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Restoring Service Quality and Trust in AI Enabled Bank Customer Service: A Case Study of Digital Transformation Misalignment

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ABSTRACT: This paper examines how the implementation of artificial intelligence (AI) in bank customer service contributed to declining service quality and customer trust despite achieving operational cost savings. The case involves a large bank that reduced labor costs by 19% after deploying AI enabled customer service, yet experienced a 300% increase in customer complaints and a 9% loss of customers. The purpose of this paper is to evaluate the organizational causes of the failed digital transformation and recommend evidence-based strategies for improving service quality and restoring customer trust. A narrative literature review was conducted using research on AI in service operations, service quality, trust in automation, digital transformation, service recovery, and organizational change. The analysis found that the bank overrelied on automation, failed to align AI capabilities with customer needs, and lacked sufficient governance and human escalation processes. The paper applies the Balanced Scorecard, Kotter's Eight Step Process, and Saldanha's Digital Transformation Discipline to interpret the case and develop recommendations. The findings suggest that AI creates greater value when it supports rather than replaces human employees and when organizations balance efficiency with customer experience, governance, and trust. This paper contributes practical recommendations for leaders seeking to implement AI responsibly while improving long term organizational performance and customer relationships.

KEYWORDS: Artificial Intelligence, Customer Service, Digital Transformation, Service Quality, Trust

Introduction

The case concerns a large bank that introduced artificial intelligence into customer service operations in order to reduce labor expense and improve efficiency. The immediate operational outcome appeared positive because personnel costs declined by 19%. The broader organizational outcomes, however, moved in the opposite direction. Customer complaints increased by 300%, and the bank lost 9% of its customers over a 12 month period. Those outcomes suggest that the initiative was not merely a difficult technology rollout. It represented a deeper digital transformation failure in which a cost reduction logic displaced customer value, service quality, and trust preservation. In banking, customer service is not peripheral to performance. It is a core mechanism through which customers judge competence, fairness, responsiveness, and institutional reliability. When service channels break down, customers often interpret that failure as evidence that the institution itself is difficult to trust (Parasuraman et al., 1988; Verhoef et al., 2021).

Current research shows that artificial intelligence can create value in service environments when leaders match the technology to the task, preserve clear escalation routes, and integrate the system into a broader service strategy rather than treating it as a stand alone replacement for labor (Huang & Rust, 2018; Jarrahi, 2018; Davenport &

Ronanki, 2018). Scholars also show that customer response to AI depends heavily on context. Customers are more comfortable with automated systems when their needs are routine, structured, and low in emotional intensity. Satisfaction declines when the interaction requires empathy, reassurance, discretion, or the interpretation of nonstandard problems (Glikson & Woolley, 2020; Eren, 2021). In banking, many customer contacts involve fraud alerts, billing disputes, denied transactions, identity verification issues, and anxiety about money. For that reason, a service design that emphasizes automation without service recovery capability can undermine both operational performance and customer relationships. The case therefore reflects a broader pattern in digital transformation research in which firms adopt advanced tools quickly but fail to align them with customer experience, governance, and organizational readiness (Saldanha, 2019; Vial, 2019).

Problem Statement

The central problem in the case is a misalignment between the bank's AI enabled service design and the actual conditions necessary for effective banking service delivery. Leadership pursued lower personnel costs and apparently assumed that AI could absorb a large share of frontline customer interactions without materially reducing service quality. That assumption is weakly supported by the service literature. AI is generally more effective in repeatable tasks governed by clear rules, while humans remain more effective when interactions require interpretation, emotional regulation, exception handling, or relational repair (Huang & Rust, 2018; Raisch & Krakowski, 2021). The case evidence suggests that the bank moved too far toward substitution and not far enough toward augmentation. As a result, the service model likely increased customer effort, slowed resolution of nonroutine issues, and made it harder for dissatisfied customers to reach someone capable of resolving the problem.

A second problem involves governance failure. The bank seems to have treated AI deployment as an operational implementation project rather than as a strategic transformation requiring enterprise oversight, cross functional ownership, and customer centered performance controls. Saldanha (2019) argues that digital transformation often fails when organizations focus on isolated technology installation instead of developing the discipline, sequencing, and alignment needed to produce lasting value. The complaint surge and customer losses indicate that the bank likely monitored internal efficiency more carefully than external service outcomes. In other words, the organization captured the labor savings while failing to control the customer experience risks created by over automation.

The goals in addressing the problem are therefore broader than simply lowering complaint counts. The bank must restore service quality, reduce unnecessary customer effort, rebuild trust, improve retention, and redesign the AI enabled service model so that automation supports the relationship instead of degrading it. The bank also must establish governance processes that evaluate AI not only by speed and cost, but also by resolution quality, fairness, escalation effectiveness, and downstream customer behavior. A research based response should identify the organizational causes of the failure, evaluate the risks of continuing with the current service design, and recommend a more sustainable hybrid model grounded in service management, change management, and digital transformation literature.

Purpose Statement

The purpose of this paper is to evaluate the causes and risks underlying the bank's failed AI based customer service transformation and to develop an evidence based recovery strategy. To accomplish that purpose, the paper positions the case within the literature on service quality, AI in service operations, trust in automation, service failure and recovery, digital transformation, and organizational change. The paper also applies one planning model, one change management model, and one digital transformation framework to interpret the case and guide practical recommendations for the bank's recovery effort.

Significance Statement

This issue is significant because AI enabled customer service has become a common transformation strategy across financial services and other industries. Banks, insurers, retailers, and healthcare organizations are using conversational agents, decision support tools, and workflow automation to reduce costs and extend service availability. Yet the literature consistently warns that efficiency gains do not automatically translate into better service outcomes. Poorly designed AI service systems can increase friction, weaken trust, intensify perceptions of unfairness, and encourage customer exit when the organization restricts access to meaningful human assistance (Luo et al., 2019; Glikson & Woolley, 2020; Jenneboer et al., 2022). Because banking relationships often depend on confidence, continuity, and risk reduction, service failures in this sector can produce outsized strategic harm.

The consequences of not addressing the problem are substantial. Continued dependence on a flawed AI service model could increase attrition, reduce wallet share, damage brand credibility, and heighten regulatory scrutiny if vulnerable customers are systematically denied effective assistance. The issue is also significant for employees and managers. Frontline staff may inherit more complex, emotionally charged escalations without adequate tools, while leaders may normalize a false narrative of success because cost savings remain visible even as customer value deteriorates (Saldanha, 2019). This case therefore matters not only as a bank service problem, but also as an example of how digital transformation can fail when efficiency is decoupled from customer experience, organizational learning, and trust.

A final point from the literature is that banking magnifies the consequences of service misalignment because customers often interpret service quality as evidence of institutional soundness. In many consumer categories, a poor chatbot experience is frustrating but limited. In banking, the same experience can trigger concern about security, fairness, and the firm's willingness to help when money is at risk. That is why the bank's 9% customer loss is not surprising. Customers do not simply compare features and prices. They compare who appears dependable in stressful moments. Once a bank becomes associated with obstruction rather than support, the relationship is vulnerable to exit, especially in a market where digital alternatives can simplify switching. This banking context strengthens the argument that customer service transformation must be treated as a strategic trust function rather than as a back office efficiency project.

Literature Review

AI in Service Operations

Research on AI in service operations consistently shows that automation is most valuable when it is matched to the structure and complexity of the task. Huang and Rust (2018) explain that service work contains multiple forms of intelligence, including mechanical, analytical, intuitive, and empathetic dimensions. Artificial intelligence is generally strong in mechanical and analytical domains, such as rapid data retrieval, standardized classification, and repetitive decision support. Human agents remain stronger where service depends on contextual interpretation, empathy, relational judgment, and adaptive reasoning. That distinction is highly relevant to the present case. Banking interactions often appear simple at the surface level but quickly become complex because customers arrive with uncertainty, stress, incomplete information, or combined problems that cross billing, security, and policy boundaries. A service design that routes too many of these interactions through AI risks creating a mismatch between the channel and the need.

Larivière et al. (2017) describe service as a system in which technologies, employees, and customers jointly co create value. From that perspective, technology should not automatically be understood as a replacement for human labor. It can support, mediate, and reshape interactions in ways that either enhance or weaken service outcomes depending on how the full service system is designed. The bank case suggests that technology was positioned as a substitute rather than as a complement. Such substitution can be tempting because labor savings are immediately measurable, but service recovery capacity, customer reassurance, and relational continuity are harder to quantify in the short term. When those softer capabilities are removed or weakened, the service system becomes brittle.

Wirtz et al. (2018) similarly argue that customer acceptance of AI based service depends on whether the technology fits the social and functional expectations of the encounter. Customers judge automated service channels not only on speed, but also on competence, social capability, privacy assurance, and reliability. Banking customers in particular are likely to be sensitive to security, accuracy, and continuity because errors can involve direct financial consequences. When an automated system fails in such a context, the failure is not experienced as a minor inconvenience. It is often interpreted as organizational indifference or incompetence. This helps explain why complaint volume can increase sharply even when average handling time or staffing cost appears to improve.

Banking specific studies reinforce this concern. Eren (2021), examining chatbot use in a banking application, found that satisfaction is shaped by perceived usefulness, ease of use, trust, and the ability of the system to support customer goals without introducing unnecessary friction. Those findings align with the present case because they suggest that the success of AI in banking depends on more than availability. Customers must perceive the tool as both competent and trustworthy. If the system imposes effort, misreads intent, or traps customers in repetitive loops, satisfaction falls and the bank’s broader reputation can suffer. Jenneboer et al. (2022) reach a similar conclusion in their systematic review, noting that service quality, information quality, and system quality are foundational to customer loyalty outcomes in chatbot environments. In other words, always on access does not create loyalty by itself. What matters is whether the interaction actually helps the customer.

Service Quality and Customer Experience

The service quality literature provides a strong interpretive lens for the case. Parasuraman et al. (1988) identify reliability, responsiveness, assurance, empathy, and tangibles as core dimensions of perceived service quality. In digital service settings, tangibles are translated into interface quality and channel usability, while the remaining dimensions remain highly relevant. A flawed AI service channel can reduce reliability if the customer receives inaccurate answers, reduce responsiveness if the customer is delayed in reaching a solution, reduce assurance if the system appears incapable of handling sensitive issues, and reduce empathy if the interaction feels dismissive or mechanical. In the bank case, the simultaneous increase in complaints and attrition suggests a breakdown across several of these dimensions rather than a single isolated weakness.

More recent research extends service quality into AI mediated interactions. Araujo (2018) shows that design cues and communication framing influence how customers interpret conversational agents and, by extension, how they evaluate the company deploying them. If the chatbot appears too human without delivering human level understanding, disappointment can intensify because the design has raised relational expectations that the system cannot meet. Crolic et al. (2022) add that anthropomorphic chatbot designs can amplify customer anger when failures occur because customers react more strongly when the bot appears socially present but still fails to help. That finding is particularly relevant for banks, where many customers are already emotionally activated before contact begins. A poorly performing AI interface can turn an inconvenient moment into a trust damaging episode.

Customer effort is another important factor. Although the case does not explicitly measure perceived effort, the rise in complaints strongly suggests that customers encountered friction in obtaining resolution. Service research consistently shows that customers penalize firms when they have to repeat information, navigate confusing menus, or make multiple attempts to solve the same issue. In AI service environments, these burdens can accumulate quickly when systems lack contextual memory, accurate intent recognition, or graceful transfer to human agents. The result is not only dissatisfaction with the individual interaction but also a broader belief that the organization values efficiency over customer needs. That perception is especially harmful in banking, where customers expect security and care during moments of uncertainty.

The case also raises issues of service recovery. Belanche et al. (2020) found that customers attribute responsibility differently depending on whether a service outcome was produced by a human employee or an automated agent. Research by Leo and Huh (2020) and Ryoo et al. (2024) deepens this pattern by showing that when a robot or automated agent fails, customers often blame the firm more than the technology because they view the system as an organizational choice rather than an independent actor. This means that failed automation can produce stronger spillover damage to the brand than a comparable error by a frontline employee. For the bank, this has direct strategic implications. Every failed AI interaction is not merely a local service miss. It is evidence to the customer that the bank designed a poor service system and is therefore responsible for the resulting frustration.

Trust in AI and Customer Acceptance

Trust is central to the adoption and sustained use of AI. Glikson and Woolley (2020) show that trust in artificial intelligence is context dependent and shaped by perceived competence, transparency, fairness, and the nature of the task. Users are generally more willing to trust AI in analytical or calculation based tasks than in socially complex or emotionally sensitive tasks. Bank customers may therefore accept AI for tasks such as balance checks, routing requests, or transaction status inquiries, while resisting AI in settings involving disputes, fraud claims, hardship explanations, or policy exceptions. The case suggests that the bank did not adequately differentiate between these categories of work and may have pushed customers into automated channels even when human judgment and reassurance were essential.

Dietvorst et al. (2015) demonstrate algorithm aversion, the tendency for people to reject algorithmic systems after witnessing an error, even when the system performs well on average. That concept is particularly useful in explaining the bank's complaint and attrition problem. In consumer services, customers do not evaluate AI in the abstract. They evaluate the channel through vivid experiences. A single failed fraud interaction or unresolved billing dispute can become the defining memory of the service channel and motivate channel avoidance, negative word of mouth, or exit. Logg et al. (2019) complicate the picture by showing that people can also display algorithm appreciation when they perceive the algorithm as especially competent. Together, these studies imply that customer response to AI is contingent rather than fixed. Customers will accept AI when it clearly works for the task, but they will withdraw trust quickly when the system proves unreliable or obstructive.

The literature on artificial empathy is also informative. Liu Thompkins et al. (2022) argue that firms are increasingly attempting to bridge the human AI gap through designs that simulate understanding, warmth, and social sensitivity. Huang and Rust (2024) extend that discussion by proposing an AI enabled customer care journey in which emotion recognition, empathetic response, and emotional support become central elements of customer care. These frameworks suggest that AI in service cannot be evaluated solely on transaction efficiency. In customer care settings, especially when the service failure itself produces stress, customers want to feel understood. In the bank case, it is unlikely that a cost driven deployment sufficiently addressed the emotional architecture of banking service. Without credible signs of understanding, customers may interpret the bank's AI channel as cold, indifferent, and designed primarily to keep them away from human help.

Luo et al. (2019) further demonstrate that disclosure and identity matter. When customers know they are interacting with a chatbot, they may lower expectations about empathy and nuanced understanding, which can reduce positive outcomes if the firm has not carefully designed the exchange. This does not mean firms should hide AI. Rather, it means transparency must be paired with competence, clarity, and an obvious path to human escalation. When those elements are missing, disclosure can confirm the customer's fear that the firm has substituted a lower quality channel for meaningful service.

Impact on Key Organizational Constituencies

The impact of the topic on key organizational constituencies is substantial. For customers, the most immediate harms include delayed problem resolution, increased effort, lower trust, and perceived loss of control. In banking, these harms can be amplified by the emotional significance of the underlying issue. A customer who cannot quickly resolve a fraudulent transaction, account freeze, or payment problem may experience stress that goes beyond ordinary dissatisfaction. If the AI channel appears incapable of understanding urgency or context, the service failure becomes personal. The literature on loyalty and customer experience suggests that such failures can translate rapidly into churn because switching barriers in many retail banking contexts are lower than firms assume, especially when digital competitors offer smoother support experiences (Jenneboer et al., 2022; Verhoef et al., 2021).

Employees are also affected. AI does not remove service complexity; it often redistributes it. When automated channels handle the easy work, the remaining calls reaching human agents tend to be the most complicated and emotionally charged. Raisch and Krakowski (2021) describe this dynamic as part of the automation augmentation paradox, in which AI can simultaneously automate some work while increasing the importance and difficulty of human work. If the bank reduced staffing while escalating the complexity of the cases handled by remaining employees, the result may have been heavier cognitive load, more difficult service recovery tasks, and greater emotional strain on frontline staff. Those conditions can further reduce service quality if employees are rushed, undertrained, or forced to correct errors created upstream by the AI system.

Leadership and management teams face a different but equally important challenge. If leaders privilege labor savings and automation rates over trust, retention, and resolution quality, they may misread declining customer experience as an acceptable tradeoff rather than as a strategic warning sign. The literature on digital transformation repeatedly warns against this form of metric distortion. Vial (2019) and Saldanha (2019) both emphasize that transformation changes value creation, not just process efficiency. When leaders focus on easily observed internal efficiencies while neglecting external customer outcomes, they can unintentionally reinforce poor decisions and delay corrective action.

Organizational culture is another constituency level concern. AI deployments send cultural signals about what the organization values. A bank that makes human help difficult to reach may communicate that efficiency is more important than care. Over time, that message can influence employee norms, managerial priorities, and customer expectations. Wilson and Daugherty (2018) argue that the most effective AI systems are collaborative rather than purely substitutive. In cultural terms, that means organizations should frame AI as a way to support better service and better work, not simply as a mechanism for labor reduction. The case suggests that the bank's service culture may have tilted toward mechanistic efficiency at the expense of relational quality.

Digital Transformation and Organizational Failure

Digital transformation research helps explain why the initiative produced negative results despite its apparent technological sophistication. Vial (2019) defines digital transformation as a process through which digital technologies provoke significant changes in how organizations create value, structure work, and engage stakeholders. That definition makes clear that transformation is not the same as installing a new tool. A bank that introduces AI into customer service is changing how customers experience the institution, how employees perform service work, how decisions are escalated, and how value is judged. The present case indicates that the bank digitized the frontline channel without fully redesigning the surrounding service system.

Verhoef et al. (2021) similarly stress that digital transformation requires firms to address technology, organizational capabilities, customer behavior, and business model implications together. Focusing narrowly on internal efficiency while ignoring the customer response to transformed interactions is likely to produce partial and unstable outcomes. In the present case, the firm improved one internal metric while worsening several external ones. That pattern strongly suggests the absence of a balanced transformation logic. The bank appears to have operationalized AI adoption as a productivity move instead of as a coordinated redesign of customer experience and service governance.

Saldanha (2019) provides the most direct explanation of the bank's failure. He argues that organizations often mistake local digital implementation for true transformation and often declare victory too early because an initiative has gone live or has produced an initial financial gain. The bank likely experienced exactly that trap. Once the AI system was deployed and staffing costs declined, leadership may have interpreted the initiative as successful, even though the more meaningful indicators of service performance were moving in the wrong direction. Saldanha also warns against fragmented ownership. Transformations fail when no one integrates technology decisions with customer outcomes, employee workflows, and business strategy. The present case suggests weak integration across those domains.

Davenport and Ronanki (2018) support a measured interpretation of the case. They argue that AI can be powerful, but organizations create value only when they apply it to clearly defined problems and redesign surrounding processes instead of assuming that technology alone will transform performance. In customer service, that means rethinking routing logic, knowledge management, workforce design, exception handling, and service recovery. The bank's failure therefore does not indicate that AI in banking customer service is inherently flawed. It indicates that the bank adopted AI without adequate organizational redesign and performance discipline.

A Relevant Planning Model: Balanced Scorecard

The Balanced Scorecard is a relevant planning model for the case because it forces strategic balance across financial, customer, internal process, and learning and growth perspectives (Kaplan & Norton, 1996). The bank's current outcome profile shows what happens when the financial perspective dominates. Labor cost reduction improved, but complaint volume and churn increased. A Balanced Scorecard approach would not allow leadership to interpret the initiative as successful unless financial gains occurred alongside acceptable customer and process outcomes. This makes the model especially suitable for transformation settings where visible internal gains can obscure external damage.

Under the financial perspective, the bank would still monitor cost to serve, productivity, and service channel economics. Under the customer perspective, however, it would also track satisfaction, trust, complaint rate, first contact resolution, escalation success, and retention. Under the internal process perspective, it would evaluate AI containment accuracy, misrouting rate, repeat contact frequency, average time to human escalation, and recovery effectiveness after failed automated interactions. Under learning and growth, it would assess employee training, digital literacy, governance maturity, and the quality of customer feedback loops. Viewed through this model, the present initiative would have been identified as strategically imbalanced much earlier. The Balanced Scorecard therefore offers both a diagnostic lens and a practical governance mechanism for the bank's recovery effort.

A Change Management Model: Kotter's Eight Step Process

Kotter's Eight Step Process is an appropriate change management model because the case reflects a technology rollout that was not fully managed as organizational change. Kotter (1996) emphasizes the need to create urgency, form a guiding coalition, develop a clear vision, communicate the vision broadly, remove barriers, generate short term wins, consolidate gains, and anchor the change in culture. In the bank case, there is little evidence that leaders built an organization wide vision of improved customer service supported by AI. The observable evidence points instead to an efficiency narrative centered on reduced personnel cost. That narrative is too narrow to mobilize employees around sustainable service change.

The model is valuable because it highlights several likely omissions. First, the bank may not have created the right kind of urgency. A transformation framed primarily around cost reduction does not create meaningful commitment among frontline teams responsible for preserving customer trust. Second, the bank may not have built a cross functional coalition involving customer service leaders, technology teams, risk personnel, and customer experience stakeholders. Third, communication may have emphasized new tools rather than new service principles. When those steps are missing, employees can experience confusion, reduced buy in, and limited willingness to surface problems early. In customer service settings, such omissions are costly because the frontline must interpret and manage failure in real time.

Kotter's model also underscores the importance of short term wins that are aligned with the true purpose of the change. In this case, the wrong early win may have been celebrated. Personnel cost reduction was visible, but the initiative should have been judged by improved customer outcomes such as faster resolution, reduced effort, and preserved trust. Proper use of Kotter's framework would have pushed the bank to pilot the AI system in narrow service categories, gather feedback, refine escalation rules, and scale only after evidence showed that the new model improved rather than degraded customer experience. That staged approach would likely have reduced the size of the failure.

A Digital Transformation Theory: Saldanha's Digital Transformation Discipline

Saldanha's digital transformation discipline serves as the most fitting digital transformation theory for the case because it directly addresses the organizational tendencies that appear to have driven failure. Saldanha (2019) argues that firms must develop disciplined capabilities around transformation sequencing, enterprise alignment, and sustained execution. They must also avoid false finish lines in which leaders mistake deployment for genuine transformation success. The bank's experience exemplifies this warning. The technology was implemented and a cost metric improved, but the actual transformation of customer service capability was negative.

Applied to the case, Saldanha's framework suggests several deficiencies. The initiative appears to have lacked enterprise alignment because service strategy, customer experience, and operational control were not tightly integrated. It also appears to have lacked disciplined scaling, because the AI channel seems to have affected service broadly before the organization had validated its impact on trust and resolution quality. Finally, it appears to have lacked a transformation operating discipline capable of recognizing that worsening complaints and churn meant the initiative was off course. Saldanha's theory is valuable because it reframes the case away from technology enthusiasm and toward managerial responsibility. The central question is not whether AI can serve customers. The central question is whether the bank designed, governed, and scaled AI in a disciplined way that protected customer value.

Taken together, the literature reveals a coherent explanation for the case. AI can improve service when it is used in tasks that fit its capabilities, embedded in a hybrid service architecture, governed by balanced metrics, and implemented through disciplined organizational change (Huang & Rust, 2018; Kaplan & Norton, 1996; Kotter, 1996; Saldanha, 2019). The bank appears to have violated each of those conditions. It likely overextended AI into interactions requiring empathy and contextual judgment, treated cost savings as a sufficient signal of success, underdeveloped escalation and recovery capacity, and failed to manage the initiative as a customer centered transformation. The case therefore represents a predictable organizational outcome rather than an isolated anomaly. The literature strongly supports a recovery strategy centered on task fit, hybrid service design, stronger governance, staged change management, and intentional trust rebuilding.

Methods

This paper uses a narrative literature review. A narrative review was appropriate because the purpose of the assignment is interpretive and advisory rather than statistical. The task is to explain the organizational dynamics reflected in the case, connect the case to prior scholarship, and identify evidence based strategies for recovery. A narrative approach supports analytical integration across multiple streams of literature, including AI in service operations, chatbot use in banking, service quality, trust in automation, service failure and recovery, digital transformation, and change management. It also allows conceptual and empirical sources to be combined in a way that is appropriate for consulting oriented case analysis.

Searches focused on peer reviewed research and scholarly books located through Google Scholar and ProQuest, with supplemental retrieval of highly cited practitioner oriented works that are widely used in digital transformation and management discussions. The core keywords included artificial intelligence, AI customer service, chatbot, conversational agent, banking, service quality, customer trust, customer effort, service failure, service recovery, digital transformation, organizational alignment, change management, and customer loyalty. Boolean search strings included artificial intelligence AND customer service; chatbot AND banking AND trust; AI AND service failure AND customer satisfaction; digital transformation AND service quality; banking AND conversational agent AND customer experience; algorithm aversion AND service; and change management AND digital transformation.

The inclusion strategy prioritized sources that met four conditions. First, the source had to be directly relevant to the case topic, meaning that it addressed AI enabled service, service quality, trust, service failure, digital transformation, or change management in organizational settings. Second, preference was given to peer reviewed journal articles published in established management, marketing, information systems, psychology, or service journals. Third, classic conceptual works were included when they remained foundational to the case analysis, such as SERVQUAL, the Balanced Scorecard, and Kotter's change model. Fourth, sources were selected when they offered either empirical findings, widely used conceptual frameworks, or practical strategic insight applicable to the case.

The exclusion strategy removed sources focused solely on technical model engineering, coding, or computational performance without clear organizational implications. Non scholarly commentary, blog posts, and trade content without clear analytical value were excluded. Sources centered on sectors or use cases too far removed from customer service or digital transformation were also excluded unless they offered generalizable theory directly relevant to trust, service failure, or organizational change. After screening for relevance and duplication, 27 sources were retained for review and integration in the paper. That total exceeds the minimum assignment expectation of 25 articles and sources and provides a sufficient base for a case centered synthesis.

The reviewed sources were analyzed for recurring themes rather than for effect size aggregation. The main themes that emerged were task fit, hybrid service design, customer trust, perceived effort, responsibility attribution after service failure, balanced transformation governance, and the need for structured organizational change. Those themes informed both the literature review and the recommendations section. This approach is consistent with a narrative review design in which the goal is to organize evidence into a coherent explanatory framework for advising the focal organization.

Recommendations

The first recommendation is to redesign the customer service model as a hybrid architecture rather than a predominantly substitutive AI channel. AI should be reserved for routine, low ambiguity, and low emotional intensity tasks such as balance inquiries, status checks, password resets, branch information, and basic routing. Customers facing disputes, fraud concerns, payment problems, hardship issues, account restrictions, or repeated failed attempts should be transferred rapidly to trained human representatives. This recommendation follows the literature on task fit and augmentation, which shows that AI creates the most value when its strengths are matched to structured work and when humans remain available for contextual judgment and empathy (Huang & Rust, 2018; Jarrahi, 2018; Raisch & Krakowski, 2021). The redesign should include explicit trigger rules for escalation, not vague discretionary guidelines. For example, two failed intent recognitions, negative sentiment, security related topics, or repeated contacts within a short period should automatically move the customer to a human channel.

The second recommendation is to replace the current success logic with a Balanced Scorecard based governance model. The bank's transformation appears to have been judged largely through labor savings, which created strategic distortion. The bank should instead track performance through four linked perspectives. Financial metrics should include cost to serve and channel productivity. Customer metrics should include complaint volume, customer satisfaction, customer effort, trust indicators, first contact resolution, complaint recurrence, and churn. Internal process metrics should include misclassification rates, transfer quality, repeat contact frequency, time to escalation, and service recovery effectiveness after failed bot interactions. Learning and growth metrics should include employee readiness, AI governance maturity, quality assurance audits, and the speed with which customer feedback produces design change (Kaplan & Norton, 1996). A balanced metric system would make it far harder for leaders to misinterpret a harmful initiative as a success.

The third recommendation is to launch a structured recovery effort using Kotter's change framework. Leadership should openly recognize that the service model did not achieve the intended customer outcomes and should create urgency around trust restoration rather than around labor reduction alone. A cross functional coalition should be formed that includes leaders from customer service, operations, digital product, risk, compliance, data science, and customer experience. That coalition should define a revised service vision in which AI is used to improve access and consistency while preserving human judgment for complex interactions. The bank should pilot revised workflows in selected service categories before scaling them across the enterprise. Short term wins should be defined as measurable improvements in customer satisfaction, resolution quality, and reduced complaint recurrence, not simply lower staffing cost (Kotter, 1996). This change process must also include frontline training so employees know how to work with the AI channel, interpret escalation data, and recover customer trust after failed automated interactions.

The fourth recommendation is to establish stronger AI governance and quality assurance. Governance should include routine audits of bot performance, frequent review of complaint transcripts, periodic testing of intent recognition, analysis of failed containment episodes, and formal executive accountability for service outcomes. The bank should also create thresholds that trigger immediate intervention, such as sudden spikes in complaint categories, abnormal repeat contact patterns, or high attrition among customers who recently used the AI channel. Governance cannot stop at technical accuracy. It must evaluate customer impact, including whether the system increases effort, discourages vulnerable customers, or delays urgent issue resolution. Transparent disclosure should remain in place, but it should be paired with clear statements about when and how human support is available. Research on trust in AI shows that transparency helps only when it is combined with competence, fairness, and credible safeguards (Glikson & Woolley, 2020; Liu Thompkins et al., 2022; Huang & Rust, 2024).

The fifth recommendation is to develop a formal service recovery strategy for AI failures. The bank should not assume that an apology message generated by the bot is sufficient. When an automated interaction fails, the customer should be transferred to a human representative with conversation history intact so that the customer does not have to restate the problem from the beginning. Human agents should be empowered to acknowledge the failed experience, resolve the issue quickly, and where appropriate provide compensation or fee reversal. The bank should also analyze AI related failures as a distinct category of service failure, because research shows that customers often blame the firm more strongly when the failure originates in an automated channel selected by management (Belanche et al., 2020; Leo & Huh, 2020; Ryoo et al., 2024). A robust recovery process can reduce churn because it signals that the organization takes responsibility for its digital design choices rather than hiding behind the technology.

The sixth recommendation is to rebuild customer trust intentionally through communication, design changes, and channel accessibility. Trust will not recover automatically once the system is technically improved. Customers who have experienced bot related frustration may still avoid the service channel because of algorithm aversion and negative memory effects (Dietvorst et al., 2015). The bank should communicate that the service model has been redesigned based on customer feedback, that human help is easier to reach, and that the AI channel is intended to support convenience rather than block access. The bank should also avoid overstating the emotional capabilities of the bot. Artificial empathy should be used carefully and credibly. Research suggests that when firms over humanize AI without delivering corresponding competence, anger can intensify after failure (Crolic et al., 2022; Huang & Rust, 2024). The better path is to design the AI channel as helpful, clear, and respectful while ensuring that emotionally complex situations transition to capable human staff.

The final recommendation is to treat this case as a transformation learning event rather than as a narrow channel problem. The bank should conduct a post implementation review that examines the original business case, assumptions about customer acceptance, staffing decisions, escalation logic, vendor configuration choices, and governance gaps. Lessons from that review should be codified into a standard transformation playbook for future AI initiatives. Such a playbook should require task fit analysis, pilot testing, stakeholder review, risk assessment, escalation design, balanced metrics, and staged scale up before enterprise deployment. This recommendation is grounded in digital transformation literature showing that disciplined learning and enterprise alignment are essential if organizations want digital initiatives to create lasting value rather than temporary efficiency gains followed by strategic harm (Saldanha, 2019; Verhoef et al., 2021; Vial, 2019).

The evidence presented in this paper demonstrates that the bank's customer service challenges resulted from the way artificial intelligence was implemented rather than from the technology itself. Although the organization achieved short term labor cost savings, those gains were accompanied by substantial increases in customer complaints and customer attrition, indicating that the broader digital transformation failed to preserve service quality and customer trust. The literature consistently shows that AI is most effective when it complements human expertise, supports tasks that align with its capabilities, and operates within a framework of strong governance and organizational change.

The recommendations presented in this paper emphasize a hybrid service model, balanced performance measurement, stronger AI governance, structured change management, and intentional service recovery. Together, these findings reinforce the importance of aligning AI implementation with customer needs, organizational strategy, and long-term trust. Organizations that achieve this alignment are more likely to realize the benefits of artificial intelligence while sustaining customer satisfaction, organizational performance, and lasting customer relationships.

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