adapt to a situation in real time as things AI cannot replicate. For lower-stakes interactions, he is comfortable with AI. He gave a positive example of Target's price-match chatbot instantly processing a refund without friction, noting that AI is reliable when it follows clear company rules consistently.

C5 raised a unique point that no other participant mentioned: accent and regional speech patterns affecting AI voice bots. He described situations where AI phone bots could not understand his accent, leading to frustrating loops that never resolved his query.

On the direct questions about AI visibility (whether interacting with AI directly versus a human using AI behind the scenes feels different), C5 said there is no difference. He also said that knowing a company uses AI would not change how he feels about them. For him, it comes down to the quality of the experience, not who or what is delivering it.

On interdependence, C5 was the only participant across all 10 interviews to directly say he does not see a connection between how employees use AI and how customers experience it. He views both groups as benefiting from AI simplification independently, without one affecting the other. This dissenting view provides a useful counterpoint to the pattern observed in the other 9 interviews.

4. Emerging Themes Across Interviews

Theme 1: Leadership Role in AI Adoption

Every employee reported some form of organizational encouragement for AI adoption, but the approaches varied significantly. E2's company took the most structured approach: usage metrics tracked per employee, active feedback collection, and iterative simplification of tools. E3's company made AI use approaching mandatory, with extensive training offerings and internal contests. E4's previous company tracked usage and required minimum weekly engagement to justify seat licenses. E1's company was more informal, with a supportive tech lead driving adoption. E5's company represents a unique case where employees drove adoption bottom-up, proposing AI integration to leadership rather than the other way around.

What varied most was the quality of the rollout. E2 and E3's companies invested heavily in making AI easy to use, while E4's company provided no training and left employees to figure it out alone, which led to frustration and eventual departures among the writing team. E5's company fell in the middle, providing documentation and knowledge transfer sessions that were described as effective.

Theme 2: Training and Support

Training quality varied widely and appears to correlate with adoption success. E2's company iteratively reduced the complexity of getting started, going from a multi-step technical setup to a single web interface over the course of a year. E3's company offered extensive workshops, classes, and peer-led demonstrations, though E3 said the most helpful element was seeing colleagues demonstrate real use cases. E5's company provided formal documentation and knowledge transfer sessions that were straightforward. E4 received no formal training and had to seek prompting courses on his own. E1 had no formal program but had a dedicated mentor.

The pattern suggests that training alone is not the key factor. What matters more is reducing friction. E2's company kept simplifying the interface until training became unnecessary. E3's company made peer learning the most effective channel. E5's team had to build custom markdown instruction files to get AI to produce usable output for their healthcare context. All approaches converge on the same principle: the easier the tool is to use in your specific context, the less formal training you need.

Theme 3: Employee Agency and Pushback

Agency ranged from high autonomy (E3) to heavily constrained (E1, E4). E3 said she is fully independent in deciding how much to rely on AI. E2 described a moderate level of agency through the "invisible feedback loop" where curious employees experiment and the company standardizes what works. E5 had meaningful input through team discussions that informed the final adoption proposal. E1 was told which tools to use despite preferring alternatives. E4 was told to hit usage metrics without being given a say in how the tools were applied.

The strongest pushback example came from E4's previous company: content writers who felt AI stripped their creativity and voice left the company rather than accept the tool. This was not a case of employees being heard; they exited. E2's company, by contrast, actively killed tools that received enough negative feedback. E5 provided the clearest example of pushback that resulted in change: his team identified that AWS's AI tools couldn't handle their GitHub workflow, proposed switching to CodeRabbit, and the company adopted it.

Theme 4: Trust and Explainability
Trust was a dominant theme across all customer interviews and several employee interviews. The consistent pattern is that trust varies based on the consequentiality of the task. For low-stakes tasks (researching, drafting emails, getting song recommendations), participants trust AI readily. For high-stakes situations (healthcare, legal, financial decisions, sensitive data), trust drops sharply and participants demand either human oversight or verifiable explainability.

C1 anchored trust in explainability: citations, reasoning traces, and working links. C2 described a stakes-based hierarchy where trust varies by task. C3 quantified his trust at 75% and drew the line at data privacy. C4 said trust has improved over time as model quality has improved, but still needs a human for financial decisions because AI lacks accountability. C5 trusts AI about 70% of the time and raised bias as a concern that companies need to address.

On the employee side, E2 noted that initial distrust was entirely about hallucination, and trust grew as models improved rapidly. E3 recalled early hallucinations in meeting summaries (invented action items) but said it's no longer an issue. E4 described a period where AI introduced more bugs than it fixed, which eroded trust until he learned to prompt more effectively. E5's team had to build custom instruction files before AI output became reliable for their healthcare domain.

Theme 5: Attitude Change Over Time
Every participant described some form of attitude shift. The patterns cluster into four types:

1. **Skepticism to full adoption:** E2 described the most dramatic shift. Employees who doubted AI just months ago now don't write a single line of code manually. The driver was rapid model improvement, not organizational pressure.

2. **Excitement to normalization:** E3 described excitement fading into routine. E5's team started with high expectations, found the output wasn't immediately usable, adjusted their setup, and reached a productive steady state.

3. **Frustration to gradual trust:** C1 was initially frustrated by AI chatbot layers but now appreciates the speed. C2 watched Rufus improve from poor to good over two years. C3 described Spotify improving from poor to a 90% hit rate. C5 left ChatGPT entirely due to freezing issues but continues using other AI tools.

4. **Resistance leading to departure:** E4's company saw content writers leave rather than accept AI tools that stripped their creative voice.

Theme 6: Human Preference for High-Stakes Situations
Every customer and three employees identified situations where humans are necessary. The common thread is consequentiality: when the stakes are high and the outcome matters, participants do not trust AI alone.

C1: healthcare diagnosis and therapy. C2: legal/tax matters and medical scenarios. C3: anything involving sensitive personal data. C4: any situation involving a real financial investment. C5: healthcare and emergency situations, where emotional intelligence and real-time adaptability are needed. E2: production infrastructure (after AI deleted systems when given full permissions). E4: personal client interactions and collecting sensitive customer information.

E5: healthcare model deployment, where data integrity and regulatory compliance require human oversight.
C4 articulated the underlying logic most clearly: humans provide accountability, real-time contextual understanding, and consistency that AI does not. C5 framed it as critical thinking and emotional intelligence.

Theme 7: Employee-Customer Interdependence
The paper's core thesis, that employee and customer AI adoption are interconnected, surfaced in 8 of 10 interviews. Each revealed it through a different mechanism:

E1: Direct feedback loop. Customers liked the AI-powered products. Positive feedback motivated the employee team.
E2: Organizational design. The company treats employees as the first customers. Products are beta-tested internally, refined, and then released externally.
E3: Confidence reinforcement. Positive customer feedback on the company's AI products increases employee confidence and motivation.
E4: Bidirectional signal. When employees feel good about AI, customers sense that competence. When customers pushed back on AI chatbots, it made employees question whether human touch was better.
E5: Indirect quality loop. AI-written code powers customer-facing products. Positive customer metrics (like improved click-through rates on notifications) validated the team's adoption decisions. Leadership emphasized that educating customers about AI use builds trust and transparency.
C1: Trust dependency. Employee competence with AI directly determines patient trust. A clinician who doesn't understand the AI system cannot credibly communicate a diagnosis.
C3: Competence visibility. Customers notice when employees are comfortable versus confused with AI. Employee proficiency translates directly into better and faster service.
C4: Product knowledge cycle. Employees who deeply know their AI product can communicate its value to customers. Customer feedback flows back to employees who use it to improve the product.
C2: Indirect evidence. C2 did not directly connect employee and customer experience but described colleagues who visibly distrust their own internal AI tools and constantly seek verification.
C5: Dissenting view. C5 was the only participant to directly say he does not see a connection between employee and customer AI experiences. He views both groups as benefiting from AI independently.

5. Additional Findings

Beyond the seven core themes, several findings emerged organically across the interviews that are relevant to the paper's framework.

1. Stakes-Based Trust Hierarchy

Trust in AI is not binary. Across all customer interviews, a consistent pattern emerged: trust varies based on the consequentiality of the task. C2 articulated this most clearly by describing a hierarchy where he trusts AI highly for research (because sources are cited), moderately for code generation (cross-checks across multiple LLMs), and not at all for legal or medical matters. C4 draws the line at financial decisions. C3 quantifies trust at 75% but drops it to zero for sensitive personal data. C1 applies strict human oversight for any healthcare decision. C5 trusts AI 70% of the time but won't use it in emergencies.

This suggests that companies cannot build trust in AI with a single strategy. Trust-building needs to be calibrated to the stakes of the interaction, which connects directly to the paper's argument about managing customer adoption differently at each stage of the hype cycle.

2. Cold Start Problem and Iterative Trust

C2 described a cold start problem: AI systems perform poorly when they have no history with a user, and trust only builds as the system learns. He gave a detailed example of Amazon Rufus initially recommending products that didn't match his purchase theme, but improving significantly by 2025. C3 described the same pattern with Spotify, where recommendations went from poor to a 90% hit rate over time. C4 noted that model quality has visibly improved month over month.

This iterative trust-building pattern maps well to the disillusionment-to-enlightenment transition in the paper's framework. Customers who persist through the initial poor experience are rewarded with better AI performance, but some may drop off before reaching that point (as C3 described retreating to saved songs after a single bad recommendation, and C5 abandoning ChatGPT entirely due to freezing).

3. Prompting Skills as a Hidden Training Gap

E4 described a period where AI actively made his work worse because he didn't know how to prompt effectively. Without proper prompting skills, the AI introduced more bugs than it solved. He had to seek training outside the company on his own. E5's team experienced a similar dynamic: AI output was not usable until they created custom markdown instruction files and predefined prompts. C5 noted that getting irrelevant answers when you don't give proper context is his main frustration. This suggests that "reskilling" (Lesson 2) includes learning how to communicate with AI effectively, a fundamentally new skill that most companies don't yet train for.

4. Loss of Professional Identity

E4's account of content writers leaving his previous company reveals a dimension of AI resistance that goes beyond practical concerns like hallucination or job loss. The writers felt that AI stripped away their creativity and personal voice, making their output feel generic. This is a professional identity concern, not a productivity concern. The paper's framework focuses on practical factors (training, agency, expectations), but this finding suggests that identity and creative ownership may also play a role in employee adoption, particularly in roles where the work product is inherently personal.

5. Peer Learning and Low-Stakes Experimentation

E3 said the most effective driver of her own AI adoption was not formal training but seeing colleagues demonstrate real use cases. She also participated in a hackathon specifically designed to get product managers experimenting with AI in a low-stakes environment, separate from their main work. This gave her the freedom to explore tools she wouldn't try on a high-stakes project. The combination of peer demonstration and safe experimentation spaces is a practical approach to the reskilling challenge (Lesson 2) that didn't show up in the paper's original framework.

6. Privacy and Data Security as a Trust Boundary

C3 drew a clear line around data privacy that is separate from accuracy or reliability concerns. He would not share his Social Security number with an AI chatbot regardless of how good the AI is, because he doesn't trust how the data is stored. C2 raised a related point about prompt injection attacks and database exposure, noting that he actively tests chatbot guardrails and loses trust when they are missing. These concerns are distinct from the trust/explainability theme and suggest that data security is its own dimension of customer trust that companies need to address separately.

7. Bottom-Up Adoption

E5's company represents a unique adoption pattern not seen in the other employee interviews. Rather than leadership rolling out AI tools top-down, employees identified the opportunity, discussed it in standups, and proposed the integration to leadership. This bottom-up model resulted in strong buy-in from the start because employees felt ownership over the decision. It also meant the adoption was calibrated to what the team actually needed rather than what leadership assumed would be useful.

8. Accent and Accessibility Bias in AI Interfaces

C5 raised a point no other participant mentioned: AI voice bots struggle with accents and regional speech patterns, creating frustrating loops where the customer's query is never understood. This is an accessibility and inclusion concern that extends beyond the paper's current framework but is relevant to the argument about tangible customer benefits (Lesson 3): if AI systems cannot serve customers with diverse linguistic backgrounds, the "benefit" is unevenly distributed.

Managerial Toolkit for AI Adoption and Leadership

1. Diagnostic Checklist (Where are we?)

Managers can use the following checklist to identify their organization's current stage of AI adoption. Assign **1 point** for each statement that applies to the organization. Add the points within each stage. The stage with the highest score indicates the organization's most likely current stage. If two stages receive similar scores, the organization may be in transition between stages.

A. Hype Stage (Early adoption / inflated expectations)

- Senior leaders have communicated internally that AI is a strategic priority.
- The organization has launched multiple AI pilots within the past 6–12 months.
- Employees are encouraged to experiment with AI even when formal use cases are not yet defined.
- The organization has not yet established clear criteria for evaluating AI project success.
- Employees do not have clear guidance on which tasks are appropriate for AI use.
- Customers try AI-enabled services out of curiosity rather than because they see clear value in them.

B. Disillusionment Stage (Reality check / adoption friction)

- At least one major AI initiative has failed to meet its initial expectations.
- Some AI pilots have been paused, abandoned, or deprioritized after initial testing.
- Employees report that AI tools add work rather than reduce work.
- Employees avoid using AI tools even when those tools are available.
- AI use has created workflow problems that have not yet been resolved.
- Customers question the value of AI-enabled services or express frustration with them, rather than treating them as useful.

C. Productivity Stage (Stabilization / value realization)

- Senior leaders have moved from broad AI enthusiasm to prioritizing specific AI use cases.
- The organization has established repeatable AI use cases that are used in regular operations.
- AI projects have clear criteria for evaluating success.
- AI tools reduce work or improve work quality in specific tasks.
- Employees have clear guidance on which tasks are appropriate for AI use.
- Customers use AI-enabled services because they see clear value in them.

2. Stage-Specific Actions

A. Hype Stage

Managing Employees

- Set realistic expectations about what AI can and cannot do.
- Explain that AI adoption will involve learning curves, errors, and workflow adjustment.
- Provide structured onboarding rather than relying on informal experimentation.
- Clarify which tasks should be completed with AI assistance and which should be completed without AI assistance.
- Set designated exploration time (even 30 min a week) to encourage employees to use and test AI themselves and share findings with colleagues.

Managing Customers

- Avoid promising seamless or transformative AI-enabled experiences too early.
- Communicate the specific customer problems that AI is meant to solve.
- Introduce AI first in low-risk, reversible customer touchpoints.
- Explain when customers are interacting with AI and what human support remains available.

Managing Employee-Customer Interdependence

- Ensure employees can explain AI use to customers in simple, credible terms.
- Prepare employees to acknowledge AI limitations without undermining customer trust.

- Monitor whether employee confidence or confusion affects customer reactions to AI.
- Hold routine Voice of the Customer (VoC) meetings where employees can share customer product experiences with new AI products, including successes and pain points.
- Avoid full automation in customer-facing interactions before both employees and customers are ready.

B. Disillusionment Stage

Managing Employees
- Invest in targeted reskilling so that employees can integrate AI into their daily roles.
- Provide practical resources for addressing recurring problems with AI-generated outputs, such as hallucinations, inaccuracies, or low-quality outputs.
- Redesign workflows so AI use reduces work rather than adding extra steps (set go/no go thresholds to decide whether its use is adding value to an existing workflow).
- Allow employees to decide when AI-generated outputs are usable, when they require revision, and when the task should be handled through human judgment alone.
- Provide simple, accessible formats for employees to give feedback on AI tools and workflows.

Managing Customers
- Acknowledge AI-related errors, inconsistencies, or disappointments directly.
- Shift messaging from novelty to reliability, usefulness, and concrete benefits.
- Provide clear fallback options, including human support or hybrid service channels.
- Offer clear explanations of how AI improves the customer experience.
- Provide options for giving feedback (whether through an employee directly or a post use/purchase survey).

Managing Employee-Customer Interdependence
- Recognize both customers and employees will have different knowledge/comfort levels in relation to AI, processes may need to be adjusted to account for these differences.
- Take employee AI feedback seriously, it will serve as an early indicator of where customers will likely experience friction with AI.
- Diagnose whether the AI adoption problems come from employee readiness, customer trust, or misalignment between employee use of AI and customer expectations of AI.
- Ensure that employee use of AI improves the customer experience rather than simply increasing internal efficiency.
- Use customer feedback to identify where employees need additional training or workflow support.
- Prevent employee frustration from becoming visible to customers during service interactions.

C. Productivity Stage

Managing Employees
- Use employees' experience with AI to identify recurring workflow problems and prioritize improvements.
- Turn proven AI practices into standard workflow steps, templates, or guidelines.
- Give employees formal channels to suggest updates to AI-related workflows, training, or review standards.

Managing Customers
- Emphasize the tangible value customers receive from AI, such as speed, personalization, reliability, or lower cost.
- Make AI-enabled services easy and affordable enough for repeated use.
- Normalize AI as part of the service experience without making AI itself the main selling point.
- Tailor AI exposure based on customer preferences, comfort, and task complexity.

Managing Employee-Customer Interdependence
- Scale configurations that create value for both employees and customers.
- Use employee feedback to improve customer-facing AI applications.
- Use customer feedback to refine employee training, workflows, and AI prompts.
- Maintain feedback loops so employee expertise and customer usage patterns jointly improve AI performance.

3. Key Metrics

A. Employee-Side Metrics

- AI usage frequency: Percentage of employees using approved AI tools weekly or monthly.
- Breadth of AI use: Number of distinct tasks for which employees use AI, such as drafting, summarizing, analysis, coding, or customer support.
- Task efficiency: Average time required to complete AI-assisted tasks compared with non-AI-assisted tasks.
- Output quality: Error rates, revision rates, supervisor ratings, or quality-audit scores for AI-assisted work.
- AI competence: Employees' self-rated confidence in using AI for role-specific tasks.
- AI reliance calibration: Percentage of AI-assisted outputs that employees accept as-is, revise, or reject.
- Employee experience: Survey ratings of whether AI makes work easier vs. harder, more meaningful, or more frustrating.
- Resistance indicators: Rates of nonuse, workaround behavior, complaints, or requests to avoid AI-enabled workflows.

B. Customer-Side Metrics

- Customer satisfaction: Satisfaction ratings after interactions involving AI.
- Perceived service quality: Customer ratings of accuracy, speed, clarity, personalization, and helpfulness.
- Trust in AI-enabled services: Customer ratings of whether the AI-enabled service feels reliable, transparent, and safe.
- AI-related complaint rate: Share of customer complaints involving AI errors, confusing responses, lack of transparency, or difficulty reaching a human, tracked over time.
- Repeat usage: Percentage of customers who use the AI-enabled service again after an initial interaction.
- Channel preference: Percentage of customers choosing AI, human, or hybrid service options when given a choice.
- Fallback demand: Percentage of customers who request a human after starting with AI.
- Customer value perception: Customer ratings of whether the AI-enabled service saves time, improves decisions, or makes the experience easier.

C. Interdependence Metrics

- Employee–customer alignment: Compare how often employees use AI for specific tasks with how comfortable customers are with AI being used for those same tasks.
- Customer response to AI-assisted employees: Ratings of employee competence, credibility, and helpfulness when AI is used.
- Service consistency: Differences in satisfaction, accuracy, or complaint rates across AI-assisted, human-only, and hybrid interactions.
- Escalation patterns: Frequency of AI-to-human transitions and satisfaction after escalation.
- Employee explanation quality: Customer ratings of whether employees clearly explain AI use.
- Business outcomes by interaction type: Conversion, retention, revenue, or renewal rates for AI-assisted, human-only, and hybrid interactions.

4. Common Mistakes to Avoid

Managers should also be aware of common mistakes that can undermine AI adoption across stages.

A. Mistakes in Managing Employees

- Treating AI adoption as a technology rollout rather than a workflow change.
- Assuming employees will know how to use AI effectively without structured training.
- Encouraging AI use broadly without clarifying which tasks are appropriate for AI assistance.
- Measuring adoption only by usage rates rather than by whether AI improves work quality, efficiency, or employee experience.
- Ignoring employee frustration when AI tools add extra steps, create rework, or reduce perceived autonomy.
- Expecting employees to trust AI outputs without giving them authority to revise, reject, or escalate those outputs.

B. Mistakes in Managing Customers

- Promising seamless or transformative AI-enabled experiences before the organization can reliably deliver them.

- Making AI itself the selling point rather than explaining the specific customer problem it solves.
- Assuming customers value AI-enabled services simply because they are novel or technologically advanced.
- Failing to disclose when AI is involved in customer-facing interactions.
- Removing human support too quickly, especially for complex, emotional, or high-risk customer needs.
- Treating customer complaints about AI as resistance to innovation rather than as diagnostic feedback.

C. Mistakes in Managing Employee–Customer Interdependence

- Optimizing AI for internal efficiency while ignoring how customers experience the resulting service.
- Training employees to use AI without preparing them to explain AI use to customers.
- Assuming employee adoption and customer acceptance will move at the same pace.
- Scaling AI-enabled services before both employee workflows and customer expectations are aligned.
- Using separate employee-side and customer-side metrics without examining whether improvements on one side create problems on the other.
- Treating AI adoption as complete once the tool is implemented, rather than maintaining feedback loops between employees, customers, and managers.